CLIMATE CHANGE AND AGRICULTURAL SYSTEM RESPONSE

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CLIMATE CHANGE AND AGRICULTURAL SYSTEM RESPONSE

Topic Editors:
Dingde Xu, Sichuan Agricultural University, China
Qirui Li, University of Bayreuth, Germany
Shaoquan Liu, Institute of Mountain Hazards and Environment, Chinese Academy of Sciences (CAS), China
Li Peng, Sichuan Normal University, China

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Impact of Agricultural Mechanization on Agricultural Production, Income, and Mechanism: Evidence From Hubei Province, China

Jiquan Peng, Zihao Zhao and Dingning Liu*

School of Economics, Jiangxi University of Finance and Economics, Nanchang, China

Increasing agricultural operating income is not only an important step in improving agricultural work for farmers in the new era, but is also a powerful way to promote rural revitalization. To improve our understanding of the high-quality development of agriculture in China, the factors limiting agricultural income and the impact of the level of agricultural mechanization on agricultural production and income and its mechanism were analysed. Based on field survey data on farmers, this study analysed the influence of agricultural mechanization level on agricultural production and income by utilizing a sample-modified endogenous merging model and a threshold effect model. The level of mechanization has a significant positive impact on the cost, output value, income and return rate of all types of crops. For every 1% increase in the level of mechanization, the yields of all crops, grain crops and cash crops increase by 1.2151, 1.5941 and 0.4351%, respectively. Heterogeneity analysis shows that the level of mechanization has a certain threshold effect on income, with a greater effect occurring after the threshold. A test of action mechanism shows that the mechanization level can increase income via a factor intensification path and quality improvement path, with the partial mediation effects of the two paths being 28.8 and 27.4%, respectively. It is recommended to increase subsidies to purchase agricultural machinery, research and promote machinery suitable for cash crops, increase the level of socialized agricultural services, and improve the ability of farmers to apply novel agricultural machinery and tools so as to increase their operating profits.

Keywords: agricultural mechanization level, agricultural production, agricultural income, ivtobit model, threshold effect model

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Edited by:
Dingde Xu,
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Reviewed by:
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Fangting Xie,
Jiangxi Agricultural University, China
Fang Su,
Shaanxi University of Science and Technology, China

****Correspondence:***
Jiquan Peng
pengjiquan@jxufe.edu.cn

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1 INTRODUCTION

As China's agriculture is moving towards a high-quality development stage, it is necessary to focus on improving the quality and efficiency of agricultural production (Huang, 2021). For many years, the limited income obtainable from agriculture has greatly dampened the enthusiasm of agricultural labourers. Although agricultural subsidies, a protective minimum grain price and other relevant policies have guaranteed the income of agricultural workers to a certain extent, they have also aggravated the problems of inverted food prices at home and abroad and weak international competitiveness of agricultural products (Gao and Wang, 2021). For example, according to The National Data Collection of Cost and Income of Agricultural Products 2009, the average output of the top three grains (rice, wheat and corn) in 2008 was 11891.4 yuan per hectare and its average total cost was 9006.15 yuan per hectare. Hence, the net profit was 2885.25 yuan per hectare, a cost profit rate of 32.04%. Ten years later in 2018, according to The National Agricultural Product Cost and Income.

Data Collection 2019, their average output value was 16175.4 yuan per hectare, the average total cost was 16633.35 yuan per hectare, the net profit was−457.95 yuan per hectare, and the cost profit rate was−2.75%. Hence, the net profit of grain has changed from positive to negative in the past 10 years, and agricultural operating income has been continuously compressed, mainly because the rate of growth in agricultural production costs has been much higher than that of output value. China's present agricultural development situation clearly shows that there is still much agricultural modernization that can be achieved (Peng et al., 2016; Jiang and Zhang, 2017). In the future, small farmers will still be the basic units of China's agricultural production and operation. Only by strengthening the connection between small farmers and modern agriculture can we achieve better agricultural modernization (Luo, 2020). Therefore, while improving the quality and efficiency of agricultural development, it is also necessary to continuously improve the confidence and enthusiasm of agricultural workers by increasing their income, which is also the basic aim of China's rural revitalization strategy. The fundamental reason for the backwardness of China's agriculture and rural modernization lies the low use of agricultural machinery, which inhibits the improvement of agricultural production efficiency and leads to unreasonable agricultural production structure and poor circulation of agricultural products market. This series of problems will inevitably affect the pace of agricultural modernization. Therefore, to accelerate the process of agricultural modernization in China, it is necessary to improve the agricultural technology adoption rate of farmers, especially the use of agricultural machinery, so as to improve agricultural production efficiency, create more agricultural surplus economy, increase the possibility of farmers' market participation, and than promot high-quality agricultural development.

2 LITERATURE REVIEW AND THEORETICAL ANALYSIS

2.1 Related Literature Review

The issue of agricultural operating income has always attracted much attention. Previous studies have mainly explored ways to improve agricultural operating income in the following aspects: 1) Agricultural land use. The loss of productivity due to land fragmentation will cause declines in agricultural profits (Lu and Hu, 2015; Wang and Tan, 2020). Increasing the scale of operation can reduce the cost of agricultural production and, thus, increase income (Zhang et al., 2018). Some scholars have tried to increase agricultural income by transferring land to expand the scale of farms (Xu et al., 2020; Yang et al., 2021). Peng et al. (2021a) found that land transfer can effectively lower agricultural production costs. Chen et al. (2014) found that the exogenous land transfer model has greater agricultural benefits than the endogenous land transfer model. Some scholars believe that land transfer cannot increase agricultural operating income but will instead reduce it due to excessively high turnover fees (Cai et al., 2015). 2) Input of factors of production. Sound agricultural infrastructure can promote the utilization of agricultural factors and income (Zeng and Li, 2015; Li et al., 2016). The availability of rural public goods and agricultural machinery can alleviate declines in operating income caused by rural aging (He et al., 2016; Yao et al., 2021). In addition, the use pesticides, agricultural films, fertilizer and division of labor also affect the agricultural per unit yield (Xiao et al., 2015; Yang and Liu, 2021; Ragasa and Chapoto, 2017), output value and profit, thereby affecting income.

3) Macro policies and institutions. She et al. (2013) found that the land transfer policy can increase the income of farmers, enterprises and the government. Zhou et al. (2017) found that policy subsidies are the main reason for the competitive price advantage of American sorghum. Liu and Wu (2019) found that inappropriate institutional arrangements lead to misallocation of agricultural land resources and reduced agricultural returns. Liu (2020) believes that collective ownership can provide equal land security for collective members, but that long-term contract relationships increase the intergenerational land interest inequality of farmers. Other perspectives also exist; for example, Chen (2019) found that the human capital of farmers increases agricultural operation income, while Lei et al. (2021) found that the internet increases the operating income of such farmers.

There has also been much research on the impact of agricultural machinery on agricultural production (Deng et al., 2020), which has two main aspects: cost savings and improvements in quality and efficiency. Firstly, rising labour costs are an important cause of the decline in agricultural profitability (Li et al., 2017). The service price of agricultural machinery is generally lower than labour costs (Tian et al., 2020). Farmers using agricultural machinery can significantly reduce labour costs (Yao, 2009; Luo and Qiu, 2021). Furthermore, agricultural machinery can perform land levelling and land preparation, which effectively improve the utilization rate of agricultural resources and reduce the need for weed and insect pest control (He et al., 2018; Nam et al., 2021). In addition, agricultural mechanization can also carry out combined fertilization and sowing, which not only ensures sowing accuracy but also reduces the cost of seeds and fertilizer (Liu and Zhou, 2018).

The second aspect is to improve quality and increase efficiency. Such improvements mainly include increased agricultural production and product quality. Agricultural machinery can perform the functions of levelling, land preparation, deep turning and deep scarification (Aslan et al., 2007), which can improve land quality better than the traditional manual and livestock operation methods, especially in the transformation of medium- and low-yield fields (Zhou et al., 2019; Peng and Zhang, 2020). Agricultural machinery can increase the degree of multiple cropping of cultivated land to provide the potential for multiple crop cycles per year, thus improving production capacity and land output rates (Peng et al., 2020; Ji et al., 2021). Mechanical irrigation and drainage, dry farming machinery and mechanical spraying can effectively mitigate risks such as drought, floods, weeds and insect pests (Berdnikova, 2018). Mechanical sowing and field management can make crop distributions more uniform and promote growth (Hu and Zhang, 2018), while the use of standardized agricultural machinery can reduce agricultural losses and improve product quality (Qu et al., 2021). In addition, the scale of land is an important factor restricting the adoption of agricultural machinery. The larger the operating area of farmers, the higher the Frontier of production, and the greater the role of agriculture in boosting agricultural output and increasing income (Chen, 2015).

Moreover, some studies have shown that the use of agricultural mechanization has an important impact on high-quality agricultural development of agriculture. Liu et al. (2021) used the improved EBM model to measure and analyze the spatial and temporal evolution characteristics of agricultural equipment allocation efficiency in China, and found that the regional differences in agricultural equipment allocation efficiency were obvious, with central and eastern regions of China being higher than the national average and western regions consistently lower than the national average. The high-quality development of agriculture requires continuous improvement of the allocation efficiency of agricultural machinery and equipment, promoting cross-regional coordination and cooperation, and give play to the radiation-driven role of high-efficiency provinces and regions. Chen and Zhang (2021), Xu and Song (2021) believe that strengthening the promotion of advanced agricultural machinery technology is one of the ways to increase the level of green and high-quality agricultural development. Peng et al. (2020) found that agricultural mechanization can improve the level of comprehensive agricultural development by optimizing the agricultural planting structure. Tang et al. (2018) found that the use of agricultural machinery can reduce agricultural production losses, thereby reducing agricultural production costs and promoting the high-quality agricultural development.

There is abundant research on agricultural operating income, some from the perspective of agricultural machinery use. However, it has the following shortcomings. First, although the macro-level data used in existing research can estimate overall agricultural operating income, it is not conducive to analyze its mechanisms. For this, finer-scale farmer household data is more useful. Second, there are different scopes of research on agricultural operating income. Most scholars use indicators of output, output value, income and rate of return, and it is difficult to obtain a complete picture of agricultural operating income by such one-sided analyses. Furthermore, existing analyses do not consider the different effects of agricultural machinery efficiency on cash and food crops. Third, there may be measurement errors in previous analyses, and the threshold effects related to operational scale have not been considered. Based on this, this paper uses data from 1,116 farmers in Hubei Province, China, and IVTobit and threshold models to analyse the impact and mechanisms of agricultural mechanization on agricultural production and income. This provides a reference for the development of agricultural mechanization and income in China.

2.2 Theoretical Analysis and Research Hypothesis

2.2.1 Factor Intensification Path

The use of agricultural machinery can enhance the utilization rate of agricultural factors and reduce the cost of various agricultural production (Peng et al., 2020). The combined tillage technology with subsoiling as the main part is adopted in the field preparation before sowing, which can replace the traditional operations such as turning, harrowing, ridge raising, stubble planing, and base fertilizer application with only one mechanical operation, thus saving agricultural tools and labor input costs (He et al., 2018). Mechanical precision sowing technology is adopted in sowing process, which can effectively save seeds and reduce seed cost (Li et al., 2021). The use of mechanical deep fertilization technology in the fertilization process can apply the fertilizer required for crop production in a fixed proportion, quantitative, fixed position, fixed depth and fixed level to the plough layer soil, so as to avoid the waste of chemical fertilizer application (Ning et al., 2018). In addtion, higher quality seeds can lead to lower pesticide costs and obtain higher agricultural yields, as well as reduce environmental pollution and lower land restoration costs (Lu, 2014).

2.2.2 Quality Improvement Path

The functions of agricultural machinery for leveling the ground, deep ploughing and deep loosening can improve the quality of the land more than the traditional human and animal work, thereby maximizing the agricultural output (Zhou et al., 2019). Moreover, the land management area will affect the use of agricultural machinery, so that there are differences in the income increase of mechanical technological progress in different management areas (Peng J.Q. and Zhang L.G, 2020). The function of scrambling for planting and harvesting of agricultural machinery will promote the repeated planting of cultivated land and improve the comprehensive agricultural production capacity and land yield rate (Ji et al., 2021). Furthermore, agricultural machinery has the function of resisting disasters such as droughts and floods, weeds and pests, and mechanical seeding and field management can make crops evenly distributed and grow well (Hu and Zhang, 2018). Standardized agricultural machinery operation can also reduce agricultural losses and improve product quality (Li et al., 2019). Agricultural machinery harvesting also allows early access to markets for agricultural products and higher agricultural yields at higher prices, thereby increasing agricultural operating income and contributing to poverty reduction (Peng et al., 2019). Based on the above theoretical analysis, this paper proposes the following research hypothesis:

Hypothesis 1: Agricultural mechanization can improve agricultural production and income.

Hypothesis 2: Agricultural mechanization has a threshold benefit on agricultural production and income, and has a greater impact on the agricultural operation income of various crops after the threshold.

Hypothesis 3: Agricultural mechanization may promote agricultural production and income through the factor intensification path and the quality improvement path.

3 MATERIALS AND METHODS

3.1 Sample and Data Source

We used data from a field survey of households in Hubei Province conducted in 2018. The survey obtained the basic information of the household, its natural and physical assets, production and operating conditions, land transfer behaviour, and farmers' knowledge of policy. The research site was in Jianli and Qichun counties of Hubei Province, China, the terrain of the above two counties includes plains, hills and mountains, basically covering all the terrain and crop varieties of Hubei Province. The level of agricultural mechanization in these two counties is 66.75%, which is basically consistent with the comprehensive mechanization level of cultivation, seeding and harvesting of major crops announced in Hubei Province, indicating that these two counties can represent the production of agriculture in Hubei Province to a certain extent. This survey adopted the method of random sampling to select the survey objects, involving 44 villages in 11 towns. There were 26 households investigated in each village, making a total of 1,144 households. After 28 invalid questionnaires were removed, a total of 1,116 valid samples were obtained.

3.2 Definition of Variables

3.2.1 Agricultural Operating Income

In this paper, agricultural operating income refers to the income obtained by farmers by cultivating land. It is mainly measured by the amount of income and rate of return, which are calculated by the net income per hectare and rate of return per hectare, respectively. In order to understand the structure of agricultural operating income sources, the output value and cost of agriculture were also investigated, which were calculated from the average agricultural output per hectare and the average agricultural cost per hectare, respectively. At the same time, considering the different influences of agricultural machinery on different crops, we also considered grain crops and cash crops separately.

3.2.2 Agricultural Mechanization Level

Researchers often measure the level of agricultural mechanization in terms of the total power of the machinery or its net value. These indicators are suitable for measuring the level of agricultural mechanization at the regional level but not at the farmer level. For this, it is more appropriate to use the calculation method of the Ministry of Agriculture and Rural Affairs, which is the weighted average of the machine farming rate, machine seeding rate and machine harvesting rate (with weights of 0.4, 0.3 and 0.3, respectively) at the farmer level (Peng et al., 2021b). This index is not only easy to obtain but is also more accurate in measuring the machinery usage behaviour of farmers.

3.2.3 Control Variables

Education level per household member (Xu et al., 2019a). Families with higher education are better at improving their operating income via the rational allocation of resources. Average age of the family labour force (Xu et al., 2019b). Agriculture is highly technical and requires experience, such that labourers with rich experience in farming gain greater benefits. Percentage of unhealthy people. Unhealthy people reduce the effective supply of family labour and also affect agricultural investment and income due to their high medical expenses. Average working hours of migrant workers. More time taken to travel to work reduces farming time and affects agricultural income (Liu et al., 2014). Area of farmland. More cultivated land resources allow greater economic benefits from agriculture. Farmland transfer-out area. The more land is transferred out, the lower the economies of scale. Proportion of farmland irrigation. More effectively irrigated farmland allows greater production and better management. Proportion of greenhouse area. As a form of protected agriculture, greenhouses can mitigate environmental risks and guarantee crop production, thereby guaranteeing income. Type of terrain. Plain areas provide better production and operating conditions than other areas, resulting in higher income.

3.3 Descriptive Statistical Analysis

Table 1shows the descriptive statistics of each variable, the total output value of agriculture is higher than the total agricultural cost, and the cost of cash crops is much higher than the cost of grain crops. The output value of grain crops is much higher than the output value of cash crops, which makes the profit and rate of return of grain crops higher than those of cash crops. The level of agricultural mechanization is 66.75%, which is slightly lower than the comprehensive mechanization level of major crops reported for Hubei Province in 2018. The mean education level per household member is 6.3 years, indicating that most rural households have a low education level. The mean age of the family labour force is 40 years, indicating that the current rural labour force is generally comprised of older people. The mean percentage of unhealthy people is 12.73%, which is a significant proportion. The mean working hours of migrant workers is 49 days with a large standard deviation, which indicates that there are large differences in labour force allocation among households. The average farmland area is 0.375 hm^2, and the average transfer-out area is 0.027 hm^2. The average proportion of farmland irrigation is 35.83%, indicating that the effective irrigated area still needs to be improved. The average proportion of greenhouse area is 0.1, which indicates that built-up agriculture is not yet popular in rural areas. The mean terrain type value is 0.33, indicating that 1/3 of the sample was in a plain area. The mean level of household savings is 9.429, indicating that the average savings of each family is 12,444 yuan.

3.4 Model

The model used to investigate the impact of agricultural mechanization on income can be written as:

$$Y_{\mathrm{i}} = \alpha_0 + \beta_0 x_i + \sum \delta_i C_i + \mu_i, \tag{1}$$

Where i denotes farmers and Y_i is an explanatory variable that includes the cost, output value, profit and rate of return per hectares for the total crop, grain crop and cash crop. x_i refers to

TABLE 1 | Descriptive statistics of the data used in this study.

Variable (units)	Description	Mean	SD	Min	Max
Total cost (yuan)	Total cost of agriculture (actual value takes the logarithm)	7.686	1.084	0	11.51
Grain crops cost (yuan)	Cost of grain crops (actual value takes the logarithm)	3.757	2.904	0	10.80
Cash crops cost (yuan)	Cost of cash crops (actual value takes the logarithm)	3.929	1.333	0	10.11
Total output (yuan)	Total output value of agriculture (actual value takes the logarithm)	8.376	0.902	0	13.22
Grain crops output (yuan)	Output value of grain crops (actual value takes the logarithm)	4.239	1.471	0	12.18
Cash crops output (yuan)	Output value of cash crops (actual value takes the logarithm)	4.137	3.661	0	12.41
Total profit (yuan)	Total profit of agriculture (actual value takes the logarithm)	0.690	2.957	0	1.64
Grain crops profit (yuan)	Profit of grain crops (actual value takes the logarithm)	0.482	1.471	0	1.18
Cash crops profit (yuan)	Profit of cash crops (actual value takes the logarithm)	0.208	3.316	0	1.06
Total return rate	Total agricultural rate of return (total profit divided by total cost)	0.181	0.146	0	0.23
Grain crops return rate	Rate on return of grain crops (grain crop profit divided by cost)	0.128	0.513	0	0.15
Cash crops return rate	Rate of return on cash crops (cash crop profit divided by cost)	0.053	0.163	0	0.11
Machine	Level of agricultural mechanization (sum of machine harvesting rate × 0.4, machine seeding and farming rates × 0.3)	0.668	0.202	0	1
Education (years)	Education level per household member (total years of education divided by number of household members)	6.335	2.555	0	13.50
Age	Average age of family labour force (total age of labour force divided by number of labourers)	40.193	9.860	14.29	64.67
Healthy	Percentage of unhealthy people (unhealthy people divided by number of householders)	0.127	0.272	0	1
Migrant (days)	Average working hours of migrant workers (total working hours divided by number of householders)	49.02	2.140	0	240
Land (hm^2)	Area of farmland (actual value)	0.375	3.931	0	1.633
Transfer (hm^2)	Transfer-out area of farmland (actual value)	0.027	1.730	0	1
Irrigate	Proportion of irrigated farmland (effective irrigated area divided by total farmland area)	0.358	0.425	0	1
Facility	Proportion of greenhouse area (greenhouse area divided by farmland area)	0.101	1.024	0	1
Terrain	Type of terrain (1 = plain; 0 = non-plain)	0.335	0.472	0	1
Village mechanization	Level of agricultural mechanization at the village level (actual value)	0.670	0.028	0.55	0.75
Income (yuan)	Level of household savings (actual value takes the logarithm)	9.429	1.358	0	11.51
Factor	Utilization rate of agricultural factors (agricultural output divided by agricultural cost)	1.199	0.783	0	5.81
Price (yuan)	Average price of agricultural products (actual value)	1.186	0.798	0	5.5

the level of agricultural mechanization, C_i is a control variable, μ_i is random perturbation term, and α_0, β_0 and δ_i are parameters to be estimated.

There may be a mutual, causal, endogenous relationship between the level of agricultural mechanization and income. Increased mechanization may increase returns, which gives farmers more capital to use machinery. In addition, some unobservable economic variables at the village level may also affect farming income, leading to the problem of model endogeneity due to omitted variables. This article adopts the instrumental variable method to solve this problem. In **Eq. 2**, the endogenous variable is $machine_i$, and the first stage of estimation by two-stage least-squares (2SLS) is:

$$machine_i = \gamma_1 Z_i + \gamma_2 C_i + \varepsilon_i, \tag{2}$$

Where Z_i is a set of instrumental variables and ε_i is a random error term.

In this paper, two instrumental variables are selected. One is the level of household savings. As the use of agricultural machinery costs money, households with more savings are better able to use it, and household savings do not affect agricultural income. therefore, the level of household savings satisfies the requirement of exogeneity of the instrumental variable. The second is the level of agricultural mechanization at the village level. When micro-level data analysis is adopted, data aggregated at the regional level can be used to calculate the instrumental variables of the model (Cadr and Krueger, 1996; Staiger and Stock, 1997). This paper used the level of agricultural mechanization at the village level as the instrumental variable. Generally speaking, this variable will not affect the income of a single family, but may affect the probability of a single farmer using agricultural machinery. When the level of agricultural mechanization in the village is high, individual farmers have greater probability of using agricultural machinery. thus, the level of mechanization at the village level also satisfies the exogeneity of the instrumental variables.

Considering that there are more instrumental variables than endogenous ones, it is necessary to carry out over-identified tests and weak instruments tests on the instrumental variables used in this model to ensure their validity.

A Tobit model was also used to solve the problem of sample selection bias that may appear in the model. Its expression is as follows:

$$Y_i^* = \alpha_0 + \beta_0 x_i + \sum \delta_i C_i + \mu_i, \tag{3}$$

$$\begin{cases} Y_i = Y_i^*, & if\, Y_i^* > 0 \\ Y_i = 0, & if\, Y_i^* \le 0, \end{cases} \tag{4}$$

To ensure that the real impact of the level of mechanization on operating income can be estimated, it is necessary to solve both the endogeneity and sample selection bias problems mentioned above. For this, a sample-corrected 2SLS estimation method, the

TABLE 2 | OLS estimation of the impact of agricultural mechanization level on agricultural cost and output value.

Variable	Total cost	Grain crop cost	Cash crop cost	Total output	Grain crop output	Cash crop output
	(1)	(2)	(3)	(4)	(5)	(6)
Machine	0.323***	0.273***	2.183***	1.813***	4.737***	1.597***
	(0.063)	(0.518)	(0.518)	(0.445)	(0.324)	(0.403)
Education	−0.033***	−0.031**	−0.042*	0.071*	0.096***	0.068
	(0.006)	(0.015)	(0.022)	(0.039)	(0.033)	(0.044)
Age	−0.003***	−0.001	−0.027**	0.015*	0.016**	0.015*
	(0.001)	(0.004)	(0.010)	(0.008)	(0.007)	(0.009)
Healthy	0.240***	0.252**	0.307	−0.698*	−1.062***	−0.604**
	(0.053)	(0.117)	(0.434)	(0.377)	(0.331)	(0.293)
Migrant	0.014**	0.009	0.037*	-0.072*	-0.092**	-0.033
	(0.006)	(0.012)	(0.020)	(0.037)	(0.044)	(0.047)
Land	−0.002***	−0.002**	−0.015**	0.021***	0.022**	0.021**
	(0.001)	(0.001)	(0.007)	(0.005)	(0.011)	(0.010)
Transfer	0.014**	0.005	0.160**	−0.120***	−0.196***	−.119***
	(0.007)	(0.014)	(0.075)	(0.024)	(0.024)	(0.019)
Irrigate	−0.146***	−0.215***	−1.558***	1.379***	1.125***	0.389**
	(0.0375)	(0.057)	(0.373)	(0.369)	(0.315)	(0.176)
Facility	−0.023***	−0.024**	−0.243***	0.393***	0.544***	0.338**
	(0.008)	(0.011)	(0.073)	(0.106)	(0.088)	(0.155)
Terrain	−0.725***	−0.684***	−0.870**	0.477*	1.834***	0.280
	(0.039)	(0.183)	(0.372)	(0.265)	(0.233)	(0.211)
Constant	5.237***	4.132***	5.517***	2.367***	5.214***	1.682***
	(0.195)	(0.656)	(0.072)	(0.520)	(0.439)	(0.566)
R^2	0.086	0.136	0.098	0.142	0.398	0.078

****, **, and * denote significance at the 1, 5 and 10% levels, respectively.*

TABLE 3 | OLS estimation of the influence of agricultural mechanization level on agricultural profit and rate of return.

Variable	Total profit	Grain crop profit	Cash crop profit	Total return rate	Grain crop return rate	Cash crop return rate
	(1)	(2)	(3)	(4)	(5)	(6)
Machine	1.597***	2.079***	1.476***	0.364**	0.389***	0.279**
	(0.403)	(0.327)	(0.562)	(0.155)	(0.040)	(0.110)
Education	0.071*	0.074**	0.066*	0.0124**	0.014***	0.010**
	(0.039)	(0.030)	(0.037)	(0.006)	(0.001)	(0.005)
Age	0.015*	0.017***	0.014*	0.013***	0.020***	0.012***
	(0.008)	(0.006)	(0.008)	(0.002)	(0.001)	(0.002)
Healthy	-1.062***	-1.186***	-0.919**	-0.168**	-0.121***	-0.111*
	(0.331)	(0.253)	(0.407)	(0.076)	(0.009)	(0.062)
Migrant	−0.092**	−0.114***	−0.014	−0.025**	−0.030***	−0.020*
	(0.044)	(0.038)	(0.053)	(0.011)	(0.002)	(0.011)
Land	0.021***	0.032***	0.011**	0.005*	0.005**	0.003***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.001)	(0.001)
Transfer	−0.110***	−0.210***	−0.082***	−0.015**	−0.020***	−0.013*
	(0.024)	(0.024)	(0.027)	(0.007)	(0.001)	(0.008)
Irrigate	1.125***	1.515***	1.010**	0.197***	0.207***	0.114*
	(0.315)	(0.323)	(0.496)	(0.061)	(0.039)	(0.062)
Facility	0.393***	0.546***	0.250***	0.067***	0.124**	0.065***
	(0.106)	(0.109)	(0.029)	(0.018)	(0.057)	(0.023)
Terrain	1.834***	2.017***	1.008***	0.228***	0.285***	0.015**
	(0.233)	(0.281)	(0.185)	(0.056)	(0.056)	(0.007)
Constant	0.787**	2.367***	0.682**	0.710***	0.810***	0.348***
	(0.392)	(0.520)	(0.304)	(0.140)	(0.018)	(0.119)
R2	0.142	0.186	0.081	0.098	0.408	0.072

****, **, and * denote significance at the 1, 5 and 10% levels, respectively.*

sample-corrected endogenous merging model (IVTobit), can be used with the following steps:

In the first stage, the residual term $\hat{\omega}_i$ is estimated using the Tobit model with Y_i as the dependent variable and C_i and Z_i as the independent variables. Then, it is brought into **Eq. 1** to obtain:

$$Y_i = \alpha_0 + \beta_0 x_i + \sum \delta_i C_i + \beta_1 \hat{\omega}_i + \varphi_i, \tag{5}$$

In the second stage, the 2SLS regression of **Eq. 5** with Z_i as the dependent variable is a non-zero sample, and the required estimated parameters can be obtained.

4 EMPIRICAL RESULTS

1. Benchmark Regression of the Impact of Agricultural Mechanization Level on Agricultural Operating Income

To analyse the impact of agricultural mechanization level on agricultural operating income in detail, this paper set dependent variables from a cost-benefit perspective. The dependent variables in columns 1) to 3) in **Table 2** are total agricultural cost, grain crop cost and cash crop cost, and the dependent variables in columns 4) to 6) are total agricultural output value, grain crop output value and cash crop output value, respectively. The dependent variables in columns 1) to 3) in **Table 3** are total agricultural profit, total grain crop profit and total cash crop profit, and the dependent variables in columns 4) to 6) are total agricultural rate of return, rate of return of grain crops and rate of return of cash crops, respectively.

The cost-regression model indicates that the level of agricultural mechanization has a significant positive impact on all types of agricultural costs, indicating that increases in mechanization increase the cost of production, with the increase in the cost of cash crops being the greatest. Each unit increase in the level of agricultural mechanization increases the costs of grain and cash crops by 0.273 and 2.183 units, respectively. The possible reason is that the more complicated operation and higher cost of using machinery for cash crops, and it is more difficult to exert its scale effect than grain crops, resulting in increasing their production cost. In terms of control variables, the education level per member of household, average age of family labour force, area of farmland, proportion of farmland irrigation, proportion of greenhouse area, and type of the terrain all have significant negative impacts on various types of agricultural costs, with a greater impact on the cost of cash crops. The percentage of unhealthy people, average working hours of migrant workers and transfer-out area of farmland all have significant positive impacts on all types of agricultural costs and have the greatest effect on the cost of cash crops.

From the regression model of output value, the level of agricultural mechanization has a significant positive impact on various agricultural output values, indicating that the use of agricultural machinery can indeed improve the production efficiency of crops. For every 1 unit increase in the level of agricultural mechanization, the total agricultural output value, grain crop output value and cash crop output value increase by 1.813, 4.737 and 1.597 units, respectively. The use of agricultural machinery has the greatest impact on grain crop output; it is likely influenced by the economies of scale, since grain crops are planted on a larger scale than cash crops. In terms of control variables, the percentage of unhealthy people, average working hours of migrant workers and transfer-out area of farmland all have significant negative impacts on the output value of each type of agriculture. The education lever per member of household, the average age of family labour force, the area of farmland, the proportion of farmland irrigation, the proportion of greenhouse area, and the type of the terrain all have significant positive impacts on the output value of each type of agriculture, and all of them have the greatest effect on the output value of grain crops.

Table 3 shows the results of the baseline regression of agricultural mechanization level on various types of agricultural profit and rates of return. The dependent variables in columns 1) to 3) are total agricultural profit, grain crop profit and cash crop profit, and in columns 4) to 6) they are total agricultural rate of return, rate of return of grain crops and rate of return of cash crops, respectively.

From the regression model of profit, the level of agricultural mechanization has a significant positive impact on the income of each type of agriculture and, for each unit increase in the level of agricultural mechanization, the total agricultural profit, profit of grain crops, and profit of cash crops increase by 1.597, 2.079 and 1.476 units, respectively, indicating that agricultural machinery can significantly increase the income of agricultural operations, with the greatest increase being for grain crops. This may be due to the differential effects of agricultural machinery on the income obtainable from cash crops and grain crops. The regression above shows that agricultural machinery is more likely to increase the cost of cash crops, but to a lesser degree than grain crops. The combined effect of these two aspects leads to greater income as agricultural machinery allows the expansion of grain crops. The direction of influence of the estimated coefficients of the control variables is also largely consistent with that of the output value regression model. From the regression model of rate of return, the level of agricultural mechanization has a significant positive effect on the income rate of each type of agriculture, with each unit increase in the level of mechanization increasing the total agricultural rate of return, rate of return of grain crops, and rate of return of cash crops by 0.364, 0.389 and 0.279 units, respectively. This indicates that the use of agricultural machinery is more likely to increase the income from grain crops. The direction of influence of the estimated coefficients of the control variables is also basically the same as that of the income value regression model and will not be repeated.

2. Endogeneity Test of the Regression Model

To resolve the possible sample selection errors and endogenous problems in the model, the instrumental variables, level of household savings and level of agricultural mechanization at the village level were brought into the IVTobit model. The results of the regressions are shown in **Tables 4**, **5**; the first stages of the IVTobit regressions are excluded to save space.

TABLE 4 | IVTobit estimation of the impact of agricultural mechanization level on cost and output.

Variable	Total cost	Grain crop cost	Cash crop cost	Total output	Grain crop output	Cash crop output
	(1)	(2)	(3)	(4)	(5)	(6)
Machine	0.738***	0.548***	5.51***	5.479**	8.543**	2.521*
	(0.088)	(0.089)	(0.974)	(2.275)	(3.877)	(1.294)
Education	−0.043***	−0.038**	−0.087***	0.121*	0.184*	0.041*
	(0.006)	(0.017)	(0.025)	(0.066)	(0.110)	(0.025)
Age	−0.004***	−0.001	−0.040**	0.009**	0.039*	0.007*
	(0.001)	(0.004)	(0.018)	(0.004)	(0.022)	(0.004)
Healthy	0.766***	0.516**	1.186***	−1.198***	−1.615***	−0.594*
	(0.074)	(0.211)	(0.311)	(0.352)	(0.605)	(0.310)
Migrant	0.024***	0.049***	0.012*	-0.161**	-0.244***	-0.012
	(0.006)	(0.007)	(0.007)	(0.081)	(0.032)	(0.035)
Land	−0.005*	−0.002**	−0.039***	0.021**	0.037***	0.009**
	(0.003)	(0.001)	(0.004)	(0.010)	(0.009)	(0.004)
Transfer	0.014*	0.003	0.288**	−0.257***	−0.798***	−0.088
	(0.008)	(0.029)	(0.108)	(0.086)	(0.253)	(0.057)
Irrigate	−0.315***	−0.243***	−4.004***	1.008***	5.735***	0.831***
	(0.062)	(0.007)	(1.206)	(0.306)	(1.608)	(0.237)
Facility	−0.032***	−0.028***	−1.243***	0.491***	1.141***	0.196***
	(0.009)	(0.009)	(0.074)	(0.158)	(0.315)	(0.054)
Terrain	−0.241***	−0.144***	−2.902**	2.955***	3.388***	1.305***
	(0.014)	(0.050)	(1.147)	(0.945)	(0.550)	(0.195)
Constant	5.415***	4.320***	6.159***	5.621***	5.947***	4.984***
	(0.196)	(0.625)	(0.568)	(1.346)	(2.157)	(0.718)

****, **, and * denote significance at the 1, 5 and 10% levels, respectively.*

TABLE 5 | IVTobit estimation of the impact of agricultural mechanization on agricultural profit and rate of return.

Variable	Total profit	Grain crop profit	Cash crop profit	Total return rate	Grain crop return rate	Cash crop return rate
	(1)	(2)	(3)	(4)	(5)	(6)
Machine	3.143**	5.479**	1.694***	1.215*	1.594***	0.435*
	(1.356)	(2.275)	(0.617)	(0.696)	(0.492)	(0.247)
Education	0.121*	0.211***	0.030*	0.033***	0.041***	0.020*
	(0.066)	(0.022)	(0.045)	(0.013)	(0.002)	(0.011)
Age	0.019***	0.027***	0.013*	0.021***	0.0315***	-0.013***
	(0.004)	(0.004)	(0.007)	(0.003)	(0.001)	(0.002)
Healthy	−1.615***	−2.312***	−0.235*	−0.253**	−0.421***	−0.176*
	(0.605)	(0.142)	(0.137)	(0.108)	(0.009)	(0.097)
Migrant	−0.161**	−0.233***	−0.015	−0.034**	−0.040***	−0.021*
	(0.081)	(0.027)	(0.054)	(0.015)	(0.002)	(0.011)
Land	0.021**	0.034***	0.012**	0.014**	0.021***	0.011***
	(0.010)	(0.004)	(0.006)	(0.005)	(0.003)	(0.001)
Transfer	−0.257***	−0.326***	−0.128***	−0.045**	−0.051***	−0.043**
	(0.086)	(0.027)	(0.048)	(0.022)	(0.003)	(0.021)
Irrigate	1.008***	1.818***	1.210*	0.194***	0.218***	0.168***
	(0.306)	(0.384)	(0.634)	(0.060)	(0.078)	(0.031)
Facility	0.491***	0.653***	-0.172***	0.077***	0.131*	0.072***
	(0.158)	(0.209)	(0.022)	(0.025)	(0.078)	(0.019)
Terrain	2.075***	3.388***	1.400***	0.503***	0.516**	0.363***
	(0.175)	(0.550)	(0.335)	(0.089)	(0.008)	(0.089)
Constant	1.647**	2.251	0.621*	1.238***	2.005***	0.788**
	(0.782)	(0.376)	(0.346)	(0.253)	(0.034)	(0.345)

****, **, and * denote significance at the 1, 5 and 10% levels, respectively.*

Considering that agricultural operating income involves multiple dependent variables, there will be many endogenous regression models and would take a lot of space to list the test results for the instrumental variables of all endogenous regression models. Therefore, the paper only reports the results of the instrumental variables when the dependent variable is agricultural profitability. To ensure the exogeneity of the instrumental variables in the model, they were subjected to overidentification tests. The *p*-value of the transitional identification test is 0.861, which indicates that the model cannot reject the original hypothesis that the instrumental variables are exogenous. A weak instrumental variable test was further conducted. The value of the F-test statistic of the first-stage instrumental variable of the two-stage least squares is 128.37, which meets the standard recommended by Staiger and Stock: that the F-test value is greater than 10 (Hansen, 2000). This shows that there is no weak identification problem of the instrumental variables in the model, and also proves that the level of household savings and level of agricultural mechanization at the village level are not weak instrumental variables (Stock and Yogo, 2005). In addition, considering that the number of instrumental variables in the model is greater than the number of endogenous variables, it is necessary to check whether the instrumental variables are redundant. The results of the redundancy test showed that the *p*-values of household savings level and agricultural mechanization level were 0.001 and 0.000, respectively, indicating that the null hypothesis—that two instrumental variables were redundant instrumental variables—is rejected.

The above tests show that the two selected tool variables meet the requirements of the model. Although the processes of the Tobit and 2SLS estimation of agricultural mechanization level on total agricultural income are not listed in this paper, the estimation results show that the coefficients of agricultural mechanization level in both the Tobit and 2SLS regressions are greater than the estimated coefficients of OLS, indicating that there is endogeneity and sample selection bias in the model and that the IVTobit results are the most reliable. From columns 1) to (3), it can be seen that for each unit increase in the level of agricultural mechanization, the total agricultural cost, grain crop cost and cash crop cost increase by 0.738, 0.548 and 5.51 units, respectively. The increase in cash crop cost is still the most significant and the estimated coefficient of IVTobit is several times greater than that of OLS. From columns 4) to 6), it can be seen that for each unit increase in the level of agricultural mechanization, the total agricultural output value, grain crop output value and cash crop output value increase by 5.479, 8.543 and 2.521 units, respectively. It is found that the grain crop output increases the most and the estimated IVTobit coefficient also increases significantly. This shows that the sample selection bias and endogeneity problems in the model have been resolved.

The IVTobit model was further used to estimate the impact of the level of agricultural mechanization on agricultural profit and rate of return (**Table 5**). It can be seen from columns 1)–3) that for each unit increase in the level of agricultural mechanization, the total agricultural profit, grain crop profit and cash crop profit increase by 3.143, 5.479 and 1.694 units, respectively. The increase in grain crop profit is the greatest, and the IVTobit estimation coefficient is also significantly higher than that of OLS. From columns 4) to (6), it can be seen that for every unit increase in the level of agricultural mechanization, the total agricultural rate of return, and those of grain crops and cash crops, increase by 1.215, 1.594 and 0.435 units, respectively, with the greatest effect being on the increase in grain crop rate of return. So far, this paper has largely confirmed that the level of agricultural mechanization increases agricultural profit, more so for grain crops. The possible explanation for this is that grain crops have strong economies of scale and greater availability of suitable agricultural machinery, while cash crops have limited scales of operation and less suitable machinery that is more costly. Therefore, agricultural machinery is likely to increase the production efficiency of grain crops.

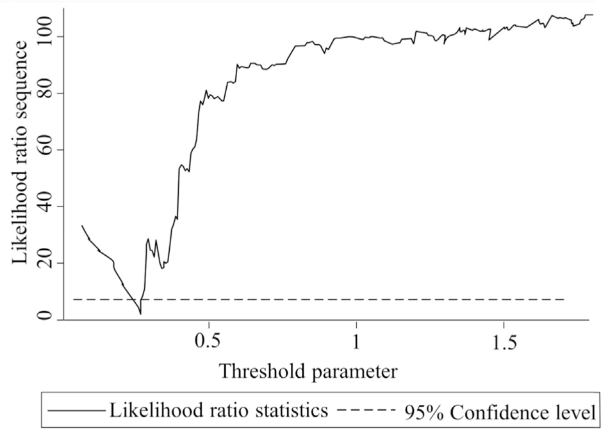

FIGURE 1 | Threshold estimated likelihood ratio.

3. Heterogeneity Analysis of Agricultural Mechanization Level on Agricultural Operating Income

Due to the relatively high cost of using agricultural machinery, its overall benefits do not always increase with the level of mechanization. When the scale of cultivated land is small, the high cost of using agricultural machinery may weaken its benefits. When farmland reaches a certain scale, the benefits of land-scale operation are sufficient to offset the cost of machinery. Therefore, the effect of agricultural machinery use may vary according to the area of cultivated land. In other words, there is an inflection point in the relationship between farmland area and the influence of mechanization level on operating income. The impact is small before the inflection point and larger after it. The key to solving the above problem is to determine the inflection point and then test the heterogeneity effect before and after the inflection point. The threshold estimation method can accurately determine the threshold value and, considering that the data used in this article are cross-sectional, Hansen's cross-sectional data threshold estimation method can be used to determine the threshold value. This can be combined with graphical analysis to show the trend in inflection point changes (Hansen, 2000).

4.1 Threshold Analysis

In this study, the area of farmland was taken as the threshold variable. The threshold effect model estimated a threshold value of 0.28 hm^2. Then, the LM test method was used to verify whether the model had a threshold effect. The LM statistic was 218.97 after

TABLE 6 | Threshold robustness test.

Estimated variables	Only farmland area	Farmland area + Basic family characteristics	Farmland area + production and operation characteristics	Farmland area + control variables other than area variables	Farmland area + all control variables
Threshold	0.265	0.266	0.275	0.279	0.280
p-value	0.015	0.004	0.003	0.001	0.000

TABLE 7 | Estimation of the threshold effect of agricultural mechanization level on agricultural profit.

Variable	Total profit		Grain crop profit		Cash crop profit	
	A ≤ 0.28	A > 0.28	A ≤ 0.28	A > 0.28	A ≤ 0.28	A > 0.28
	(1)	(2)	(3)	(4)	(5)	(6)
Machine	1.071***	3.499***	3.047***	6.002***	1.043***	2.002***
	(0.071)	(0.046)	(0.039)	(0.024)	(0.046)	(0.046)
Education	0.118***	0.304***	0.019***	0.310***	0.013***	0.035***
	(0.012)	(0.012)	(0.006)	(0.005)	(0.002)	(0.002)
Age	0.797*	1.006**	0.021***	0.311***	0.011*	0.228***
	(0.441)	(0.508)	(0.003)	(0.082)	(0.007)	(0.006)
Healthy	−0.135*	−3.021***	−1.002***	−3.001***	−0.145***	−0.325***
	(0.080)	(0.043)	(0.038)	(0.035)	(0.053)	(0.053)
Migrant	−0.119*	−0.212***	−0.143***	−0.301***	−0.014**	−0.016***
	(0.065)	(0.013)	(0.031)	(0.004)	(0.006)	(0.006)
Land	0.016***	0.189***	0.033***	0.047**	0.011***	-0.052*
	(0.003)	(0.002)	(0.009)	(0.020)	(0.003)	(0.030)
Transfer	−0.129**	−0.371***	−0.187***	−1.660***	−0.095*	−0.998**
	(0.051)	(0.022)	(0.056)	(0.315)	(0.056)	(0.437)
Irrigate	0.801***	1.394***	1.310**	2.130***	0.874***	2.094***
	(0.309)	(0.270)	(0.242)	(0.158)	(0.282)	(0.278)
Facility	0.361***	2.088***	0.134***	2.232***	0.942**	1.764***
	(0.075)	(0.409)	(0.035)	(0.004)	(0.477)	(0.486)
Terrain	0.291***	3.194***	2.093***	4.232***	0.525***	1.519***
	0.079	(0.063)	(0.052)	(0.032)	(0.111)	(0.112)
Constant	0.920***	2.277***	1.210***	3.053***	0.533**	1.350**
	(0.222)	(0.616)	(0.451)	(0.320)	(0.206)	(0.582)

****, **, and * denote significance at the 1, 5 and 10% levels, respectively.*

500 bootstraps with a *p*-value of 0.000, indicating that there was indeed a threshold effect in the model. In addition, a graphical representation of the inflection point changes is shown in **Figure 1**. The inflection point of the likelihood rate series curve is obvious at 0.28 hm^2, where the likelihood rate is far below the 95% threshold (dashed line in the figure), so it can be judged that 0.28 hm^2 is the threshold value of the model.

To ensure the robustness of the threshold estimation, control variables were gradually introduced into the model. Their validity was verified by comparing the threshold values estimated by different models. The result is shown in **Table 6**. The control variables were divided into three categories: basic household characteristics, production and operation characteristics, and regional variables. The basic household characteristics variables included education level per household member, average age of family labour force, and percentage of unhealthy people, while the production and operation characteristics variables included the average working hours of migrant workers, area of farmland, transfer-out area of farmland, proportion of farmland irrigation, and proportion of greenhouse area. The control variables were added into the threshold model in batches and it was found that with increases in the control variables, the threshold value tended to be more stable and the *p*-value became more significant. Finally, the threshold value of cultivated land area estimated by the threshold effect model was 0.28 hm^2. Therefore, it can be considered that the estimated threshold value is a credible "convergence point" when all control variables are added to the model.

4.2 Estimation of the Threshold Effect of the Level of Agricultural Mechanization on Agricultural Income

After determining the threshold value, the sample was divided into two subsamples according to the threshold value (≤0.28 and >0.28) in order to examine the effect of the level of agricultural

TABLE 8 | Estimation of the threshold effect of agricultural mechanization level on the rate of return.

Variable	Total rate of return		Grain crop rate of return		Cash crop rate of return	
	A ≤ 0.28	A > 0.28	A ≤ 0.28	A > 0.28	A ≤ 0.28	A > 0.28
	(1)	(2)	(3)	(4)	(5)	(6)
Machine	0.897***	1.446***	0.928***	2.248***	0.147**	0.501**
	(0.156)	(0.146)	(0.079)	(0.033)	(0.071)	(0.144)
Education	0.010***	0.031***	0.030***	0.055***	0.016**	0.045***
	(0.009)	(0.009)	(0.001)	(0.001)	(0.007)	(0.010)
Age	0.013***	0.035***	0.020***	0.040***	0.002*	0.022***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Healthy	−0.175**	−0.347***	−0.308***	−0.509***	−0.167***	−0.291***
	(0.076)	(0.075)	(0.007)	(0.007)	(0.059)	(0.086)
Migrant	−0.014***	−0.016***	−0.030***	−0.050***	−0.017**	−0.224***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.011)
Land	0.008***	0.021***	0.011***	0.030***	0.011***	0.020***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
Transfer	−0.034**	−0.051***	−0.040***	−0.060***	−0.037***	−0.062**
	(0.017)	(0.017)	(0.001)	(0.001)	(0.013)	(0.030)
Irrigate	0.107*	0.287***	0.173***	0.290***	0.107**	0.227***
	(0.062)	(0.060)	(0.064)	(0.033)	(0.043)	(0.067)
Facility	0.064***	0.161***	0.108***	0.134***	0.041***	0.058**
	(0.018)	(0.017)	(0.026)	(0.028)	(0.008)	(0.024)
Terrain	0.237***	1.236***	0.204***	0.615***	0.111***	0.450***
	(0.056)	(0.056)	(0.006)	(0.005)	(0.037)	(0.061)
Constant	0.655***	1.777***	1.011***	3.011***	0.406***	1.119***
	(0.139)	(0.137)	(0.014)	(0.012)	(0.080)	(0.134)

****, **, and * denote significance at the 1, 5 and 10% levels, respectively.*

mechanization on the agricultural profit and rate of return before and after the threshold value. The results of the IVTobit model are shown in **Tables 7**, **8**. **Table 7** shows the estimate of the threshold effect of the level of mechanization on the profits of various crops. From the total agricultural profit model, the regression coefficients of mechanization level before and after the threshold are different. For each unit increase in mechanization level, the total profit before and after the threshold increase significantly, by 1.071 and 4.1 units, respectively. This indicates that increasing the level of agricultural mechanization will increase the total income of farmers with large operating areas, which basically confirms the validity of the threshold value. From the perspective of the profit of grain crops, each unit increase in the level of mechanization significantly increases the profit by 3.047 and 6.002 units before and after the threshold, respectively. For cash crop profit, each unit increase in the level of mechanization significantly increases the profit by 1.043 and 2.002 units before and after the threshold, respectively.

Table 8 shows the estimated threshold effect of agricultural mechanization level on the rate of return of various crops. For the model of the total agricultural rate of return, each unit increase in the level of mechanization significantly increases the total agricultural rate of return before and after the threshold by 0.897 and 1.446 units, respectively. This indicates that machinery is more conducive to increasing the total agricultural rate of return after the threshold. For grain crops, each unit increase in the level of mechanization significantly increases the rate of return by 0.928 and 2.248 units before and after the threshold, respectively. For cash crops, each unit increase in the level of mechanization significantly increases the rate of return before and after the threshold by 0.147 and 0.501 units, respectively. These coefficients are smaller than those of grain crops before and after the threshold. It can be seen that the level of mechanization has heterogeneous effects on operating income. Firstly, in terms of the scale of household farming, the use of machinery is more likely to increase the profit and rate of return of farmers with larger farms. The threshold value of the operating scale tested in this paper is 0.28 hm^2; in other words, farmers who exceed the operating threshold area will have higher incomes. Second, grain machinery is better developed and more available and cost-effective. Therefore, it can more easily increase the profit and rate of return of grain crops.

4. Mechanism of the Effect of Agricultural Mechanization Level on Agricultural Operating Income

The above section confirmed that the level of agricultural mechanization indeed improves agricultural operating income. This section analyses the mechanisms underlying this effect. **Table 9** shows the results of the mechanism of action test. Considering the simplicity of the test process, only the total agricultural rate of return was selected as the target variable of agricultural operating income in the model. In general, machinery can effectively improve the yield and quality of crops and this paper also analyses these two paths. The first is the factor-intensification path, in which the use of agricultural machinery can effectively increase labour productivity and land

TABLE 9 | Mechanism of the effect of agricultural mechanization level on profit.

Variable	Factor-intensive path			Quality improvement path	
	Total rate of return	Factor utilization	Total rate of return	Product price	Total rate of return
	(1)	(2)	(3)	(4)	(5)
Machine	0.364**	0.442*	0.430**	0.216***	0.129*
	(0.155)	(0.262)	(0.201)	(0.008)	(0.068)
Factor			0.350***		
			(0.032)		
Price					0.163***
					(0.023)
Education	0.014***	0.027*	0.021**	0.034**	0.014**
	(0.001)	(0.014)	(0.009)	(0.014)	(0.007)
Age	0.020***	0.011***	0.011**	0.014***	0.004***
	(0.001)	(0.003)	(0.002)	(0.003)	(0.001)
Healthy	−0.121***	−0.049**	−0.043*	−0.241*	−0.149***
	(0.009)	(0.023)	(0.023)	(0.130)	(0.056)
Migrant	−0.030***	−0.031*	−0.012**	−0.033***	−0.018**
	(0.002)	(0.018)	(0.006)	(0.011)	(0.007)
Land	0.005**	0.012**	0.011***	0.014***	0.003***
	(0.001)	(0.005)	(0.002)	(0.003)	(0.001)
Transfer	−0.020***	−0.010	−0.044**	−0.045***	−0.013***
	(0.001)	(0.026)	(0.021)	(0.006)	(0.004)
Irrigate	0.207***	0.247**	0.108**	0.133**	0.235***
	(0.039)	(0.124)	(0.052)	(0.067)	(0.052)
Facility	0.124**	0.083***	0.091***	0.069***	0.077***
	(0.057)	(0.020)	(0.012)	(0.019)	(0.015)
Terrain	0.285***	0.264***	0.209***	0.386***	0.242***
	(0.056)	(0.098)	(0.053)	(0.076)	(0.038)
Constant	0.810***	0.892***	1.084***	0.929***	−0.733***
	(0.018)	(0.231)	(0.148)	(0.166)	(0.091)

****, **, and * denote significance at the 1, 5 and 10% levels, respectively.*

productivity. Obtaining more agricultural products will spread out the cost of agricultural production, thus enhancing the utilization rate of agricultural production factors and increasing income. Therefore, the first mechanism variable chosen is the factor utilization rate, using agricultural output divided by agricultural cost; the second is the quality improvement path. The use of machinery can effectively increase the degree of standardization of agricultural production. Standardized production improves the quality of agricultural products and, hence, their sales price and resulting income. Therefore, the second mechanism variable chosen was the price of agricultural products. Considering the wide variety of agricultural products, this paper uses the average price of agricultural products for measurement.

From the factor-intensification path test, column 2) in **Table 9** shows that the level of mechanization has a significant positive effect on the utilization rate of agricultural factors. Column 3) shows that the utilization rate has a significant positive effect on the total agricultural rate of return. Since the estimated coefficients of mechanization level and the utilization rate of agricultural factors in columns 1) to 3) pass the significance test, it indicates that factor utilization rate plays a partial intermediary role in the model, with a 28.8% mediation effect. It also shows that the effect of mechanization in increasing yield improves the utilization rate of agricultural factors, thus improving income. The quality improvement path test in column 4) shows that the level of mechanization significantly improves the quality of agricultural products. After controlling for the level of mechanization, the price of agricultural products still has a significant positive impact on the total income. The estimated coefficients of the level of mechanization and price of agricultural products in columns 4) and 5) both pass the significance test, indicating that the price of agricultural products plays a partially mediating role in the model with an effect size of 27.4%. This also indicates that the effect of mechanization level on improving the quality of agricultural products increases their price and, thus, income.

5 CONCLUSIONS AND POLICY INSIGHT

Improving agricultural operating efficiency is not only an effective means to increase farmers' income and agricultural efficiency, but is also the essence of the Rural Revitalization Strategy. Based on a field survey of 1,116 farmers in Hubei Province in 2018, this paper analysed the impact of the level of agricultural mechanization on agricultural production and income by using a sample-modified endogenous consolidation model (IVTobit) and threshold-effect model. The results show that 1) the level of agricultural mechanization has a significant positive impact on the production cost, output value, income and yield of all kinds of crops. For every unit increase in the level of mechanization, the costs of all crops, grain crops and cash crops increase by 0.738, 0.548 and 5.51 units, the output values increase by 5.479, 8.423 and 2.521 units, the incomes increase by 3.143, 5.479 and 1.694 units, and the rate of return rise by 1.215, 1.594 and 0.435 units, respectively. 2) From the perspective of heterogeneity analysis, there is an obvious threshold effect of mechanization level on income, with a threshold value of 0.28 ha. Subject to scale effects, the mechanization level has a greater impact on the agricultural operation benefits of various crops after the threshold. 3) The action mechanism test showed that mechanization can increase income via the factor intensification path and quality improvement path. The partial mediating effects of the factor utilization rate and agricultural product price on the agricultural total return rate are 28.8 and 27.4%, respectively.

To sum up, this paper found that agricultural mechanization can effectively improve agricultural income. Increasing income is a basic requirement for the high-quality development of agriculture. We should give full play to the positive role of agricultural machinery in increasing agricultural efficiency and farmers' income. Improving the level of mechanization is also an effective way to promote agricultural modernization. First, we should continue to increase subsidies for the purchase of agricultural machinery, improve and optimize the levels of agricultural machinery and equipment, increase subsidies for machines and tools to overcome weak links in grain production and cropping in hilly and mountainous areas, promote green intelligent agricultural machinery, promote the scrapping and upgrading of agricultural machinery, and transform farmland to make it suitable for mechanization. Second, we should accelerate the research and development and popularization of machinery related to major cash crops, reduce the usage cost of cash crop machinery, and gradually mechanize the whole process of cash cropping, from sowing to field management to harvesting. Third, we should promote the development of socialized service organizations for agricultural machinery operations, improve the standard system of socialized service for agriculture, accelerate the improvement of agricultural socialization service levels, form a new pattern of diversified and shared socialized services for agriculture, and improve the utilization rate of agricultural machinery and level of mechanized operation. Fourth, we should give full play to agricultural cooperatives in the promotion of mechanization, deepen the integration of agricultural machinery and agronomy, vigorously promote advanced and second-round exams, promote intelligent, green and novel agricultural machines and tools, improve farmers' ability to apply new agricultural machinery technologies and new machines and tools, and provide strong scientific and technological support for agricultural transformation and upgrades, and quality and efficiency improvement.

This study also has some limitations. Subject to the sample size, this paper did not subdivide the varieties of grain crops and cash crops. The level of mechanization may have different effects on the operating incomes of different grain and cash crops. However, this paper also has some progress, that is, it avoids analyzing only the total cost or total income of agriculture in previous studies, and considers the threshold effect of agricultural machinery use, which is more meaningful for analyzing the mechanism of action and policy making. In addition, this paper did not investigate the impacts of different agricultural machinery operations on income and it may be conducive to policy-making to explore these impacts. Therefore, survey data with a larger sample size is needed to analyse the above problems in future.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

PJ conceived of the idea for this study. PJ and ZZ conducted the statistical analysis. LD contributed to the final write-up.

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The Widening Wealth Inequality as a Contributor to Increasing Household Carbon Emissions

Xiaodi Qin[1], Haitao Wu[1], Xiaofang Zhang[1] and Wei Wang[2]**

[1]School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China, [2]College of Management, Sichuan Agricultural University, Ya'an, China

The Sustainable Development Goals call for taking urgent action to combat climate change and reduce inequalities. However, the related actions have not been effective. Global CO2 emissions in 2021 are projected to rebound to approaching the 2018–2019 peak, and wealth inequality has been increasing at the very top of the distribution resulting from the COVID-19 pandemic. To test whether a trade-off exists between social and environmental benefits, this study calculates county-level wealth inequality with the Gini coefficient and consumption-based household carbon emissions with the emissions coefficient method and input–output modeling. Data are collected from the China Family Panel Studies, the Visible Infrared Imaging Radiometer Suite, the Chinese National Bureau of Statistics and Carbon Emission Account and Datasets in 2014, 2016 and 2018. In addition, a high-dimensional fixed-effects model, an instrumental variable model and causal mediation analysis are adopted to empirically test how wealth inequality influences household carbon emissions and explore the underlying mechanisms. The results show that county-level wealth inequality has a positive impact on household carbon emissions per capita. This means that policies designed to narrow the wealth gap can help reduce carbon emissions, making progress toward multiple SDGs. Moreover, the study reveals that the social norms of the Veblen effect and short-termism play an important role in mediating the relationship between wealth inequality and consumption-based household carbon emissions. This finding provides a new perspective to understand the mechanism behind wealth inequality and household carbon emissions related to climate change.

Keywords: wealth inequality, household carbon emissions, climate change, veblen effect, short-termism

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*Shaoquan Liu,
Institute of Mountain Hazards and Environment (CAS), China*

Reviewed by:
*Zhi Chen,
Hubei Academy of Social Sciences, China
Zhiqiang Li,
Nanjing University of Information Science and Technology, China*

****Correspondence:***
*Haitao Wu
wuhan_haitao@aliyun.com
Wei Wang
wangwei@sicau.edu.cn*

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INTRODUCTION

Extreme weather events around the world are becoming increasingly frequent, posing a serious threat to the survival of humankind, especially for the poor. Increasing carbon emissions, contributing greatly to global warming and climate change, have therefore become a matter of global concern (IPCC, 2018). The household sector has been one of the largest contributors to carbon emissions due to the direct energy consumption and indirect consumption activities of households (Hertwich and Peters, 2009; Li et al., 2019). Households consume 29% of global energy and are responsible for 21% of the total carbon emissions[1] In the case of China, the largest emitter, the household sector accounts for over 40% of the total carbon emissions and maintains stable growth (Fan et al., 2013; Shi et al., 2016; Shigetomi,2018). 12In May 2020, the Chinese government proposed the *domestic-international dual circulation* model, which prioritizes domestic consumption to achieve

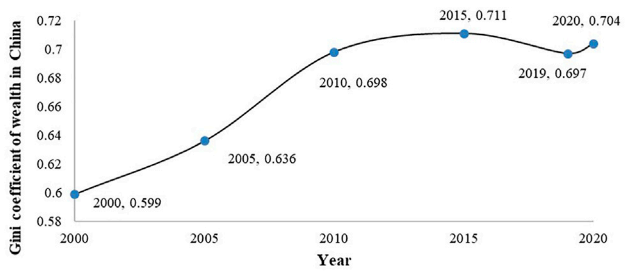

FIGURE 1 | Gini coefficient of wealth in China during 2000-2020.

sustainable economic development. The dual circulation plan may further increase the proportion of consumption-based carbon emissions from the household sector.

The increasing significance of consumption-based carbon emissions leads us to rethink the driving factors for household consumption to find effective paths to achieving the carbon-neutral goals outlined in the Paris Agreement (Rogelj et al., 2019). Among the driving factors, the role of inequality, another important SDG and climate action, has also gained great attention from researchers (Piketty and Chancel, 2015; Jorgenson et al., 2017; Rojas-Vallejos and Lastuka, 2020).

Past research has suggested a relationship between income inequality and carbon emissions but failed to achieve consensus (Guo, 2014; Uddin et al., 2020). Ravallion et al. (2000) investigated the relationship between income inequality and carbon emissions from production and proposed that higher inequality comes with less emissions. Sager (2019) further studied the relationship between income inequality and consumption-based carbon emissions using input–output analysis and found that lower income inequality contributes to higher consumption-based carbon emissions. Other researchers insist that income inequality is positively related to carbon emissions (Golley & Meng, 2012; Zhu et al., 2018).

A limitation of these studies is that they have only focused on income inequality and fail to consider the role of wealth inequality. However, wealth is much more concentrated than income because wealth can accumulate over time (Jones, 2015). More importantly, income inequality has declined over the past years, but wealth inequality is worsening following the rapid growth and transformation in China (Wan et al., 2018; Wan et al., 2021). According to the Global Wealth Report in 2021 by Credit Suisse, the Gini coefficient of wealth for China was 0.599 in 2000, rose quickly to 0.636 in 2005 and reached 0.704 in 2020 (see **Figure 1**). It is therefore imperative to investigate how wealth inequality influences consumption-based carbon emissions.

There have been several attempts to study the relationship between wealth inequality and consumption-based carbon emissions. One study, by Knight et al. (2017), reveals that wealth inequality is positively connected with consumption-based carbon emissions in high-income countries. Another study, by Aye (2020), found that wealth inequality has positive effects on carbon emissions. A limitation of these two studies is that they use the top decile of the wealth share to measure wealth inequality. The top decile of the wealth share is easy to calculate but fails to consider the whole wealth distribution. In addition, these studies are limited in that they only use the concentration of political and economic power to explain how wealth inequality influences carbon emissions. However, as some scholars have argued, social norms, including the Veblen effect and short-termism, may also link inequality to consumption-based household carbon emissions, which needs to be verified from the perspective of wealth inequality (Berthe & Elie, 2015; Liobikien, 2020). Moreover, most of the existing studies use mediation analysis to test the mediating mechanism but fail to ensure accurate causal estimation of the relation between the mediator and dependent variable. Mayer et al. (2014) and Kisbu-Sakarya et al.(2020) proposed causal mediation analysis to address this problem.

Against this background, we focus on how wealth inequality influences household carbon emissions and make the following contributions. First, we utilize the Gini coefficient of wealth to measure wealth inequality at the county level. The Gini coefficient can capture variation in the head and tail of the wealth distribution. Moreover, wealth inequality is measured at the county level, while most previous studies focus on the provincial or municipality level. County-level wealth inequality has special links tbo consumer behavior given the similar norms within a county. Besides, as a global problem, carbon emissions decision-making may come from global, national, provincial or municipality strata, but is tangibly implemented at county levels. Therefore, county-level wealth inequality can better reveal the impact of wealth inequality on consumption-based carbon emissions and enrich the limited literature regarding wealth inequality in China. Second, we calculate direct and indirect consumption-based household carbon emissions based on a household survey spanning from 2014 to 2018 in China. This supplements the most recent data on consumption-based carbon emissions in China. Third, we use the instrumental variable method and causal mediation analysis to address the endogeneity problem when evaluating how wealth inequality influences household carbon emissions. Finally, there is no study explaining the influencing mechanism of wealth inequality on consumption-based household carbon emissions based on the role of social norms, including the Veblen effect and short-termism. Our study aims to fill this gap and enriches the literature regarding the specific mechanisms that may link wealth inequality to emissions.

DATA AND METHODS

To determine how wealth inequality influences household carbon emissions, we apply four databases: 1) Samples of China households from the China Family Panel Studies (CFPS) in 2014, 2016 and 2018; 2) The county-level Night Light Development Index (NLDI) from the multitemporal dataset of the Visible Infrared Imaging Radiometer Suite (VIIRS) in 2014, 2016 and 2018; 3) China's Input–Output Tables (IOTs) in 42 economic sectors from the Chinese National Bureau of Statistics (CNBS) in 2015, 2017 and 2018; and 4) Sectoral emission factor

TABLE 1 | Variable definition.

Variable	Variable definition
Wealth inequality at county level	County-level Gini coefficient of wealth
HCEs_total	Household total carbon emissions per capita (ton)
HCEs_diect	Household total direct carbon emissions per capita (ton)
HCEs_indiect	Household total indirect carbon emissions per capita (ton)
Child_r	Child dependency ratio of a household
Old_r	Elderly dependency ratio of a household
Health_r	Proportion of healthy people of a household
Fami_size	Family size
Ln_pinc	Log of adult per capita income (yuan)
Inter_access	Access to the internet (yes = 1, no = 0)
Rural	Household location (rural = 1, urban = 0)
Gender	Gender of the head of household (male = 1, female = 0)
Party	CPC member of the head of household (yes = 1, no = 0)
Medicare	Covered by medicare of the head of household (yes = 1, no = 0)
Age	Age of the head of household
SAge	Squared age of the head of household
Married	Marital status of the head of household (married = 1, unmarried = 0)
Qualification	Qualifications (junior middle school or above = 1, primary school or below)
ANLI	Average nighttime light index at county level

CNBS and CEADs, IOTs and sectoral carbon emissions intensity.

information Carbon Emission Account & Datasets (CEADs) in 2014, 2016 and 2018.

The CFPS and VIIRS: wealth, expenditure, demographics and county features.

The CFPS dataset, launched by Peking University, collects household data on the economic and noneconomic information and wellbeing of the Chinese population at the individual, family, and community levels. It covers 25 provinces/municipalities/autonomous regions in China and does not include Hong Kong, Macao, Taiwan, Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia and Hainan (Xie & Lu, 2015). The stratified, three-stage, and probability-proportionate-to-size sampling approach is adopted to improve the randomness and representativeness of the CFPS dataset. First, we feature household wealth by collecting total net assets in the CFPS. Wealth is defined as all household assets minus liabilities, including net housing assets, net financial assets, nonhousing debt, fixed productive assets, land assets, consumer durables and other assets. Second, to calculate indirect household carbon emissions, we collect consumption expenditures in the CFPS. Referring to the classification of household expenditures in the CNBS, consumption expenditures are classified into seven categories of expenditures on food; clothing; residence; household facilities and services; health care and medical services; transportation and telecommunication; and education, culture and recreation.[2] However, the classification of expenditures in the CFPS does not directly match the 42 economic sectors in the CNBS. To match the two datasets, we disaggregate the consumption expenditure in the CFPS into corresponding sectors in the CNBS, based on the proportion of urban and rural households' output in 42 economic sectors in IOTs. Third, to measure direct household carbon emissions, we collect expenditures on cooking with fuel, heating with fuel and driving with petrol in the CFPS. Fourth, some scholars assert that conspicuous consumption is the representative case of the Veblen effect. Therefore, referring to Kaus (2013), Berthe & Elie (2015), and Zhou et al. (2018), the Veblen effect is defined as the total household consumption expenditures and proportion of consumption on clothing, residence, transportation and telecommunication to the total expenditure in the CFPS. In addition, the CFPS dataset collects people's attitudes toward the severity of the environmental problem in China, with scores from 0 to 10. "0" represents "not severe", while "10" represents "extremely severe". Echavarren (2017) proposes that people are more likely to emphasize environmental awareness and engage in low-carbon consumption when they perceive the severity of environmental pollution. As those who are short-sighted usually lack environmental awareness and tend to score low for that question (Xu et al., 2017; Xu et al., 2019; Cruz & Manata, 2020), low scores are used to represent the weakening environmental awareness of households caused by short-termism. Fifth, we collect data on household demographic variables, including the child and elderly dependency ratio, proportion of healthy people, log of adult per capita income, access to the internet, and household location. In addition, we capture the characteristic variables of the head of household, such as gender, membership, medicare, age, squared age, marital status and qualifications. Finally, we collect NLDI data in 2014, 2016 and 2018 from the VIIRS to depict county-level economic activities (Chen & Nordhaus, 2015; Wu et al., 2018; Xu et al., 2020; Zhou et al., 2021). These characteristic variables have significant effects on wealth and consumption-based carbon emissions. The definitions of the key variables are displayed in **Table 1**.

To apply the I-O approach to calculate consumption-based household carbon emissions, we need to integrate household consumption expenditures into IOTs in the CNBS dataset and sectoral carbon emission factors in the CEADs dataset. Given that the CNBS dataset only provides IOTs in 42 economic sectors in 2015, 2017 and 2018, we match IOTs from the CNBS dataset in 2015 and 2017 to corresponding data from the CFPS and CEADs datasets in 2014 and 2016, respectively. Sector classifications are almost the same in the CNBS and CEADs datasets, which greatly reduces the bias due to data matching. With these two datasets, we can calculate the Leontief inverse matrix, which is essential for measuring indirect household carbon emissions and emissions derived from sectoral IOTs and per-yuan carbon emission factors.

Calculation of Wealth Inequality

Following Knight et al. (2017), Liu et al. (2019) and Wan et al. (2021), we adopt the commonly used Gini coefficient to measure wealth inequality at the county level. The Gini coefficient evolves from the Lorenz curve framework and can measure the wealth distribution within a population. It has the benefit of providing an all-inclusive measure of wealth inequality and capturing changes in the head and tail of the wealth spectrum. The Gini coefficient of wealth can be simply expressed as follows:

$$Gini = \frac{1}{2n^2\mu}\sum_{h1=1}^{n}\sum_{h2=1}^{n}\left|Wh_1 - Wh_2\right| \tag{1}$$

where *Gini* denotes the county-level Gini coefficient of wealth per adult; n denotes the number of households in the county; and μ denotes the average per adult household wealth of all households in the county. Wh_1 and Wh_2 represent the per adult wealth of households h_1 and h_2. Theoretically, *Gini* ranges from 0 (complete equality) to 1 (complete inequality), which means that the higher *Gini* is, the greater the wealth inequality is.

Calculation of Direct and Indirect HCEs

As expressed in **Eq. 2**, the total consumption-based carbon emissions $HCEs_{i\_total}$ for households consist of the direct carbon emissions $HCEs_{i\_direct}$ and the indirect carbon emissions $HCEs_{i\_indirect}$. We use the emissions coefficient method (ECM) from the IPCC (2006) to calculate the direct carbon emissions $HCEs_{i\_direct}$ for households and input–output modeling (IOM) to calculate the indirect carbon emissions $HCEs_{i\_indirect}$.

$$HCEs_{i\_total} = HCEs_{i\_direct} + HCEs_{i\_indirect} \tag{2}$$

Emissions Coefficient Method (ECM)

The ECM has been widely used to calculate direct carbon emissions in previous studies (Munksgaard et al., 2000; Wiedenhofer et al., 2017; Zhang, et al., 2020). The direct carbon emissions $HCEs_{i\_direct}$ for households are calculated as follows:

$$HCEs_{i\_direct} = \sum_j f_j Energy_{ji} \tag{3}$$

where $Energy_{ji}$ denotes the energy j consumed by the household and f_j is the carbon emissions factor from energy source j. In the CFPS, there are three main sources of energy consumed by the household: cooking with fuel, heating with fuel and driving with petrol. First, the CFPS dataset classifies cooking fuel into electricity, natural gas, LNG, coal, solar energy and others. Carbon emissions from electricity consumption are usually regarded as indirect HCEs, and emissions from solar energy and others are negligible. Therefore, we calculate energy consumption from cooking fuel based on expenditure and price on natural gas, LNG and coal. Second, given that urban residents in China usually depend on central heating to heat a house, the HCEs of urban households are regarded as indirect carbon emissions, relying on the sector of "Electricity, gas, steam and air conditioning supply". Because rural residents in China depend on coal for heating, we calculate the energy consumption from heating fuel in rural areas based on the expenditure on heating and the price of coal. Third, local transportation expenses are split into expenditures on public transportation and petrol for self-driving, according to the ratio of urban and rural households' output in the sectors of "Transportation, Storage, Post and Telecommunication Services" and "Petroleum Processing and Coking" in IOTs. We consider consumption on public transportation as indirect HCEs and calculate the energy consumption from driving petrol from petrol expenditures and prices. We can calculate the direct HCEs by multiplying the direct consumption by the corresponding emissions factors and sum up the results.

Input-Output modeling (IOM)

IOM has also been widely used to calculate the indirect carbon emissions of households (Golley and Meng, 2012; Wiedenhofer et al., 2017), which is similar to the consumer lifestyle approach (CLA). Both IOM and LCA are closely linked to the consumption patterns of the household, while IOM has the unparalleled advantage of systematically covering all the indirect linkages between different industrial sectors. We can use IOM to calculate the indirect carbon emissions $HCEs_{i\_indirect}$ as follows:

$$HCEs_{i\_indirect} = D(I - A)^{-1}Exp_i \tag{4}$$

where D_i denotes the row vector of emission factors for sector i. $(I - A)^{-1}$, called the Leontief inverse matrix, is essential to the calculation of $HCEs_{i\_indirect}$ through the IOM method, where I denotes an identity matrix and A denotes a matrix of direct requirements coefficients. Exp_i is a column vector of expenditure on commodities and services for the household. First, we calculate D_i by $D_i = E_i/V_i$, where E_i denotes the total carbon emissions and V_i denotes the total output for sector i. We can obtain E_i from the CEADs database and V_i from the Chinese National Bureau of Statistics. Second, we multiply D by the Leontief inverse matrix $(1 - A)^{-1}$ and obtain the total sectoral carbon emission intensity matrix $D(I - A)^{-1}$. Third, we multiply the desired expenditure Exp_i by $D(I - A)^{-1}$ and obtain the consumption-based indirect carbon emissions by sector. Finally, we classify the sectoral indirect carbon emissions and summarize them by the classification of individual consumption to obtain the indirect carbon emissions for the household. In summary, by applying the CAEDs database, we reduce uncertainty as much as possible. Matching the CEADs database, Chinese National Bureau of Statistics and CFPS database greatly helps us increase the accuracy of the calculation of indirect HCEs (Zhang, et al., 2020).

High-Dimensional Fixed-Effects Model

To evaluate the influence of widening wealth inequality on household carbon emissions, we apply the high-dimensional fixed-effects (HDFE) model. With the HDFE model, it is possible to examine the influence of multiple levels of fixed effects. The household carbon emissions (HCEs) as a function of wealth inequality (WealthInequality) at the county level are represented as follows:

$$HCEs_i = \alpha_0 + \alpha_1 WealthInequality_i + X_i\beta + \lambda_j + \upsilon_t + \mu_i \tag{5}$$

In this equation, the HDFE model uses control variables (X_i) as well as the dependent variable of household carbon emissions and the explanatory variable of wealth inequality. $HCEs_i$ denotes consumption-based carbon emissions of the *ith* household, and

$WealthInequality_i$ denotes the Gini coefficient of wealth in the county where the *ith* household is located. X_i is a vector of control variables, including features of the household, head of the household and county. Household features refer to the child and elderly dependency ratio, proportion of healthy people, family size, household income per capita, access to the internet and household location. Features of head of the household refer to gender, party, medicare, age, squared age, marital status and qualification. The county feature refers to socioeconomic activities, which is represented by the average nighttime light index at the county level. Region-invariance and time-invariance are captured by the fixed effects, which are λ_j and υ_t. Finally, μ_i is the error term.

Instrumental Variable Model

Although we use the HDFE model to improve the robustness of the estimation results, reverse causality and omitted variable bias may occur and cause endogeneity problems. To address such an endogeneity problem, we further use an instrumental variable model (IV) and choose rainfall as an instrumental variable. Rainfall may influence agricultural production and physical assets, especially in rural China. Therefore, rainfall may affect county-level wealth inequality and consumption-based household carbon emissions. Rainfall may not directly influence household carbon emissions, which is an exogenous variable (Yang and Choi, 2007; Akobeng, 2017; Mulubrhan et al., 2018; Zeng et al., 2021). Using the IV, HCEs as a function of wealth inequality can be expressed as:

$$\boldsymbol{WealthInequality_i = \alpha_0 + \alpha_2 Rainfall_i + X_i\beta + \lambda_j + \upsilon_t + \mu_i} \quad (6)$$

$$\boldsymbol{HCEs_i = \alpha_0 + \alpha_3 \widehat{WealthInequality_i} + X_i\beta + \lambda_j + \upsilon_t + \mu_i} \quad (7)$$

where parameter α_3 is estimated by standard 2SLS estimation. $\widehat{WealthInequality_i}$ stands for the estimated values of $WealthInequality_i$ in the first stage. The instrumental variable, $Rainfall_i$, denotes the average annual precipitation in the county where the *ith* household is located.

Causal Mediation Analysis

To disentangle the mechanisms underlying the association between wealth inequality and household carbon emissions, we need to use mediation analysis. However, typical mediation analysis is essentially a causal model and depends on assumptions that are not consistent with causal conclusions. Therefore, we use mediation analysis (CMA) to improve the accuracy of causal estimation (Mayer et al., 2014; Dippel et al., 2020; Kisbu-Sakarya et al., 2020). The estimation procedure of CMA to identify all linear coefficients is as follows:

1) Under linearity and with the instrument, parameter α_3 is identified by standard 2SLS estimation, described by **Eq. 8** and **Eq. 9**. $Rainfall_i$ and $WealthInequality_i$ have the same meanings as above.

$$\boldsymbol{WealthInequality_i = \alpha_0 + \alpha_2 Rainfall_i + X_i\beta + \lambda_j + \upsilon_t + \mu_i} \quad (8)$$

$$\boldsymbol{Mediator_i = \alpha_0 + \alpha_3 \widehat{WealthInequality_i} + X_i\beta + \lambda_j + \upsilon_t + \mu_i} \quad (9)$$

2) Then, we use $Rainfall_i$ as an instrument for $Mediator_i$, when conditioned on $WealthInequality_i$, by the following 2SLS model:

TABLE 2 | Description of county-level wealth inequality, household carbon emissions per capital and control variables. Source: Calculated by the authors based on CFPS, IOTs and CEADs in 2014-2018.

Variable	Mean	Year		
		2014	2016	2018
Wealth inequality at county level	0.54	0.52	0.55	0.54
HCEs_total	2.84	2.61	2.69	3.22
HCEs_diect	0.28	0.31	0.27	0.28
HCEs_indiect	2.55	2.3	2.42	2.95
Child_r	0.23	0.22	0.23	0.25
Old_r	0.23	0.22	0.24	0.25
Health_r	0.5	0.64	0.63	0.23
Fami_size	3.78	3.8	3.8	3.74
Ln_pinc	0.49	0.14	0.54	0.78
Inter_access	0.56	0.44	0.58	0.65
Rural	0.52	0.53	0.52	0.51
Gender	0.55	0.6	0.51	0.52
Party	0.1	0.1	0.1	0.11
Medicare	0.91	0.91	0.92	0.9
Age	51.79	51.79	51.41	52.18
SAge	28.82	28.62	28.51	29.34
Married	0.84	0.87	0.84	0.82
Qualification	0.5	0.5	0.47	0.53
ANLI	18.86	19.04	18.3	19.23

Gini coefficient of wealth per adult by province in 2018.

$$\boldsymbol{Mediator_i = \alpha_0 + \alpha_{4ra} Rainfall_i + \alpha_{4wi} WealthInequality_i + X_i\beta + \lambda_j + \upsilon_t + \mu_i} \quad (10)$$

$$\boldsymbol{HCEs_i = \alpha_0 + \alpha_{5m} \widehat{Mediator_i} + \alpha_{5wi} WealthInequality_i + X_i\beta + \lambda_j + \upsilon_t + \mu_i} \quad (11)$$

where parameters α_{5m} and α_{5wi} are the expected values of the estimators of a 2SLS regression where $\widehat{WealthInequality_i}$ plays the role of a conditioning variable. $\widehat{Mediator_i}$ is the estimated value of $Mediator_i$ in the first stage.

RESULTS

Descriptive Statistics

Table 2 displays the summary statistics of county-level wealth inequality, household carbon emissions per capita, and control variables. As **Table 2** shows, wealth inequality shows an average value of 0.54 and holds steady with the growth of wealth. In addition, we obtain the average total, direct and indirect household carbon emissions per capita in China during 2014-2018 by means of the application of ECM and IOM. The average total household carbon emissions per capita are 2.8 tons. The total direct carbon emissions per capita are 0.28 tons, which is much smaller than the total indirect carbon emissions per capita of 2.52 tons. **Table 1** also displays the direct and indirect household carbon emissions per capita across different years. The total, direct and indirect carbon emissions per capita show a stable increment from 2014 to 2018. Most control variables fluctuate

TABLE 3 | Estimation results: HDFE and IV regression for $HCEs_{\_total}$ during 2014-2018.

	(1) HDFE	(2) HDFE	(3) IV	(4) IV
Wealth Inequality	0.148	1.384***	23.336***	12.615***
Child_r		−1.607***		−1.755***
Old_r		−0.001		−0.018
Health_r		−0.188		−0.234
Fami_size		−0.314***		−0.315***
Ln_pinc		0.931***		0.943***
Inter_Access		0.173**		0.197**
Rural		−0.026		−0.042
Gender		0.074		0.027
Party		0.356***		0.368***
Medicare		0.115		0.143
Age		−0.027		−0.019
SAge		0.007		−0.002
Married		−0.139		−0.154
Qualifications		0.261***		0.353***
ANLI		0.009***		0.015***
Year-fixed effect		Yes		Yes
Region-fixed effect		Yes		Yes
Constant	2.724***	4.404***	−9.675***	−1.951
Cragg-Donald Wald F	—	—	331.514	682.216
Observations	37,070	28,814	31,593	28,814

Significance relationships are shown as indicated by p-values: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

slightly throughout the year. Log income per adult in the household increases stably.

Gini Coefficient of Wealth per Adult by Province in 2018

In addition, **Figure 2** displays wealth inequality measured by the Gini coefficient of wealth per adult by province in 2018. Both Zhejiang and Heilongjiang obtain relatively low Gini coefficients of wealth per adult, scoring between 0.48 and 0.52 and representing low wealth inequality. The Gini coefficient of Chongqing is much higher, with a score reaching 0.83, followed by Guizhou, Gansu, Hebei, Guangdong, Shandong, Fujian, Sichuan, Jilin and Shaanxi, with scores ranging from 0.62 to 0.7.

Figure 3 shows the average direct and indirect carbon emissions structure during 2014-2018. We classify the carbon emissions in **Table 2** into 7 main categories generated by consumption from food; clothing; residence; household facilities and services; health care and medical services; transportation and telecommunication; and education, culture and recreation. The pie chart shows that indirect carbon emissions per capita account for 90.04%, far more than direct carbon emissions.

Direct and Indirect Carbon Emissions Structure

Figure 4 displays the total, direct and indirect household carbon emissions per capita across different wealth percentiles. Both the direct and indirect carbon emissions per capita first show a slight decrease and then increase with household wealth. These results preliminarily reveal the relationship between household carbon emissions and wealth inequality. However, how wealth inequality influences household carbon emissions needs to be further explored by means of the HDFE and CMA models.

Results of HDFE and IV Models

Table 3 provides the estimated results based on the HDFE and IV models. Columns 1) and 3) in **Table 3** display the estimation results without the control variables. To reduce the confounding impact of irrelevant variables, we further control for variables at the individual, family, and county levels in Columns 2) and (4). The estimated results of these two columns show that wealth inequality has a significantly positive effect on total household carbon emissions per capita, with coefficients of 1.384 in the HDFE model and 12.615 in the IV model at the $p = 0.01$ level. For the control variables, we find a significantly negative correlation between the child and elderly dependency ratio and household carbon emissions per capita in both models. This means that a higher dependency ratio may reduce household carbon emissions per capita. In addition, other variables, including Ln_pinc, Inter_Access, Party, Qualifications and ANLI, have a significantly positive effect on household carbon emissions per capita in both models. These findings indicate that higher income, easier access to the internet, being a CPC member, higher qualifications and faster socioeconomic development may help increase the total carbon emissions per capita of the household.

To further capture the relationship between wealth inequality and household carbon emissions, we describe the estimated results of the regression of the total, direct and indirect household carbon emissions based on the HDFE and IV models in **Figure 4**. As it shows, wealth inequality increases household carbon emissions per capita mainly by promoting indirect household carbon emissions. These impacts can be seen in both the HDFE and IV models with significantly positive coefficients. On the other hand, wealth inequality may reduce direct household carbon emissions per capita, with the estimated coefficient being significantly negative in the IV model and insignificantly close to 0 in the HDFE model.

The Role of Social Norms

To study the role of social norms from the perspective of the Veblen effect and short-termism, the IV and CMA models are adopted to test the mediating role of the Veblen effect and short-termism, and the results are displayed in **Tables 4**, **5**, respectively.

Column 1) in **Table 4** reveals that wealth inequality can give rise to the growth of total consumption expenditure. Column 1) in **Table 5** indicates that the growth of total consumption expenditures that accompanies wealth inequality plays a mediating role in intensifying household carbon emissions per capita. Column 2) in **Tables 4**, **5** indicates that wealth inequality reduces the conspicuous consumption ratio instead of increasing it. No evidence is found for the role of the conspicuous consumption ratio in wealth inequality increasing household carbon emissions per capita.

As shown in **Table 4**, Column 3) indicates that the wealth gap can weaken the environmental awareness of households. Column 3) in **Table 5** further reveals that greater wealth inequality can increase household carbon emissions per capita by weakening the environmental awareness of households caused by short-termism.

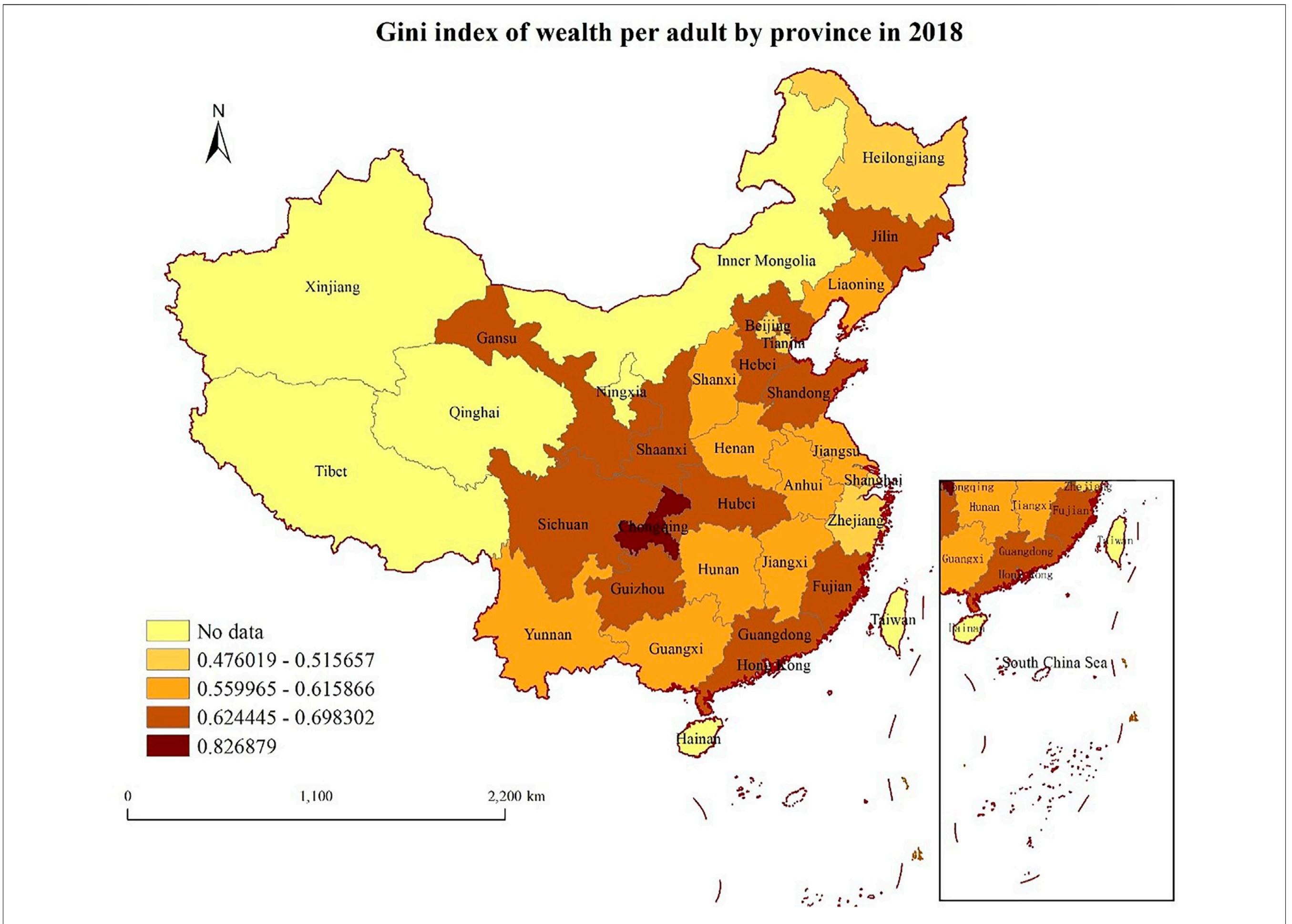

FIGURE 2 | Gini coefficient of wealth per adult by province in 2018.

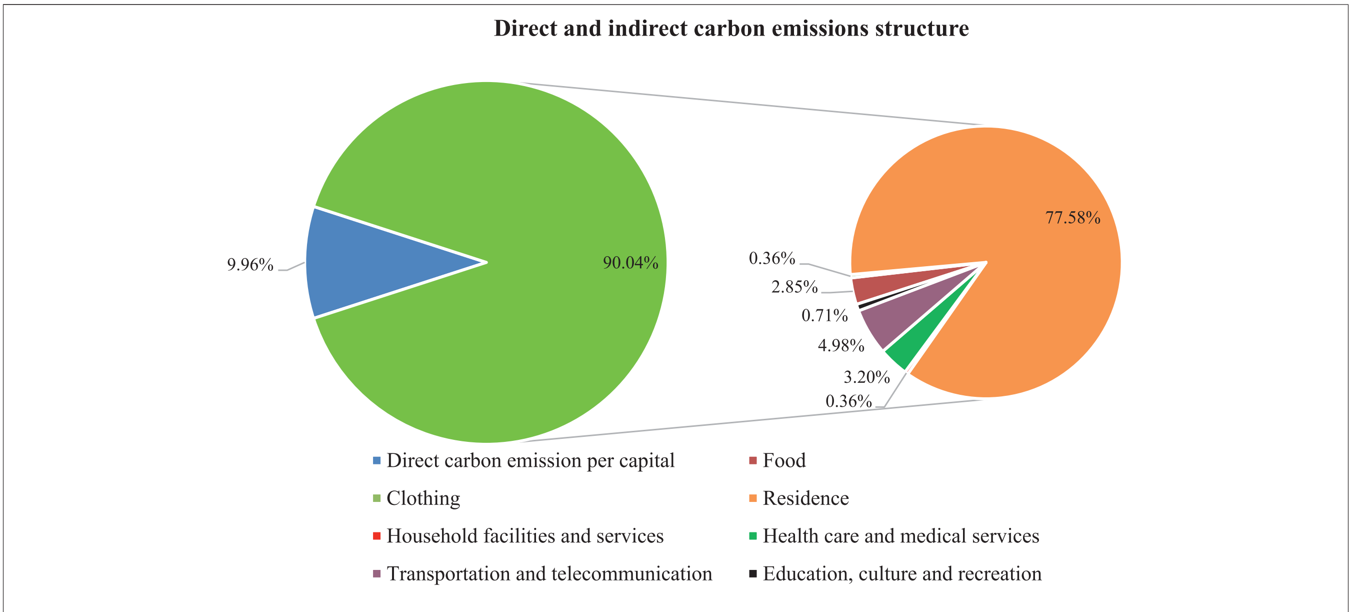

FIGURE 3 | Household carbon emissions across wealth percentiles.

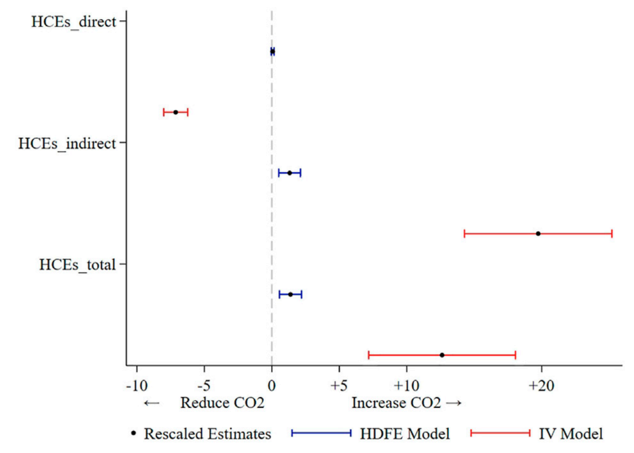

FIGURE 4 | The estimated results of regression of the total, direct and indirect household carbon emissions based on HDFE and IV model.

DISCUSSION, CONCLUSION AND FUTURE RESEARCH

In this study, we have introduced the Gini coefficient to measure wealth inequality at the county level to display the all-inclusive wealth distribution. The ECM and IOM are used to calculate the direct and indirect HCEs with the most recent large-scale data from the CFPS, CNBS and CEADs spanning 2014 to 2018 in China, making it possible to estimate consumption-based household carbon emissions over time though household-level data. HDFE, IV and CAM are applied to effectively test the impact of wealth inequality on household carbon emissions and the role of social norms of the Veblen effect and short-termism.

The main findings reveal that higher county-level wealth inequality has similar positive influences on household carbon emissions per capita by promoting indirect household carbon emissions as income inequality. The positive impact of income inequality on household carbon emissions has been proven by previous studies (Baek & Gweisah, 2013; Lutz, 2019). This finding is also consistent with the findings of (Knight et al., 2017), who also focuses on wealth inequality. However, (Knight et al., 2016), does not exploit data at the county level and tries to explain the mechanism with political economy theories instead of social norms. Our study aims to fill this gap using a dataset from the CFPS, VIIRS, CNBS and CEADs in 2014, 2016 and 2018.

The second important finding indicates that wealth inequality may increase consumption-based household carbon emissions through the Veblen effect. This finding is consistent with previous studies (Berthe & Elie, 2015; Nielsen et al., 2021). These previous scholars state that consumption is far more than a simple factor of individual utility, but it also plays an important role as social value. Greater wealth inequality in a society means greater differences in social status, therefore causing fierce competition. Such competition is commonly represented by conspicuous consumption, not only in the total consumption level but also in the consumption structure. The middle and lower classes are inspired to copy the consumption patterns of the rich, who tend to overconsume and prefer carbon-intensive products, such as central air conditioning. The Veblen effect highlights the emulative influence of people with high socioeconomic status on increasing household carbon emissions. However, it also offers solutions for reducing household carbon emissions and climate damages if people with high socioeconomic status can assume social responsibilities by reducing unnecessary consumption and consuming low-carbon products.

Another important finding is that wealth inequality has positive effects on consumption-based household carbon emissions by aggravating the short-termism of consumers. This finding also confirms the results of a previous study by Boyce (1994), who proposes that growing wealth inequality may induce short-termism among the rich, middle class and the poor. In such a case, the poor focus on short-term material concerns and are particularly vulnerable to consumerism. They may fail to consider the long-term environmental consequences of their consumption. This means that they may lack environmental awareness and are not inclined to adopt pro-environmental behavior and are prone to carbon-intensive consumption. The rich and middle class may also become trapped in short-termism due to the fear of being caught up with by the lower class in consumption. In this way, wider wealth inequality also raises household carbon emissions through short-termism (Slawinski et al., 2017). This finding highlights the important role of short-termism and adds to a growing body of

TABLE 4 | Estimation results: IV model for mediator.

	(1) IV Total consumption	(2) IV Conspicuous consumption ratio	(3) IV Environmental awareness
Wealth Inequality	4.378***	−0.777***	−18.803***
Conspicuous consumption ratio	−0.210***		
Total consumption		−0.007***	
Family-fixed effect	Yes	Yes	Yes
Household-fixed effect	Yes	Yes	Yes
County-fixed effect	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes
Constant	7.612***	0.816***	17.802***
Cragg-Donald Wald F	683.093	657.250	665.252
Observations	27,283	27,283	28,416

Significance relationships are shown as indicated by p-values: *p < 0.10, **p < 0.05, ***p < 0.01.

TABLE 5 | Estimation results: CMA model for mediator.

	(1) CMA Total consumption	(2) CMA Conspicuous consumption ratio	(3) CMA Environmental awareness
Indirect Effect	26.508***	−3.25	11.543***
Family-fixed effect	Yes	Yes	Yes
Household-fixed effect	Yes	Yes	Yes
County-fixed effect	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes
1st-stage F statistic	706.052	681.112	705.033
2nd-stage F statistic	160.82	111.27	199.284
Observations	27,283	27,283	28,416

Significance relationships are shown as indicated by p-values: *$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.*

literature on how wealth inequality influences household carbon consumption.

In addition, this article notes that the total indirect carbon emissions are usually much larger than the direct carbon emissions. In fact, the total indirect carbon emissions are usually much larger than the direct carbon emissions, which is in line with previous studies (Feng et al., 2011; Yang et al., 2017). Compared with previous studies, the calculation results of carbon emissions are similar to the findings of Zhang, et al. (2020), who reported total household carbon emissions ranging from 2.32 to 3.37 during 2012-2016. In addition, as shown in **Table 1**, the residential sector is the largest indirect carbon emissions sector in China, which supports evidence from a previous study (Li et al., 2019; Cheng, et al., 2020).

Finally, it is worth noting that both Zhejiang and Heilongjiang obtain similarly low Gini indices of wealth per adult (see **Figure 1**), but they represent totally different stories. Zhejiang, as the demonstration zone for achieving common prosperity in China, has ensured both fairness and efficiency by realizing low wealth inequality accompanied by a high speed of economic growth. Heilongjiang, one of the northeast old industrial bases in China, lost the benefit of the high speed of GDP growth in 1949-1978 and currently fails to achieve efficiency even with low wealth inequality. These findings are similar to those reported by Liang et al. (2021) and Li (2021), who owe the success of Zhejiang to the rural reforms of homestead land, arable land transfer and land expropriation.

In summary, considering the constant attention to climate change and wealth inequality around the world and in China, we refine the understanding of how county-level wealth inequality influences consumption-based household carbon emissions from the perspective of social norms, including the Veblen effect and short-termism. These findings provide useful information for addressing the challenges of climate change and wealth inequality, both of which are key goals of the SDGs. Social and environmental benefits can be achieved at the same time because policies targeted at reducing wealth inequality can also help reduce household carbon emissions. In addition, the impact of the Veblen effect can be used, and consumption-driven short-termism should be prevented to achieve the carbon neutral target in 2030.

Although we have figured out the effect and mechanisms of the wealth inequality on the consumption-based household carbon emissions with empirical models, there are some limitations in this study. First, this article mainly focused on how county-level wealth inequality on the consumption-based household carbon emissions and the underlying mechanisms, we did not consider the efforts made by Chinese government in environmental protection in recent years, such as energy cleaning, which can directly affect household carbon emissions. Future research can explore the impact and mechanism of Chinese government in environmental protection on household carbon emissions in depth. Second, due to limited availability of quality data, we fail to figure out the relationship and mechanisms between wealth inequality and household carbon emissions for many countries and years. Future research can concentrate on this topic if better data can be available.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://opendata.pku.edu.cn/ https://earthdata.nasa.gov/learn/backgrounders/nighttime-lights http://www.stats.gov.cn/ https://www.ceads.net.cn/.

AUTHOR CONTRIBUTIONS

XQ contributed to data collection, statistical analysis and the manuscript edition. HW significantly contributed in design of study and revise of the manuscript. XZ lead writing and compilation of figures and tables. WW helped in the conceptualization of the work and final overview.

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Are the Agro-Ecosystems Sustainable? Measurement and Evaluation: A Case Study of Sichuan Province, China

Xiaowen Dai[1]*, *Yi Chen*[2], *Xin Wu*[2], *Yanqiu He*[2] *and Fang Wang*[2]

[1]*Sichuan Center for Rural Development Research, Sichuan Agricultural University, Ya'an, China,* [2]*College of Management, Sichuan Agricultural University, Sichuan, China*

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Shaoquan Liu,
Institute of Mountain Hazards and Environment (CAS), China

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Shili Guo,
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Abdul Rehman,
Henan Agricultural University, China
Tian Yun,
Zhongnan University of Economics and Law, China

Correspondence:
Xiaowen Dai
daixiaowen@sicau.edu.cn

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In recent years, with the frequent occurrence of global climate problems, China has paid great attention to sustainable development and ecological environment governance. Sichuan Province is a significant grain production and a reserve base in western China, and its sustainable development in agriculture is an important foundation for the healthy development of the regional agricultural economy and food security. In this study, we divided the agricultural production land in Sichuan into cultivated land, water area, grassland, and forest land. We used the ecological footprint method to investigate the ecological footprint and the carrying capacity of agriculture in Sichuan comprehensively. We conclude that 1) generally, the overall agricultural ecosystem in Sichuan has been in a state of ecological surplus for the past 20 y, and the environmental pressure is gradually decreasing. However, the development within the ecosystem is uneven. 2) In terms of subdivision, the cultivated land, forest land, and water area in Sichuan have always been in a state of ecological surplus, but the grassland is in an ecological deficit state. In terms of the trend, the ecological status of cultivated land has declined significantly, while the forest land has gradually improved, and the water area is relatively stable. Yet, the deficit of grassland is still severe. 3) Forest land is considered the most sustainable type and has a high resource utilization rate all the time, followed by water area, cultivated land, and grassland, when measured by ecological indicators. At the same time, in terms of the coordination between economy and ecology, all lands have been improved.

Keywords: Sichuan Province, ecological footprint, ecological carrying capacity, index evaluation, sustainable development

Abbreviations: ECC, ecological carrying capacity; ECCC, ecological carrying capacity per capita; EF, ecological footprint; EFC, ecological footprint per capita; ES, ecological surplus; ESC, ecological surplus per capita; ED, ecological deficit; EDC, ecological deficit per capita; EFI, ecological footprint index; EPI, ecological pressure index; WEFI, 10 thousand yuan GDP ecological footprint.

1 INTRODUCTION

Agriculture is a nation's fundamental base and a prerequisite for people to live in peace and social stability. The sustainable development of the agricultural ecosystem determines the quality of the agricultural economy. To a certain extent, agricultural sustainability determines the sustainable development of a nation and human society. China is a traditional agricultural country, and the government has always attached importance to agricultural development. From 2004, the No.1 document from the Central Committee of the Communist Party of China (CCCPC) has worked in rural areas for 18 y, which stresses efforts to maintain a healthy and stable development of agriculture. In China's 14th Five-Year Plan and 2035 long-Term goals, the Chinese government plans to comprehensively push forward rural revitalization and improve the quality and stability of ecosystems to achieve sustainable agricultural development.

Agricultural sustainability is closely related to environmental sustainability. The global discussion on environmental sustainability mainly focuses on how to reduce greenhouse gases and solve climate problems, such as adjusting fiscal policy (Chishti, 2021), suppressing CO_2 emissions from the transport sector (Rehman et al., 2021a), developing renewable energy and adjusting the energy system (Rehman et al., 2021b; Murshed et al., 2021), and controlling international trade (Rehman et al., 2021c; Hussain and Rehman, 2021; Weimin et al., 2021). During the China's 14th Five-Year Plan period, achieving carbon peak and carbon neutrality goals was an important goal and vision for various social and economic activities in various industries. The "double carbon" goal is a representative of China's environmental sustainability. As the only industry that can both absorb and also emit GHG, the role of agriculture in achieving the goal of environmental sustainability cannot be underestimated. However, studies so far have shown that environmental sustainability, represented by carbon emission reduction and agricultural sustainability, has not shown a two-way positive effect. On the one hand, the accumulation of carbon dioxide in the atmosphere has surged due to various human activities such as deforestation and agriculture. Rapidly growing agriculture and agricultural mechanization have led to a substantial increase in global energy use and carbon dioxide emissions (Rehman et al., 2021d; Rogers, 2014). Crop production hinders CO_2 emissions in both the long and short terms (Rehman et al., 2021e; Rehman et al., 2021f), whereas forestry production has a constructive effect on CO_2 emissions (Henderson et al., 2021), the forestry carbon sink is also a key industry for the achievement of the overall carbon neutrality goal (Apb et al., 2021). On the other hand, the massive emission of GHG leads to global warming, and the generation of extreme weather, which will adversely affect agricultural production and sustainable agricultural development, such as deforestation and land degradation (Havlik et al., 2014; Rehman et al., 2021g). Agricultural GHG emission reduction is an important starting point for sustainable agricultural development. Sustainable agricultural development is an important way to achieve the goal of carbon neutrality, that is, environmental sustainability, and an important part for the construction of ecological civilization. In this context, the scientific assessment of the sustainable development potential of agriculture will provide the basis for agricultural GHG emission reduction, carbon neutrality goals, and green development.

The ecological footprint model examines the resilience of the ecological environment from the perspective of ecosystem carrying capacity (ECC). The concept of the ecological footprint (EF) was first proposed by a Canadian ecologist William Rees in 1992. With the continuous efforts of scholars, the ecological footprint model has been matured. Compared to sustainable evaluation methods such as the energy analysis method and the comprehensive evaluation method of the index system, the ecological footprint method has simple characteristics and strong operability and is one of the powerful tools for testing sustainability. It is widely recognized and applied. The scope of research using the ecological footprint method to study sustainability issues is extremely wide. Wackernagel and Rees (1997) first applied the ecological footprint model for the study of ecological sustainability in 52 countries and regions around the world (Wackernagel and Rees, 1997). Since then, the ecological footprint model has been extensively used as an essential research tool and analysis framework in sustainable development (Korkut, 2021; Ojonugwa et al., 2021; Umit, 2021; Zahid et al., 2021), socioeconomic development (Neagu, 2020; Enu and Sya, 2021), tourism development (Mehdi et al., 2012; Lin et al., 2017), and energy consumption (Sharma et al., 2021; Ullah et al., 2021). The application of the ecological footprint method in agriculture is divided into two parts: one is the impact of different agricultural production management methods on the agricultural environment, such as land use and farm management (Viglizzo et al., 2011, Hayo et al., 2007), and the second is to evaluate the sustainable utilization of agricultural resources such as water resources and arable land resources, combining the agricultural water footprint (Hoekstra et al., 2011; Wang et al., 2014), agricultural carbon footprint (Maier et al., 2017; Li et al., 2018), and crop footprint (Ferng, 2011; Budreski et al., 2016). In the ecological footprint study of China's agriculture, researchers, respectively, measured the ecological footprint and carrying capacity per capita of cultivated land, water area, grassland, and forest land in Henan (Cao, 2020), Guangxi (Zhang, 2020), and Shandong provinces (Yang et al., 2016), and all the studies found that the provinces have different degrees of ecological deficits. As for the research on the ecological situation of Sichuan, there are differences among scholars. Some scholars believe that both the EF and ECC of Sichuan are increasing, but ECC is always lower than EF, showing an ecological deficit (Qiu and Guang, 2015), but some scholars hold the opposite view (Zhao et al., 2019).

To sum up, research show that the China's regional agro-ecological situation is not optimistic. With the rapid development of the agricultural economy driven by agricultural modernization, the agricultural environment inevitably has been affected negatively. In the application of research methods, the application of the ecological footprint model is relatively mature and extensive, but the research on the sustainable development of agricultural land, forest land, grassland, and water area in the field of agriculture is lacking. At the same time, there are many pieces of research on the estimation of EF and ECC, but only less research related evaluation indicators.

Sichuan is a significant grain production and storage base in western China. The sustainable development of agriculture in this region plays an important role in ensuring the sustainable development of agriculture for the whole nation. However, there are only a few studies and reports on the agricultural sustainability of Sichuan, and existing studies are still inconsistent. Therefore, we choose the environmental carrying capacity perspective as a clue for this research. On one hand, we use the ecological footprint model to measure the EF and ECC of the four land types. Then, three sustainability evaluation indicators are calculated to classify the status and grade of those four types of land. Based on these studies, it is hoped that we can provide a reference for the healthy development of agriculture for Sichuan in the future and the regions that have similar conditions.

2 METHODS AND DATA

2.1 Study Area Introduction and Data Source

2.1.1 Study Area Introduction

Sichuan is located in inland southwest China. It has a vast territory, a large population, rich natural resources, a superior geographical environment, good natural conditions, and a wide variety of crops. It is also one of the important commodity grain bases in China. Sichuan is a typical agricultural province and a province with a large population. Its agricultural production value ranks among the top five in China for many years. In 2019, the total population of Sichuan accounted for 6.7% of the national population, and the rural population of Sichuan Province accounted for 46.21% of the permanent population. At the same time, as the main water source and supply area in the upstream area of the Yangtze River, Sichuan's ecological situation directly affects the ecological state of the Yangtze River basin, especially, the ecological environment of the downstream area of the Yangtze River. With the advancement of agricultural development, the ECC and EF of Sichuan are gradually increasing (Qiu and Guang, 2015). How to protect the ecological environment of agriculture, and improve the quality of agriculture, is of great significance for the sustainable development of agriculture across the country.

2.1.2 Data Source

All the data used in this research are from the *Sichuan Provincial Statistical Yearbook*[1], *China Statistical Yearbook*[2], and *Sichuan Yearbook*[3] from 2001 to 2020. The missing data of some years are supplemented by employing imputation. The data of the world's average production capacity of agricultural consumption projects are from the global average production capacity of different land types, which are released by the World Wildlife Fund (WWF) in 2005.

2.2 Methods Introduction

2.2.1 Calculation of Agricultural Ecological Footprint and Ecological Carrying Capacity

The calculation of EF is carried out in different types, as for agriculture, it can be divided into cultivated land, water area, forest land, and grassland (Yang et al., 2016; Cao, 2020; Zhang, 2020), and based on the classification **Table 1**, the ecological carrying capacity per capita (ECC) and the ecological footprint per capita (EF) can be calculated accordingly.

ECC represents the maximum number of people that can be supported by limited resources in a region without compromising regional productivity. It can be expressed by **Formula 1** as follows (Cao, 2020):

$$ECC_j = (1 - 12\%) \times \left(M_j \times Z_j \times R_j\right). \tag{1}$$

In **Formula 1**, j represents the land type, and M_j is the size of each land type, and Z_j is the yield factor of each land type, meaning the ratio of the productivity of a certain type of land in a country or region to the world's average productivity of that type of land. The yield factor of cultivated land, water area, forest land, and grassland are 1.66, 1.0, 0.91, and 0.19, respectively. R_j is the balance factor of each land type. The balance factor of cultivated land, water area, forest land, and grassland are 2.8, 0.2, 1.1, and 0.5, respectively. According to the recommendations of the World Commission on Environment and Development (WCED), due to the land need for biodiversity conservation, the calculation results of ECC are all deducted 12% from the results.

After obtaining the ECC, we further carried out the calculation of the EF. The carbon footprint expresses the amount of GHG brought by human activities, and the EF can further measure the impact of GHG on the environment. The EF also represents the size of land with biological productivity that is needed to maintain the survival of a person, a city, a country, or all human beings and can absorb emissions from human activities. It reflects the sustainable development ability of the human economy and society. The higher the EF value, the more serious is the human damage to the ecosystem. The EF (Cao YP, 2020) can be expressed by **Formula 2** as follows:

$$EF_j = R_j \sum_{i=1}^{n} \left[K_{ji} / \left(Q_{ji} \times N\right)\right]. \tag{2}$$

In **Formula 2**, j is the land type, N is the total population, and i is the agricultural project under the j land type. R_j is the balance factor of each land type, which represents the ratio of the average productivity of a certain type of productive land to the average productivity of all productive lands on a global standard. The balance factor of cultivated land, water area, forest land, and grassland are 2.8, 0.2, 1.1, and 0.5, respectively. K_i is the average

[1]http://tjj.sc.gov.cn/scstjj/c105855/nj.shtml.
[2]http://www.stats.gov.cn/tjsj/ndsj/.
[3]https://scdfz.sc.gov.cn/szfz/scnj1.

TABLE 1 | Classifications of agricultural projects of four types of productive land.

Types of productive land	Agriculture project
Arable land	11 items including rice, wheat, corn, beans, potatoes, oilseeds, raw hemp, sugar cane, tobacco leaves, vegetables, edible fungi, and fruits
Water area	Aquatic products
Forest land	Three items of lacquer, tung oilseed, and oil tea seed
Grassland	Three items of meat, poultry eggs, and milk

TABLE 2 | Classification of EFI.

Scope	State
EFI ≤ −100%	Seriously unsustainable
-100% < EFI ≤ 0%	Unsustainable
0% < EFI ≤ 50%	Weakly sustainable
50% < EFI ≤ 100%	Strongly sustainable

TABLE 3 | Classification of EPI.

Scope	State
EPI < 0.5	Particularly safe
0.5≤.EPI <0.8	Safe
0.8≤.EPI <1.0	A bit insecure
1.0≤.EPI <1.5	Insecure
1.5≤.EPI <2.0	Very insecure
EPI e2.0	Extremely insecure

annual output of the agricultural project, and Q_{ji} is the agricultural production capacity of the ith agricultural project on the land type j. EF_j means the EF on the j-th type land.

When the EF is greater than the ECC, it is an ecological deficit status, and this also means that the socioeconomic development of the region is in an unsustainable state. Otherwise, it is an ecological surplus status, which means the regional production and consumption activities have not exceeded the ecosystem's carrying capacity. The ecological surplus or deficit (Cao YP, 2020) can be expressed by the following formula:

$$EQ_j = ECC_j - EF_j. \quad (3)$$

In **Formula 3**, EQ_j means the ecological surplus (ES) or ecological deficit (ED) of each land type, ECC_j and EF_j represent the ECC and EF of j-th land, respectively.

2.2.2 Calculation of Sustainable Development Evaluation Index

2.2.2.1 Ecological Footprint Index

Ecological footprint index (EFI) (Wu, 2005) is one of the indexes to assess sustainability; it can be divided into four levels, and the specific calculation formula and classification are shown in **Formula 4** and **Table 2**.

$$EFI = \frac{ECC - EF}{ECC} \times 100\%. \quad (4)$$

2.2.2.2 Ecological Pressure Index

Ecological pressure index (EPI) (Wang et al., 2018) represents the ecological environment pressure capacity, and it usually has six levels. The specific calculation formula and classification are shown in **Formula 5** and **Table 3**.

$$EPI = \frac{EF}{ECC} \times 100\%. \quad (5)$$

2.2.2.3 Ten Thousand Yuan GDP Ecological Footprint (WEFI)

The EF per 10,000 yuan of GDP represents the ecological footprint occupied by residents producing 10,000 yuan of GDP (Haber et al., 2004). The larger the value, the lower the efficiency of resource utilization, and vice versa. The calculation formula is as **(6)**. P_{GD} is the gross product.

$$WEFI = EF/P_{GD}. \quad (6)$$

3 ANALYSIS OF THE RESULTS

3.1 Calculation and Evaluation of Agricultural Ecological Carrying Capacity

3.1.1 Overall Evaluation of Agricultural Ecosystem

Through the calculation of EF and ECC, we found that the agricultural ecosystem in Sichuan Province was in good condition from 2000 to 2019, and the ECC has increased. The increased population has not affected the EF significantly, and the agricultural ecosystem has strong sustainable development capabilities. The agricultural ecosystem of Sichuan Province was always in an ecological surplus during the study period. The lowest surplus year was 2005, which was 0.23 hm^2/p, and the highest surplus year was 2000, which was 0.33 hm^2/p. The total ECC showed a trend of decline first and then uprising. The total carrying capacity stabilized at 4,755.42 hm^2 before 2008 and fell back to 4,641.72 hm^2 from 2009 to 2013. After 2013, it remained above the level of 5,200 hm^2. At the same time, the ECCC is similar to the total ECC, which dropped from 0.59 hm^2/p in 2,000 to hm^2/p in 2013, and then began to rise in 2014 and reached 0.62 hm^2/p in 2019.

The total EF showed a volatile, rising state. The total EF of Sichuan Province was below 2,500 hm^2 before 2002. In the following years, the total EF of every year has exceeded 2,500 hm^2 except 2019 and reached a maximum of 2,047 hm^2

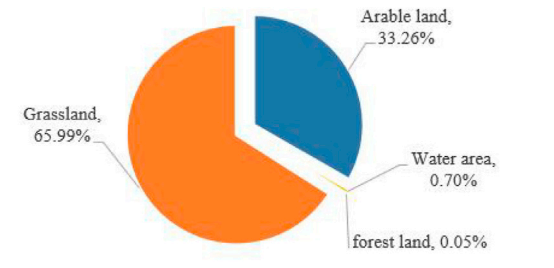

FIGURE 1 | Ecological footprint of Sichuan agricultural system in 2000.

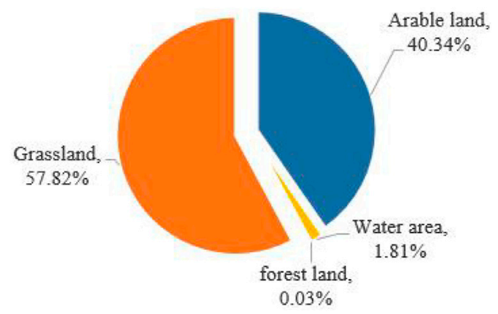

FIGURE 2 | Ecological footprint of Sichuan agricultural system in 2019.

in 2016; meanwhile, the EFC also waved. From the period 2000–2005 and the period 2007–2017, the EFC has increased year after year, and significantly decreased in the period 2005–2006 and the period 2018–2019, and remained at 0.25–0.32 hm^2/p as a whole. After decomposing the agricultural ecosystem, we found that four types of lands' ecological footprint remain in the same structures, but has some changes in quantity **Figure 1** and **Figure 2**. In the structure, the grassland has the largest proportion, accounting for more than half from 2000 to 2019, and the following are arable land, water area, and forest land, and the total rise of water area and forest land was below 2%. In quantity, grassland and the arable area had a big change from 2000 to 2019 compared with the water area and forest land; the grassland's ecological footprint accounted 65.99% in 2000, but in 2019, it declined to 57.82%; however, the arable land's ecological footprint increased from 33.26% in 2000 to 40.34% in 2019. In other words, the damages caused by the agricultural production declined in grassland but increased in arable land.

3.1.2 Evaluation of Different Land Types

During the study period, all types of agricultural bio-productive land were maintained at a high ecological surplus except the grassland. The grassland has continued to be in an ecological deficit state from 2000 to 2019, and the situation was very serious with a tendency to deteriorate. From 2000 to 2008, sorting according to the amount of ecological surplus has the following relationship: arable land > forest land >> water area. After 2009, the ecological surplus of forest land exceeds compared to arable land, the sorting changes to forest land > cultivated land >> water area.

3.1.2.1 Evaluation of Sustainability of Cultivated Land

In **Figure 3** from 2000 to 2019, the overall ECC of Sichuan's arable land showed a trend of decline first and then uprising, and the ECCC also had the same trend. The overall ECC of arable land began to drop from 2,767.04 hm^2 in 2000 to 2,452.63 hm^2 in 2009 and remained at a low level until 2013, then began to increase in 2014 and rise to 2,759.81 hm^2 until 2019. During the study period, the ECCC of arable land was between 0.30 and 0.34 hm^2/p and the EFC was between 0.08 and 0.12 hm^2/p and was increasing gradually. The ESC of arable land was between 0.19 and 0.27 hm^2/p. The ESC in 2019 was 17.21%, which was lower than that in 2000.

According to the statistical data from the National Bureau of Statistics, the size of arable land showed a trend of decrease first and then increase from 2000 to 2019, and the size of arable land per capita faces the same trend. The total size of arable land dropped from 6.77 million hm^2 in 2000 to 5.99 million hm^2 in 2009 and then increased to 6.72 million hm^2 in 2019, the fluctuation range of the changing trend is large. At the same time, the population increased from 82.35 million to 83.75 million between 2000 and 2019. During this period, the agricultural products output from arable land showed a significant downward trend. The consumption of crops, oils, and vegetables, which depend on arable land, showed a trend of volatility and decline during the period 2000–2019 with a decline of 28.93%. This also indirectly indicates that population growth does not cause a substantial increase in arable land agricultural products, and the decline in surplus of arable land in Sichuan has no direct relationship with the increased population.

We believe that the decline in the ecological surplus of arable land is mainly due to the arable land quality decrease caused by the increase in the use of pesticides, chemical fertilizers, and plastic membranes. From 2000 to 2019, pesticide usage in Sichuan showed a trend of increase first and then decrease. During the period, the maximum value was 0.62 Mt in 2010 and the minimum value was 0.46 Mt in 2019. Potash fertilizer and compound fertilizer are increasing year after year. The total amount of potash fertilizer used was raised from 0.1 Mt in 2000 to 0.17 Mt in 2019, and compound fertilizer increased from 0.38 Mt in 2000 to 0.60 Mt, the growth rate is 74 and 60.8%, respectively. The usage of plastic membrane increased from 0.73 Mt in 2000 to 0.13 Mt in 2016, and then slowly decreased to 0.12 Mt in 2019.

3.1.2.2 Sustainability Evaluation of Water Area

In **Figure 4** the overall ECC of Sichuan's water area showed a gradually increasing trend from 2000 to 2019, which is from 326.27 hm^2 in 2000 to 389.75 hm^2 in 2019. However, the ECCC kept declining from 2014 after fluctuations between 2000 and 2013. The ECCC of the water area showed an upward trend during the period 2000–2014, from 0.0396 to 0.0479 hm^2/p, and it showed a downward trend during the period 2014–2019. The ECCC in 2019 was 0.0465 hm^2/p. The overall EF has increased year after year, from 14.72 to 45.22 hm^2, and the growth rate has more than doubled; the EFC has shown an upward trend, from 0.0018 to 0.0054 hm^2/p from 2000 to 2019. Correspondingly, the ESC in the water area fluctuated from 2000 to 2013 and kept declining after a sudden increase in 2014. There are two main reasons for this status in the water area: 1) Sichuan is rich in water resources. There are nearly 1,400 large and small rivers in total in Sichuan Province. Sichuan's water resource ranks second in the country in terms of total water resources and sixth in the country in terms of water resources per capita. By the end of 2019, the total surface water resources in Sichuan accounted for approximately 274.77 billion m^3. The groundwater resources accounted for approximately 61.62 billion m^3. The total water resources amounted to 274.89 billion m^3, and water resource per capita is up to 3 288.9 m^3. 2) On one hand, the protection of water bodies in Sichuan is very strict. On the other hand, the output and supply of aquatic products have gradually increased, but the demand for aquatic products from the people in Sichuan is relatively limited. Although the size of the water area has dropped from 1.09 to 1.04 million hm^2 in the past decades, the government of Sichuan has always been vigorously protecting natural water bodies and advocating rational fishing. Through hard work, the problem of water pollution has been effectively addressed, and the output of aquatic products increased from 0.51 to 1.58 Mt from 2000 to 2019, and the growth rate is as high as 207.32%. Moreover, demand for aquatic products in Sichuan increased from 0.01 to 0.08 Mt, but the output of aquatic products is far greater than the consumption.

3.1.2.3 Evaluation of Sustainability of Forest Land

All indicators of forest land are showing an upward trend, yet, the gap between the ECCC and the EFC of forest land is the largest in four types of land. From the **Figure 5** the ECCC of forest land is 1,500 to 3,600 times of the EFC, and the ESC is between 0.20 and 0.24 hm^2/p. The increase of the forest land ES and the enhancement of ecological sustainability are mainly due to the effective implementation of the "Natural Forest Protection Project" and "Sloping Land Conversion Program" in Sichuan Province.

According to the published data (Mu, 2019), Sichuan Province started the pilot program of returning farmland to forest and grassland in 1999. In 2019, Sichuan has launched two rounds of returning farmland to forest and grassland with nearly 2.67 million acres, ranking third place in China, and the forest land distributed in 21 administrative areas includes 178 counties. With the help of the project, Sichuan's long-term overloaded ecosystem is restored, and the area of forest and grass has expanded significantly. Statistics show that merely by returning farmland to forest, Sichuan's forest coverage increased more than 4%. Due to the implementation of the project of returning farmland to forests and natural forest protection, the forest coverage rate reached 38.83%, which was 15.87% higher than the national average. In addition, thanks to these protection projects, Sichuan has achieved great efforts in water source protection, water and soil conservation, air quality improvement, and biodiversity restoration and maintenance. At the end of 2018, the

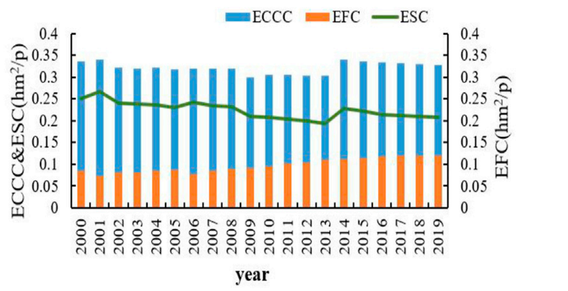

FIGURE 3 | 2000–2019 ECCC, EFC, and ESC of cultivated land in Sichuan province.

Province's conversion of water resources through the "Sloping Land Conversion Program" is 5.83 billion m^3. Compared with 1998, the sediment content of the mainstream of the Yangtze River floating in Sichuan in 2018 has been reduced by 46%.

3.1.2.4 Evaluation of Grassland Sustainability

Grassland is the only land type in Sichuan Province that experienced an ecosystem deficit during the investigation period. From the **Figure 6** the total ECC of grassland was gradually decreased, while the EF was increased year by year in the past decades. At the end of 2019, the EF of grassland was 1,445.04 hm^2, yet the ECC of grassland was only 102.07 hm^2. The ECCC of grassland in Sichuan fluctuated between 0.014 and 0.016 hm^2/p from 2000 to 2013. Since 2014, the ECCC has begun to decrease, and the digit in 2019 was 0.12 hm^2/p. Meanwhile, the EFC fluctuated between 0.17 and 0.21 hm^2/p during the observing period, the maximum value of the EFC was 0.26 hm^2/p in 2005. From 2000 to 2019, ecological deficit (ED) of grassland in Sichuan has been maintained above 0.15 hm^2/p and reached a maximum value of 0.24 hm^2/p in 2005.

There are three main reasons for the serious deficit of the ECC of grassland in Sichuan: First, the size of grassland in Sichuan has been greatly reduced in the past decades. Statistically, during the period 2000–2019, the grassland area in Sichuan Province experienced a sharp decrease. The decrease rate researched was 20.34%, and the size of grassland shrunk from 15.3 million hm^2 in 2000 to 12.21 million hm^2 in 2019. Meanwhile, the population increased from 82.34 to 83.75 million, accordingly the grassland per capita dropped 0.19–0.15 hm^2/p. Second, there is serious grassland degradation in northwestern Sichuan, which are present in diverse types and widely distributed. At the end of 2020, the total area of desertified land in Sichuan Province was 0.86 million hm^2, the area of rocky desertification was 0.73 million hm^2, and the area of arid and semi-arid areas was 1.34 million hm^2; third is the continuous increase in demand for meat and egg products. The consumption of meat from 2000 to 2019 rose from 2.29 to 3.30 Mt, which was a 44.12% increase. The egg consumption increased from 303.86 to 754.59 Mt, which was 148.33%. The production of meat and dairy products relies on

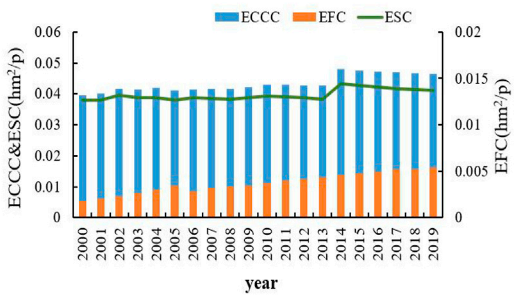

FIGURE 4 | 2000–2019 ECCC, EFC, and ESC of waters areas in Sichuan province.

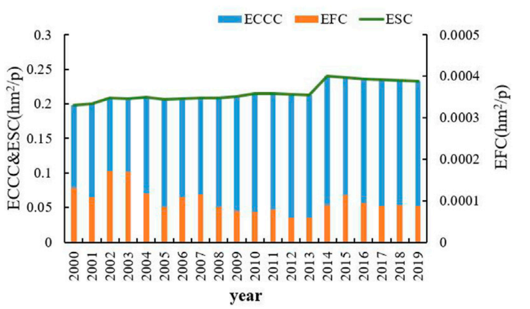

FIGURE 5 | 2000–2019 ECCC, EFC, and ESC of forest land in Sichuan Province.

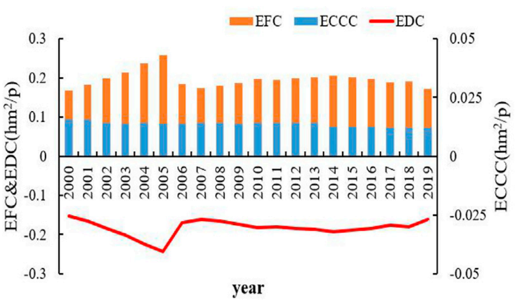

FIGURE 6 | 2000–2019 ECCC, EFC, and EDC of grassland in Sichuan Province.

grassland, and the area of grassland is constantly declining, and the grassland degradation caused a gap between the supply and the demand of meat, dairy products, and other products rely on the grassland. These three reasons have jointly caused the continuous deficit of the grassland in Sichuan .

3.2 Calculation and Evaluation of Sustainability

From 2000 to 2019, the agriculture of Sichuan remains in a sustainable state, but according to the EFI and EPI, overall sustainability has declined. At the same time, there is an extremely unbalanced situation in the four lands. After all, the sustainable ability and environmental antipressure ability of forest land are the best, a little better than water area, but far better than arable land, and grassland is the worst. In terms of the ecological and economic coordination of the sub-industry, all lands are showing a downward trend, indicating that their resource utilization efficiency is improving, using relatively few resources, and producing relatively more economic benefits.

3.2.1 The Evaluation of Ecological Sustainability

As shown in **Figures 7**, **8**, arable land, water area, and forest land are always strongly sustainable, and the EFI of the water area and forest land is close to 100% from 2000 to 2019, of which forest land has been very stable, and water land has a small drop. Arable land is between 63.30 and 74.80%, in keep falling. Then about grassland, it is the worst condition all the time, EFI is always below −1,000%. So, according to the rating, it is seriously unsustainable from 2000 to 2019.

Most of the time, all the systems are strongly sustainable in most years from 2000 to 2010. However, in the following 9 y, it has been in a weakly sustainable state for a long time, and the overall ecological situation has declined. In general, the overall sustainability status is fluctuating. The overall trend is to first decline, then rise, and then decline. The worst was 39.8% in 2005, and the best was 56.92% in 2001.

3.2.2 The Evaluation of Stress on the Ecological Environment

As shown in **Figures 9**, **10** the EPI of forest land is close to zero, meaning it almost has no danger. The EPI of the water area is a little higher than that of forest land and keeps increasing, below 0.12. Arable land has the same trend as water land, it increases to 0.367 in 2019. The first three types of land in particularly safe, yet grassland is extremely insecure in all studies, and EPI of grassland has been continuously rising from 2000 to 2005 and 2007 to 2015, and a comprehensive analysis of all land types and years shows that arable land, waters, and grassland have declined significantly from 2005 to 2006 during all the study periods.

Based on the analysis of the ecological resistance of the four types of land, we have also carried out corresponding calculations and analyses on the ecological carrying capacity of the overall agricultural ecosystem. The EPI from 2003 to 2005 and from 2010 to 2018 was higher than 0.5, and the situation deteriorated from 2003 to 2005 and from 2010 to 2014, the worst situation was 2005. On the whole, although Sichuan's ecological antistress level fluctuates, the overall situation is relatively good. Among them, the situation of cultivated land and grassland needs attention, especially grassland.

3.2.3 The Evaluation of Resource Utilization

According to the **Figure 11** during the study, arable land, water area, grassland, and the whole agricultural system are all

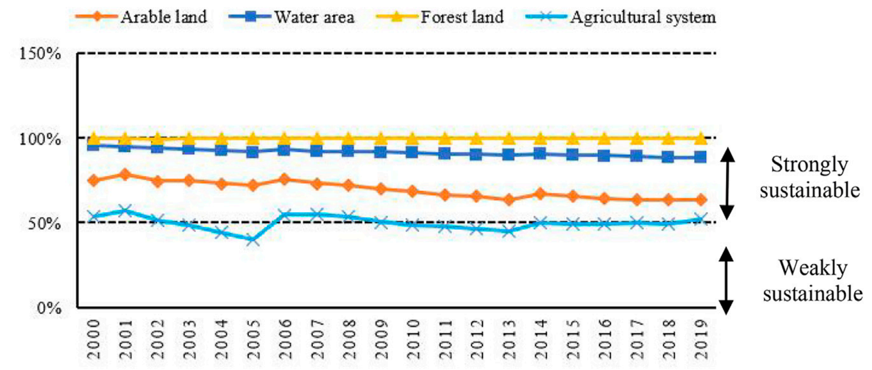

FIGURE 7 | Trend chart of the EFI of arable land, water area, and forest land seriously unsustainable (EFI = −100%).

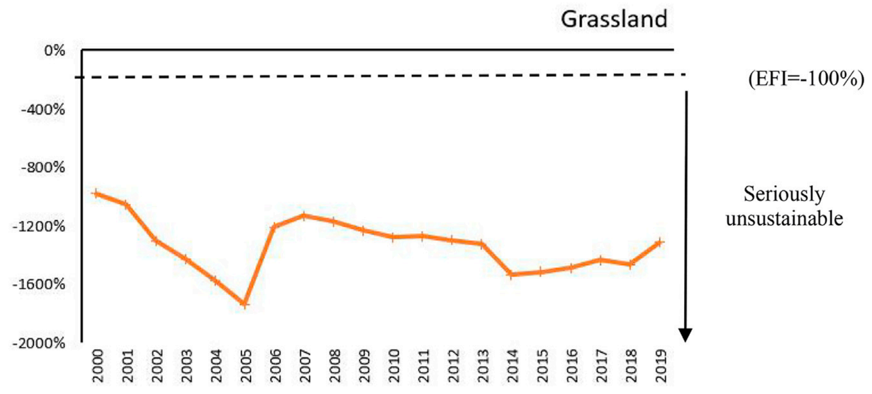

FIGURE 8 | Trend map of the EFI of grassland.

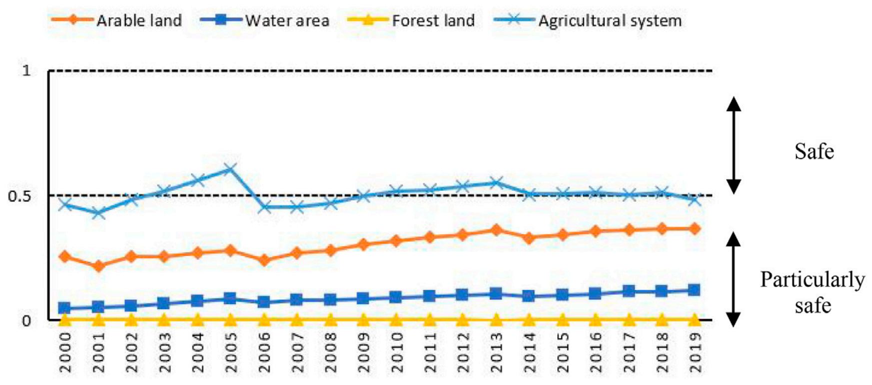

FIGURE 9 | Trend map of EPI of cultivated land, water area, and forest land (EPI = 2).

in decline, forest land is not only the smallest but also the most stable one. In 2000, the WEFI of the four lands have a big difference, grassland is over 0.0002, and the other three lands are all below 0.001, from largest to smallest is arable land, water land, and forest land. Then in 2019, the order has not changed, but the gap has narrowed a lot. From the data, we can have a basic conclusion: the coordination of the ecological conditions and economic development of the four types of land is gradually improving, it also means that the utilization efficiency of agricultural resources in Sichuan Province has been continuously improved, and the production model has shifted from extensive to intensive.

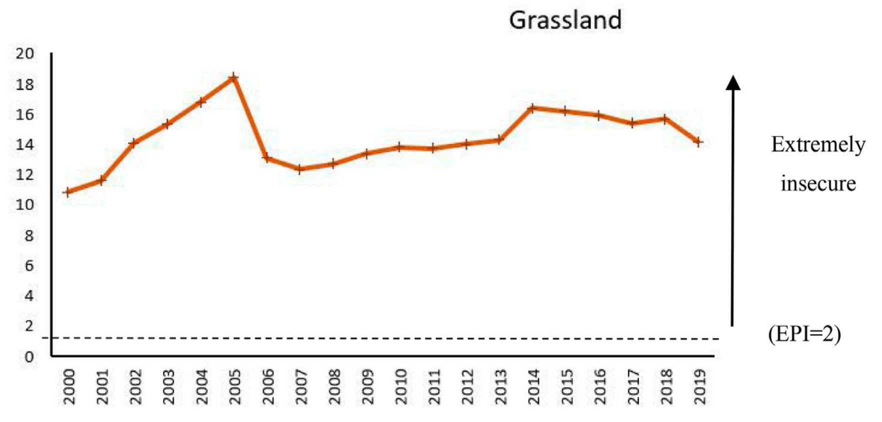

FIGURE 10 | Trend map of grassland EPI extremely insecure.

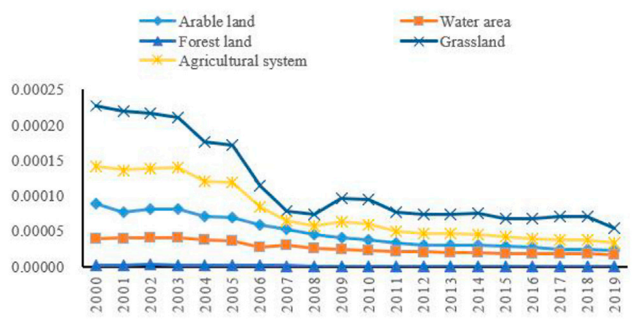

FIGURE 11 | WEF of lands in Sichuan from 2000 to 2019.

4 DISCUSSION

4.1 Comparison With Other Research

Different from previous studies, our research divides the agricultural system into four types: cultivated land, water area, forest land, and grassland. We conduct a detailed and in-depth study on the sustainability of those four types of productive land. The calculation of EF and ECC helped to analyze the ecological status of the four types of land. With the EFI, EPI, and WEFI, sustainability, the ability to withstand the ecological stress, and coordination with the economic development of the four types of land are investigated. These may provide a reference for other scholars' research.

Due to the great differences in geographical location, resource conditions, and subsequent ecological protection measures, the ecological conditions of agricultural systems are different all over China. Among the traditional agricultural provinces, both Shandong and Henan are in a state of deteriorating ecological deficit, and Shandong is more severe than that of Henan Province (Zhang CJ, 2020, Yang J et al., 2016). After subdividing the land types, it is found that the deficit of cultivated land and grassland in Henan Province has increased, and the fluctuation of forest land and the water area is not obvious; the EF of cultivated land in Shandong Province accounts for the largest proportion, as high as 75%, and the quality of the overall agricultural system is determined by a large proportion of cultivated land quality. However, the EF of cultivated land, forest land, and water area in Sichuan Province is smaller than that of Henan and Shandong provinces, but the EF of grassland is larger than that of Henan. In the case of ECC, the situation is reversed. There is also research about Guangxi Province (Cao, 2020), also a western province in China. Comparing Sichuan with Guangxi, it is found that the cultivated land and forest land in Guangxi and Sichuan are both in ecological surplus, and the grasslands in both provinces are also in ecological deficit. The difference is that the water area in Guangxi is in deficit while Sichuan is in surplus. The ecological situation of cultivated land in Sichuan is not as good as that in Guangxi. The ecological surplus of forest land in Sichuan is similar to that in Guangxi, and the deficit of grassland in Guangxi is more serious than that in Sichuan.

In conclusion, the situation of sub-types of agro-ecosystems differs due to the different basic conditions in different regions, but the available studies show that the ecological deterioration of grasslands is a common problem. The study for Sichuan provides some patches for this type of study and enriches the research in this area.

4.2 Research Outlook

Based on the existing research, we propose the following three research perspectives. First, the average level of domestic agricultural consumption items need to be determined and unified, and then the agricultural consumable items in each land type need to be further refined and adjusted. Second, the scope of the agricultural sustainable evaluation can be expanded. Agricultural sustainability is not only to examine the sustainability of agricultural ecosystems but also should take the sustainability of agricultural economic development into account. Therefore, future studies can include social indicators such as agricultural economic level, rural governance level for a wider range of research, and this will make a more profound evaluation for the sustainable development of agriculture in a broad sense.

5 CONCLUSION AND SUGGESTION

5.1 Conclusion

We analyzed the time series changes of the ecological footprint and the ecological carrying capacity of arable land, forest land, grassland, and waters in Sichuan Province and explored its possible influencing factors in combination with realistic trends. We selected 18 agricultural consumption items based on the actual situation in Sichuan. Our research conclusions are as follows:

1) The agricultural ecosystem in Sichuan Province is in a sustainable developing status. The ECC of forest land is the strongest, showing an upward trend, followed by the ECC of water areas. The ECC of cultivated land has a downward trend, and the grassland is facing a severe problem of sustainable development. However, in general, the agro-ecosystem of Sichuan is in a sustainable development status during the past decades.
2) Arable land degradation and scale fluctuation have led to a decline in the ES of arable land. However, the ES of the water area has increased, since the abundant water resources and the aquatic products supply exceeded the demand. The "Natural Forest Protection Project" and "Sloping Land Conversion Program" have also helped to increase the forest land coverage, thereby increasing the ES of the forest land. Due to the desertification and increased demand for meat and eggs, the grassland has been in an ecological deficit status, and the situation has not been improved.
3) In the calculation of sustainability, four lands' states are unchanged. Forest land is the most sustainable land out of the four and has the highest resource utilization all the time, and the sustainable state from the best to the worst is water land, arable land, and grassland. When deep into the numerical, we can find the EFI of arable land and water land is declining year by year, and the EPI of them are increasing all the time, which means these two kinds of ecosystems are in a process of transition from a strongly sustainable state to a weakly sustainable state. However, fortunately, in the coordination of ecology and economy, the WEFI of all kinds of ecosystems are in a good condition, which implies their utilization efficiency has improved.

Although this article makes a detailed analysis of the sustainable capacity of cultivated land, forest land, water area, and grassland in Sichuan Province, there are still some inevitable limitations in practice. The first is the lack of authoritative data on the average production capacity of China's agricultural consumption projects. Therefore, our study draws on some data from both existing studies and investigations domestically and internationally. The advantage of this research is that it is conducive to international or inter-regional comparison in the future. Second, due to the limitation of data acquisition, we can only make calculations based on data from various statistical yearbooks as much as possible. Therefore, there are deviations in the final calculation results of the EF and the ECC.

5.2 Policy Recommendations

As we described earlier, the agricultural ecosystem in Sichuan Province is in a state of sustainable development, and the ecosystem has a strong carrying capacity and supporting capacity. Yet there are still many aspects to be improved. Based on the research, we propose corresponding solutions and policy recommendations as follows:

First, the government should pay more attention to the Sichuan grassland ecosystem. Increasing demand for animal protein inevitably affected the bearing capacity of grass. Although the central and local governments have stepped up protection and restoration efforts in recent years, the situation of grassland is still severe since the chronic overloading and overgrazing in the past decades. In the future, the government should speed up the establishment of a sub-system of grassland monitoring and evaluation, grassland restoration and management, grassland protection, grassland law enforcement supervision, grassland industry, and grassland culture to lay a firm foundation for stabilizing a comprehensive and effective grassland system.

Second, protect and exploit the rich forest resources in Sichuan Province. Forest land protection projects of Sichuan have achieved remarkable results, the development trend of forestry is good. Sichuan has the world's first CCB (Climate, Community, and Biodiversity Standard) Gold-Certified CDM (Clean Development Mechanism) afforestation and reforestation project: The Northwest Sichuan Degraded Land Afforestation and Reforestation Project, and then, forestry projects can well balance ecological and economic benefits. Forest carbon sinks will become an important environmental asset in the future. We believe that forests will be the key to driving the overall ecological transformation of Sichuan in the future. Forestry projects about carbon sink or ecological protection should be supported intensively.

Third, plan and utilize the ecological resources and agricultural materials scientifically. As a veritable "Land of Abundance," Sichuan has abundant water resources, land resources, forestry resources, etc., and has favorable conditions for agricultural development. Yet, the current resource utilization efficiency is low. Meanwhile, the use of agricultural materials, such as chemical fertilizers, pesticides, and agricultural mulch, has significantly increased in the past decades. Therefore, the agro-ecological environment is facing huge pressure. The governments should formulate a reasonable mechanism, making agricultural production neither burden the ecosystem nor waste the ecological environment resources and finally improve the quality of agriculture.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. These data can be found here: http://tjj.sc.gov.cn/scstjj/c105855/nj.shtml.

AUTHOR CONTRIBUTIONS

Conceptualization: XD; formal analysis: XD, YC, and XW; funding acquisition: XD and FW; methodology: YC and YH; supervision: FW; visualization: YC and XW; writing—original draft: XD, YC, and XW; writing—review and editing: XD, YH, and FW.

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Effect of Broadband Infrastructure on Rural Household CO_2 Emissions in China: A Quasi-Natural Experiment of a "Broadband Village"

Pan Rao[1], *Fangting Xie*[2,3]*, *Shubin Zhu*[4]*, *Caiwang Ning*[1] *and Xiaojing Liu*[1]

[1]School of Management and Economics, Changbei Economic and Technological Development Zone, Jiangxi Agricultural University, Nanchang, China, [2]College of Economics and Management, Zhejiang A&F University, Hangzhou, China, [3]Research Academy for Rural Revitalization of Zhejiang Province, Zhejiang A&F University, Hangzhou, China, [4]Institute of Rural Development, Changbei Economic and Technological Development Zone, Jiangxi Agricultural University, Hangzhou, China

This paper explores how broadband infrastructure affects rural household carbon dioxide emissions (HCE). Based on the Environmental Kuznets curve hypothesis, a quasi-natural experiment of a "Broadband Village" (B&V) in China is conducted. Panel data from 9,790 rural households were collected as part of the China Family Finance Survey (CHFS). The consumer lifestyle approach was used to calculate HCE and a Difference-in-Differences (DID) model was used to analyze the impact of a B and V pilot project on rural HCE. The results of DID model showed that B and V significantly increases rural HCE, with an influencing coefficient 1.7. Subsequently, Threshold Model was utilized to examine the nonlinear relationship between household broadband penetration and rural HCE. The results revealed the threshold effect between rural household broadband penetration and rural HCE. Namely, the growth effect of B and V to rural HCE would be much weaker, if rural household broadband penetration goes above a threshold level, 31.32%. Our analysis provides important insights for policymakers to formulate digital village and income redistribution policies to support rural carbon dioxide (CO_2) emissions reductions.

Keywords: CO2 emissions, rural household, broadband village, difference-in-differences, China

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Li Peng,
Sichuan Normal University, China

Reviewed by:
Xin Deng,
Sichuan Agricultural University, China
Xiong Zhou,
Beijing Normal University, China
Kangyin Dong,
University of International Business and Economics, China

Correspondence:
Fangting Xie
fountain_xie@163.com
Shubin Zhu
shubinzhu@163.com

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1 INTRODUCTION

Overcoming the challenge of more frequent and extreme weather events has captured much attention from researchers (Howden et al., 2007; Huang et al., 2015; IPCC, 2018). Carbon dioxide (CO_2) is the main gas causing climate change and greenhouse effects (World Bank, 2007). Climate change has substantial impacts on water balance, affecting the surrounding industry and agriculture and economic sectors (Zhou et al., 2018; Zhou et al., 2021). Therefore, reducing CO_2 emissions and promoting low-carbon development have become global development goals. Currently, most mitigation efforts are focused on the production side, such as emissions trading schemes (Cui et al., 2014; Liu et al., 2015; Wang et al., 2015; Arce et al., 2016; Xiong et al., 2017), and the development of low-carbon energy technology (Chen et al., 2011; Li et al., 2011; Du and Mao, 2015; Xue et al., 2015). However, approximately 72% of global CO_2 emissions can be attributed to household consumption (Hertwich and Peters, 2009; Wilson et al., 2013). A reduction of household CO_2 emissions (HCE) is essential for achieving the goals of the Paris Agreement (Dubois et al., 2019), which set to keep global temperature rise below 1.5°C below pre-industrial

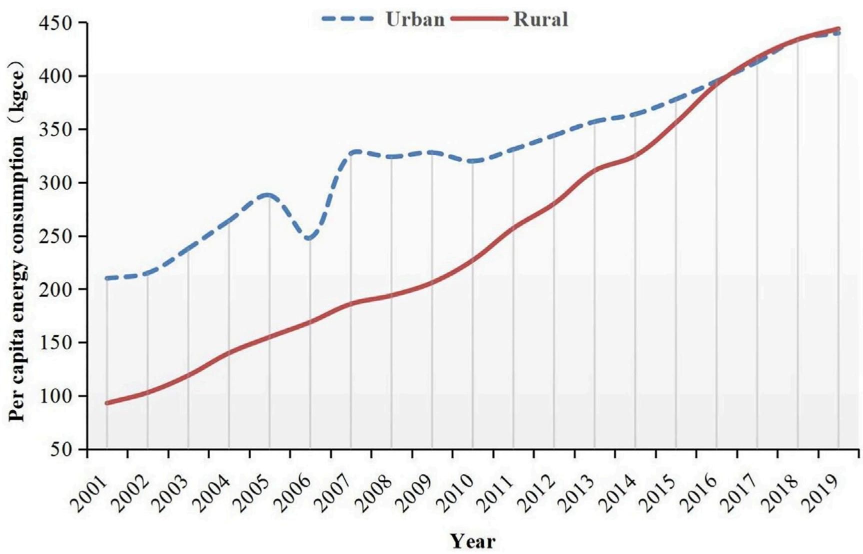

FIGURE 1 | Urban and rural living energy consumption from 2001 to 2019 in China.

levels. Therefore, the issue of HCE has drawn increasing attention from researchers (Zeng et al., 2021). HCE mainly including CO_2 emissions related to heating, air conditioning, cooking, water heating, food consumption, clothing, housing, transportation, and communications (Maraseni et al., 2015; Li J. et al., 2016).

The history of HCE research can be traced back to the 1990s. There were a series of studies on household energy requirements and related CO_2 emissions from consumption activities in developed countries, such as Netherland (Vringer and Blok, 1995), Australia (Lenzen, 1998), and Denmark (Munksgaard et al., 2000). Subsequently, relevant studies were also carried out in developing countries, such as India (Pachauri, 2004), Brazil (Cohen et al., 2005). These studies endeavored to find the solutions to mitigating or limiting the CO_2 emissions impacts from household consumption patterns and lifestyles.

In China, HCE has also grown rapidly in recent years (Zhou and Gu, 2020; Wu et al., 2019). For a long time, the energy consumed by rural households in China was mainly sourced from non-commercial traditional biomass, such as crop straw, firewood, and biogas (Zhang et al., 2014). Since China's energy market reformed in 1993, the energy consumed by rural residents has undergone a clear shift towards commercial energy sources. However, in the first decade of the 21st century, the annual growth rate in rural per capita CO_2 emissions was almost twice the urban rate (Yao et al., 2012). **Figure 1** shows the trends in per capita energy consumption in China's urban and rural areas from 2011 to 2019, which indicates that rural consumption has gradually increased to a similar level as that of urban consumption. In China, about 500 million people live in rural areas, and their contribution to CO_2 emissions cannot be ignored. In addition, the emissions of CO_2 and other air pollutants generated by rural energy consumption have also attracted research attention (Tonooka et al., 2003; Zhang et al., 2010). Even though it is necessary to provide modern energy sources to rural residents, avoiding rapid increases in greenhouse gas emissions is a pressing issue (Yao et al., 2012). In response, the Chinese government is actively implementing a carbon peaking and carbon neutral strategy to deal with the challenges posed by global climate change. To achieve this goal, we need to focus on low-carbon consumption.

At the same time, rural areas are vigorously building digital villages. However, during the production of information and communication technology (ICT) equipment, processing, distribution, and installation waste significantly contribute to CO_2 emissions (Shahnazi and Shabani, 2020). E-waste production and harmful ICT equipment, such as large data centers and mobile data traffic use, pose a threat to environmental quality (Lennerfors et al., 2015). The use of ICT mainly increases energy consumption and CO_2 emissions (Park et al., 2018). However, dematerialization and online distribution, transport and travel substitution, monitoring and management applications, and product stewardship and recycling together reduce energy efficiency and reduce CO_2 emissions (Danish B. et al., 2018; Ozcan and Apergis, 2018).

From the earlier literatures, the relationship between ICT and CO_2 emissions is ambiguous. So it is particularly important to study the impact of broadband infrastructure on rural HCE. With the help of the policy impact of the B and V pilot, we analyzed the impact of broadband infrastructure on rural HCE. Broadband penetration can be used instead of the effectiveness of broadband infrastructure (Koutroumpis, 2009). Then, we analyzed the nonlinear relationship between rural household broadband penetration and rural HCE. Our results should help determine the implementation effects of rural broadband infrastructure and provide a basis for policymakers to formulate pertinent policies under the constraints of rural income equality. Meanwhile, China can achieve the goal of peaking CO_2 emissions by 2030. Accordingly, this study provides several novel contributions.

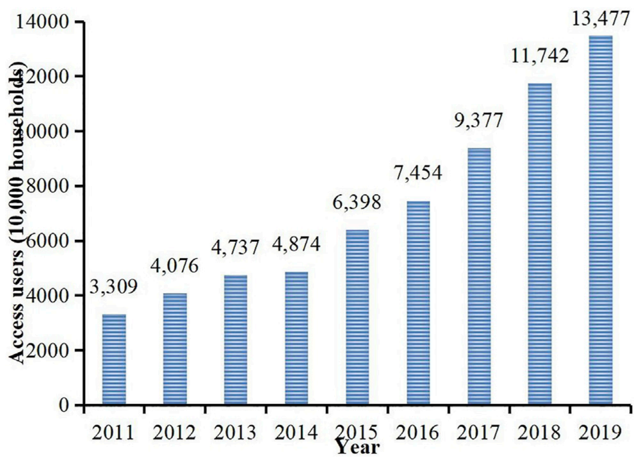

FIGURE 2 | Rural broadband access users from 2011 to 2019 in China.

First, unlike most of the previous studies, this study focuses on rural HCE. Second, we analyze the impact of broadband infrastructure on rural HCE using DID model. Third, we discuss the nonlinear relationship between rural broadband penetration and rural HCE.

This paper is organized as follows. After the Introduction, **Section 2** reviews the literature. Then we introduce the background to "Broadband Village" (B and V) in China in **Section 3**; **Section 4** describes the analytical framework, data source, and methodology. **Section 5** presents our empirical results, which are subjected to a series of robustness tests. **Section 6** concludes the paper.

1.1 Literature Review

Some scholars have explored CO_2 emission reduction strategies from the perspective of energy use (Chung et al., 2009; Dong et al., 2016). For example, Dong et al. (2019) examined the emission-growth-renewables nexus for a global panel of 120 countries, and found renewable energy consumption had a negative effect on CO_2 emissions, but its effect was not significant. Scholars have also investigated other mechanisms that reduce CO_2 emissions, such as financial development (Zhao et al., 2021); ICT investments (Wang et al., 2021).

Broadband infrastructure, as high speed internet via broadband, may further facilitate economy-wide growth by accelerating the distribution of information, reduction of transport and transaction costs (Röller and Waverman, 2001; Czernich et al., 2011). Broadband access positively affects the retail sector in rural areas (Aldashev and Batkeyev, 2021). Household broadband penetration within a region is used to represent ICT development level (Akerman et al., 2015; Haller and Lyons, 2015; Fabling and Grimes, 2016). Since the impact of broadband infrastructure on CO_2 emissions is less studied, we will further analyze the impact of ICT on CO_2 emissions. Many studies have confirmed that ICT has positive impacts on economic growth, particularly in China (Gruber et al., 2014; Han and Zhu, 2014; Kumar et al., 2016; Ghosh, 2017). ICT has brought many positive changes to Chinese residents in terms of income and consumption, with rural areas benefiting more than urban ones (Gao et al., 2018). However, the impact of ICT on household energy consumption is not yet conclusive (Portier, 2005; Bernstein and Madlener, 2010; Ishida, 2015; Salahuddin and Alam, 2016).

At the national and sector levels, studies have suggested that ICT can support technological progress in different economic sectors and improve the operational and energy efficiency of infrastructure (Houghton, 2010; Salahuddin et al., 2015; Lin and Zhou, 2021). However, other studies have taken the opposite view; that the heavy use of Internet-related equipment, such as computers and data centers, can lead to significant increases in energy consumption with negative environmental impacts (David et al., 2018). Danish M. A. et al. (2018) used panel data from emerging economies from 1990 to 2015 to analyze the impact of ICT on environmental pollution. The results showed that the regulatory effect of ICT stimulated the level of CO_2 emissions. Higón et al. (2017) studied the impact of ICT on CO_2 emissions in 116 developing and 26 developed countries and obtained empirical results suggesting that there is an inverted "U"-shaped relationship between ICT and CO_2 emissions.

From a household-level perspective, ICT reduces outdoor activity by overcoming spatial barriers, thereby reducing energy consumption (Danish B. et al., 2018; Ozcan and Apergis, 2018). In addition, ICT can replace physical books with e-books, regular mail with e-mail, and phone conversations instead of face-to-face communication (Park et al., 2018; Ulucak et al., 2020). Bastida et al. (2019) found that ICT can reduce overall electricity consumption by 0.5%. However, some studies have shown that China is in the stage where the development of the Internet is increasing per capita CO_2 emissions (Li and Song, 2019). To sum up, the impact of ICT on CO_2 emissions is not uniform at the national, regional, or household levels.

Importantly, expanding household consumption and controlling CO_2 emissions are long-term policy goals of the Chinese government. However, there may be a degree of incentive incompatibility between them. The Environmental Kuznets Curve (EKC) illustrates that rising income contributes to pollution but after up to a point, after which pollution decreases. However, pollution changes with income due to scale, composition, and technique effects (Grossman and Krueger, 1992, 1995). Therefore, it makes sense to explore the impact of ICT on CO_2 emissions as an external technical effect (Zhou et al., 2019).

Although scholars have explored the impact of ICT on CO_2 emissions, certain research gaps still exist. 1) In China, the potential for carbon reduction in rural is huge. Few previous studies have focused on the issue of rural HCE under the constraints of rural income equality. Based on the EKC hypothesis, this study analyzes the main influencing factors of rural HCE by using micro-tracking data from the CHFS. 2) Few scholars studied the impact of ICT or broadband infrastructure on HCE. We take the B and V pilot as a quasi-natural experiment and analyze the impact of broadband infrastructure on rural HCE using DID model 3) We also explore the nonlinear relationship between rural household broadband penetration and HCE. We

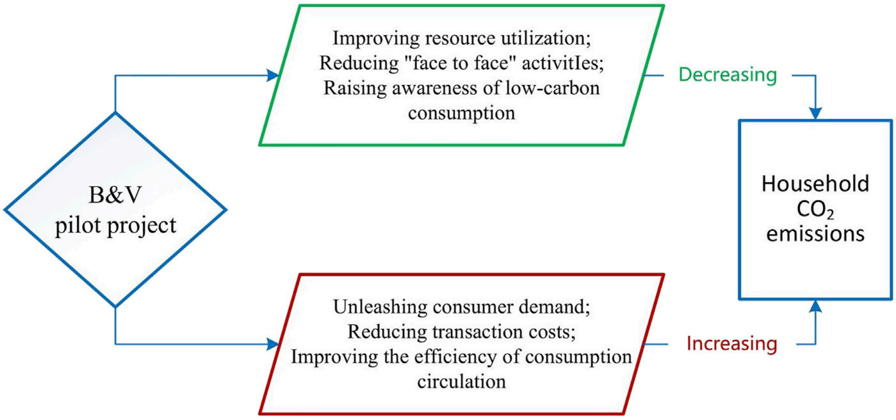

FIGURE 3 | Transmission mechanism of B&V pilot project and rural HCE**.**

found a significant threshold effect between them. The growth effect of B&V to rural HCE would weaken a lot, if rural household broadband penetration goes above a threshold level.

1.2 Background to B&V in China

B&V is an important part of the Chinese government's strategy of "Broadband China"[1]. On 17 August 2013, the *"Broadband China" Strategy and Implementation Plan* was formally issued by the State Council. Due to China's urban-rural dual structure, the construction of rural broadband has lagged that of urban areas for a long time. In June 2014, with the overall planning of the goals of the Broadband China strategy, a B&V pilot project was conducted jointly by the National Development and Reform Commission, the Ministry of Finance, and the Ministry of Industry and Information Technology to achieve the rural broadband development goals. The project emphasizes the installation of optical cable in administrative villages and the development of 3G, 4G, and LTE networks to provide faster, cheaper Internet to rural residents[2].

Sichuan Province and Yunnan Province were selected for the first phase of the B&V pilot project. Both provinces officially launched B&V construction projects in July 2014. In terms of the specific implementation, Sichuan and Yunnan Provinces were finally selected for the first phase of the B&V pilot project, which was contracted by Sichuan Telecom and Yunnan Mobile. Sichuan invested 659 million yuan, and Yunnan invested 628 million yuan in this project.

Figure 2 shows the number of broadband users in rural areas from 2011 to 2019. The growth in rural broadband users accelerated between 2012 and 2015. According to the *Communication Industry Statistical Bulletin*, by the end of December 2015, the net increase in rural broadband users was 15.24 million compared with 2012. It increased by 31.3% from the end of 2014 to the end of 2015. Since China provided Internet access to the public in 1994, Internet construction in rural areas has made great progress in terms of the user penetration rate, Internet tariff level, and average downward speed, which have largely benefited from the B&V strategy.

2 MATERIALS AND METHODOLOGY

2.1 Theoretic Analysis Framework

This study analyzes the EKC hypothesis considering the role of broadband infrastructure. The nexuses between broadband infrastructure and HCE are complicated. But we can use ICT instead of broadband infrastructure to analyze the influences on HCE. The micro mechanism of ICT's impact on HCE is divided into two strands. In the first strand, ICT mitigates the level of CO_2 emissions. ICT provides new alternatives, such as electronic bills instead of paper bills, phone conversations instead of face-to-face communication and reducing outdoor activities (Shabani and Shahnazi, 2019; Ulucak et al., 2020). The sharing economy and mobile payments brought by ICT greatly improve people's utilization of resources and reduce CO_2 emissions. Moreover, residents trust public positive information the most and trust private negative information the least (Xu et al., 2020). The spread of positive information, such as environmental protection, has been accelerated by the popularization of ICT. This has promoted the awareness of low-carbon consumption in daily life. The development of the Internet has allowed people to quickly access information related to environmental pollution causes and hazards (Jiang et al., 2018).

[1]Broadband refers to Internet with a downlink speed of at least four Mbps (Federal Communications Commission 2011 standard). See http://www.gov.cn/zwgk/2013-08/17/content_2468348.htm for "Broadband China" strategy.

[2]The basic objectives of the Broadband China strategy are divided into two steps. In the first step (2013–2015), the national fixed broadband household penetration rate reached 50%, the administrative village broadband rate reached 95%, the 3G/LTE user penetration rate reached 32.5%, and the urban and rural household broadband access capacities reached 20 Mbps and four Mbps, respectively. In the second step (2016–2020), the national household fixed broadband penetration rate will reach 70%, the administrative village broadband rate will exceed 98%, the penetration rate of 3G/LTE users will reach 85%, and the broadband access capacity of urban and rural households will reach 50 Mbps and 12 Mbps, respectively.

TABLE 1 | Variables definition.

Variable Symbol	Variable Definition
HCE	Household CO_2 emissions (MtC: metric ton of CO_2)
Broadband (Post×Treat)	Interaction term (dummy variable_year×dummy variable_experimental group)
Computer	Family owned computer (Owned = 1; Otherwise = 0)
Family_size	Family population (Persons)
Total_income	Annual household income (10,000 yuan)
Total_income square	Annual household income square
Age	The age of householder (Years)
Gender	The gender of householder (Male = 1; Female = 0)
Primary	Householder's highest degree of education is primary (Yes = 1; Otherwise = 0)
Junior	Householder's highest degree of education is junior (Yes = 1; Otherwise = 0)
Secondary	Householder's highest degree of education is secondary (Yes = 1; Otherwise = 0)
Higher	Householder has received higher education (Yes = 1; Otherwise = 0)
Risk_p	Householder risk preference: (investing in high-risk project = 1; Otherwise = 0)
Risk_a	Householder risk aversion: (Investment in Low Risk Project = 1; Otherwise = 0)
LnGDP	Logarithm of provincial GDP

Note: One USD, was about 6.09 and 6.46 Chinese yuan as of December 2013; December 2015, respectively.

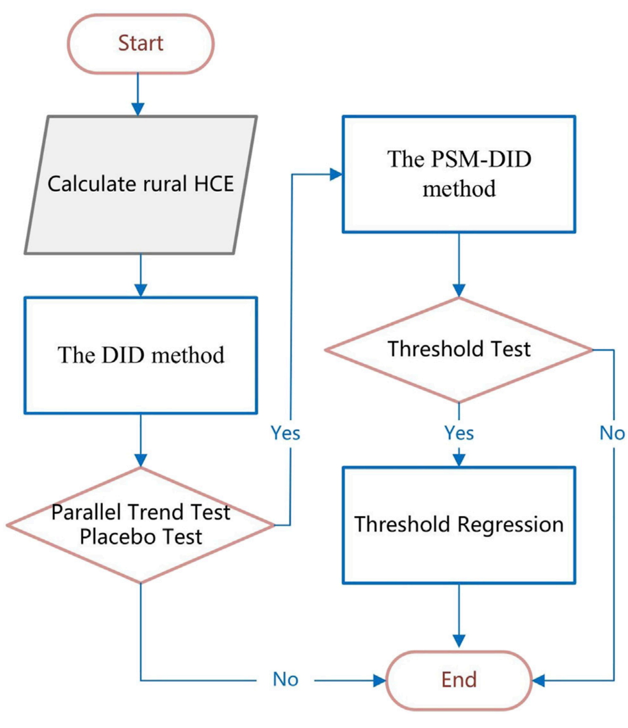

FIGURE 4 | The methodological framework.

Meanwhile, the second strand of argument dealt with the adverse impacts of that ICT on the environment. With ICT, the prices of goods and services fall, leading to higher consumer demand by residents and increased CO_2 emissions (Shabani and Shahnazi, 2019). At the same time, the development of the Internet has reduced transaction costs and promoted trade activities (Ozcan and Nath, 2016). For residents, the use of the Internet has significantly improved their consumption circulation efficiency (Zhang, et al., 2020). **Figure 3** shows the theoretical analytical framework of this study.

2.2 Data

2.2.1 Sources of Data

The dataset used in this study was obtained from four rounds of the CHFS conducted in 2011, 2013, 2015, and 2017. The CHFS is a nationwide survey of households across China, excluding Tibet, Xinjiang, Inner Mongolia, Hong Kong, Macao, and Taiwan. Each round of the investigation was based on respondents' family activities in the previous year. The CHFS data cover 29 mainland provinces and municipalities, 1,481 communities, and 40,011 households. The survey questionnaire included questions on 20 household consumption and expenditure items, including family clothing, food, housing, transportation, education, medical treatment, family visits, and tourism. The survey provides a comprehensive understanding of household consumption-related HCE. Sichuan and Yunnan Provinces have launched B&V pilot project in July 2014. In each of these years, 9,790 rural households were observed, making a total of 19,580.

2.2.2 Core Variables

The explained variable included household CO_2 emissions (HCE). We used Lee and Park's (2007) methods to calculate HCE from the perspective of household consumption. The specific steps are as follows. First, we referred to the scale of energy consumption in different years published in the *China Statistical Yearbook (2010–2018)* and the United Nations Intergovernmental Panel on Climate Change's (IPCC) reports to calculate the CO_2 emission scales of different industries across the country. The specific calculation formula is:

$$CE_i = CEP_i \times CEC_i \tag{1}$$

In **Formula 1**, CE_i indicates the CO_2 emission scales of industry i, CEP_i indicates the energy consumption of industry i, and CEC_i indicates the CO_2 emissions index of the various energy sources consumed by industry i.

$$CI_i = \frac{CE_i}{GDP_i} \tag{2}$$

TABLE 2 | Describes statistical analyses.

Variables	Year	Control group (1)	Treatment group (2)	Difference (1)-(2)	T-Test
HCE	2013	6.1507	4.8459	1.3048	3.2690***
	2015	8.7449	9.0214	–0.2765	–0.4326
Computer	2013	0.1971	0.1054	0.0916	5.8590***
	2015	0.2370	0.1362	0.1008	6.0155***
Family_size	2013	4.0397	4.0922	–0.0525	–0.7042
	2015	4.3015	4.3734	–0.0719	–0.9095
Total_income	2013	3.5301	3.0549	0.4752	1.8928**
	2015	4.2474	3.2589	0.9885	2.2241**
Age	2013	53.8543	52.8185	1.0358	2.0651**
	2015	55.6827	55.0849	0.5978	1.1900
Gender	2013	0.8883	0.8609	0.0274	2.1533**
	2015	0.8754	0.8507	0.0247	1.8583**
Primary	2013	0.3768	0.5417	–0.1649	–8.4813***
	2015	0.3765	0.5417	–0.1652	–8.4965***
Junior	2013	0.3568	0.2562	0.1006	5.2844***
	2015	0.3550	0.2518	0.1032	5.4293***
Secondary	2013	0.1125	0.0571	0.0554	4.4717***
	2015	0.1131	0.0586	0.0545	4.3865***
Higher	2013	0.0107	0.0088	0.0019	0.4696
	2015	0.0111	0.0088	0.0023	0.5605
Risk_p	2013	0.0941	0.0937	0.0004	0.0373
	2015	0.0674	0.0673	0.0001	0.0030
Risk_a	2013	0.7316	0.7204	0.0112	0.6322
	2015	0.6610	0.6340	0.0270	1.4268*
lnGDP	2013	28.1021	28.0402	0.0619	1.9956**
	2015	28.2755	28.2401	0.0354	1.1559

*Note: 1. See **Table 1** for definitions of the variables; 2. ***p < 0.01, **p < 0.05, and *p < 0.1.*

TABLE 3 | Results of model estimation.

Variables	DID Method		PSM-DID Method
HCE	Model 1	Model 2	Model 3
Broadband	1.5812**	1.7212**	1.7235**
Computer	—	5.0693***	5.1811***
Family_size	—	0.5986***	0.5906***
Total_income	—	1.9223***	1.9652***
Total_income square	—	–0.0255***	–0.0254**
Age	—	0.0606***	-0.0598***
Gender	—	–0.1664	-0.1535
Primary	—	0.5075	0.5058
Junior	—	1.5809***	1.5646***
Secondary	—	1.0606**	1.0398**
Higher	—	3.6223***	3.5666***
Risk_p	—	1.9998***	2.0509***
Risk_a	—	–0.5065**	–0.5201**
LnGDP	—	–0.0785	–0.0902
Year	Yes	Yes	Yes
Experimental group	Yes	Yes	Yes
_cons	6.1507***	6.9481*	7.2383
N	15940	15490	15490*
Adj.R^2	0.01	0.09	0.09

*Note: 1. See **Table 1** for definitions of the variables; 2. Models one did not add control variables, whereas Models two to three did; 3. ***p < 0.01, **p < 0.05, and *p < 0.1.*

In **Formula 2**, CI_i represents the CO_2 emissions per unit of GDP by industry and GDP_i represents the industry's GDP increment. Then, household consumption/expenditure items were classified by different industries. The amount of household expenditure was multiplied by the per-unit-GDP CO_2 emission intensity of the industry to obtain the CO_2 emissions generated by household consumption. Finally, the CO_2 emissions from each consumer add up to the HCE. The specific calculation formula is as follows:

$$HCE = \sum_{i=1}^{n} CI_i \times consumption_i \tag{3}$$

In **Formula 3**, HCE is each household's annual CO_2 emissions, and $consumption_i$ means that the household's consumption expenditure in the industries i. Detailed descriptions of rural households' consumption expenditure are listed in **Supplementary Table S1** in **Supplementary Material S1**

B and V (Policy) was chosen as the core explanatory variable of our study. The value of the province's implementation of the B and V in 2014 is one; otherwise, it is 0. Our study drew on the research methods of Cheng et al. (2019). If a province implements a policy, all areas of the province would be subject to the policy simultaneously.

The factors affecting HCE are complex, so we also incorporated control variables. Some scholars have focused on changes in family income and consumption patterns, and the heterogeneity of the family members. CO_2 emissions vary among households and income levels are the most important influence on this (Weber and Matthews, 2008; Golley and Meng, 2012; Sager, 2019). The higher the monthly income, the higher the energy consumption of travel, and the CO_2 emissions of wealthy households can be more than three times those of poor ones (Druckman and Jackson, 2008).

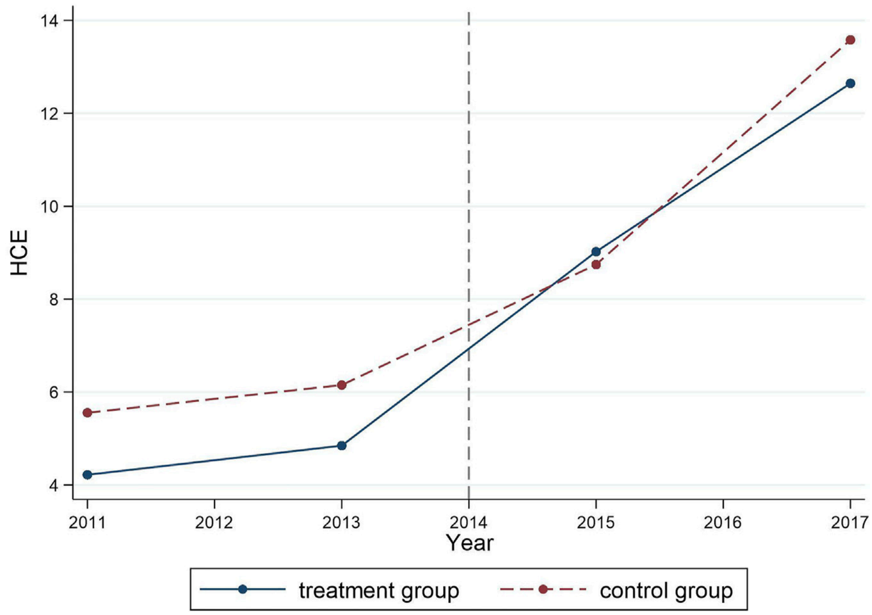

FIGURE 5 | Dynamic effects of the B and V on rural HCE.

So, we chose the annual household income (*Total_income*) as a control variable (row 5, **Table 1**). The impact of families on environmental pollution and resource loss is not entirely determined by the number of families, and the heterogeneity of families will also have an important impact on household consumption. Indicators of household heterogeneity include family size, age of the household head, gender, education level, etc. The household head plays a very significant role in the household's consumption-related decision-making. The age, gender, and education level of the householder have crucial impacts on the scale and structure of household energy consumption (Golley et al., 2008; Liu et al., 2013). So, we chose *Family_size* (row 4, **Table 1**) to reflect the family population. *Age*, *Gender*, *Primary*, *Junior*, *Secondary*, *Higher*, *Risk_p*, and *Risk_a* (rows 7–14, **Table 1**) were selected as indicators of household heterogeneity. Some studies believe that the impact of household heterogeneity exceeds those of income and consumption level (Starkey, 2012). Finally, we chose *LnGDP* (row 15, **Table 1**) as a provincial macroeconomic control variable. **Table 1** defines the variables used in the econometric model of this study.

3 METHODOLOGY

The methods used in this study were divided into two parts. First, to explore the impact of B and V on rural HCE, we used trace survey data from 2013 to 2015 for a Difference-in-Differences (DID) analysis. Second, in order to further verify the non-linear relationship between rural household broadband penetration level and HCE, threshold model were conducted with CHFS data from 2013, 2015, and 2017. The methodological framework of this article is shown in **Figure 4**.

3.1 DID Model

The data used in this paper are microscopic data, and B&V is a policy implemented by the central government at the provincial level. It is difficult for rural HCE to directly affect the formulation of this policy. Therefore, the B and V pilot program can be approximately considered as a quasi-natural experiment. The DID model is often used in the empirical research of policy evaluation (Wooldridge, 2010). To analyze the impact of B and V on HCE, the following DID model was constructed.

$$HCE_{it} = \beta_1 + \beta_2 Post_t + \beta_3 Treat_i + \beta_4 (Post_t \times Treat_i) + \beta_5 X_{it} + \varepsilon_{it} \tag{4}$$

In **Formula 4**, HCE_{it} is the CO2 emissions of household i at time t, $Treat_i$ is a virtual variable stating whether the household is located in an experimental group province ($Treat_i = 1$ for the experimental group provinces of Sichuan and Yunnan; otherwise, $Treat_i = 0$), $Post_t$ is a virtual variable of the year (when $t = 2015$ then $Post_t = 1$; otherwise, $Post_t = 0$). The coefficients of the interaction term (β_4) describe the effects estimated by our paper. X_{it} is a control variable, such as household and householder characteristics and the logarithm of provincial GDP.

3.2 Threshold Model

The threshold effect refers to the phenomenon in which when one parameter reaches a certain value or range, which is the threshold value, its effect on another parameter is reversed. The threshold value can be calculated by the threshold model. Compared with the linear model, the threshold model can explore the relationship between explanatory variables and explained variables more accurately. Before performing the threshold effect analysis, a

TABLE 4 | Results of placebo test.

Variables	Model 4	Model 5
Broadband	–0.7099	–0.6932
Controls	No	Yes
Year	Yes	Yes
Experimental group	Yes	Yes
_cons	6.1137***	6.3215
N	15940	15940
Adj.R^2	0.01	0.09

*Note: 1. See **Table 1** for definitions of the variables(Controls variables:Computer, Family_size, Total_income, Total_income square, Age, Gender, Primary, Junior, Secondary, Higher, Risk_p, Risk_a, LnGDP); 2. ***p < 0.01, **p < 0.05, and *p < 0.1.*

number of threshold effect tests were conducted. Using the indicative function $I(\cdot)$, suppose there are two thresholds, the threshold regression model is as follows:

$$HCE_{it} = \mu_i + \beta_1^{'} x_{it} \cdot I(x_{it} \le \gamma_1) + \beta_2^{'} x_{it} \cdot I(\gamma_1 \le x_{it} \le \gamma_2) + \beta_3^{'} x_{it} \cdot I(x_{it} > \gamma_2) + \beta' x_{it}^{'} + \varepsilon_{it} \quad (5)$$

In **Formula 5**, HCE_{it} is the CO_2 emissions of household i at time t. The individual intercept term μ_i represents the fixed-effect mode, and ε_{it} is the interference term. x_{it} is a threshold variable, γ_1 and γ_2 are the threshold value, $\beta_1^{'}$, $\beta_2^{'}$ and $\beta_3^{'}$ represent the influence of x_{it} on HCE_{it} of the threshold variable. $x_{it}^{'}$ are the other independent variables.

4 RESULTS

4.1 Descriptive Statistics

Table 2 shows the descriptive statistics of the variables. In the whole sample of 2013 and 2015, the average rural HCE was 7.40 MtC. After the pilot project in 2014, the average rural HCE was 8.77 MtC. The average rural HCE increased by 2.73 MtC before the pilot project, and the per capita CO_2 emissions of rural households was 2.03 MtC. Shi et al. (2020) utilized data from China micro surveys conducted in 2012, 2014, and 2016, and calculated an 2.81 MtC of HCE (including cities). It can be seen that in 2015, there was still a certain difference in the HCE of urban and rural households. After the B and V pilot project, household computer ownership increased from 19 to 23%. The rural household population did not differ significantly between the two surveys, both of which were about four persons. In 2015, the average household income after the pilot project increased by about 7,000 yuan compared to 2013. The mean age of rural householders was 54.7 years and 88% were male. In terms of the highest degree of education, 39% of householders had primary education. The risk-preference of householders accounted for 9% in 2013 and 6% in 2015, and there was no significant difference between the control and experimental groups. The proportion of risk-avoidant families decreased from around 72% in 2013 to around 65% in 2015, and the number of risk-neutral households increased.

4.2 Estimated Results

Our study was designed to explore the impact of B and V on rural HCE. **Table 3** shows the estimates of the impact of B&V on rural HCE. Model 1 (column 2, **Table 3**) controls the year and experimental virtual variables. The coefficient of the interaction term (*Broadband*) is 1.5812 and is significant at 5%. The results show that without adding the control variables, the B&V pilot project significantly improved the rural HCE. Model 2 (column 3, **Table 3**) adds control variables such as household, household head, and provincial macroeconomic characteristics. The coefficient of the interaction term (*Broadband*) is 1.7217 and is significant at 5%. The interaction term coefficients of Model one and two varied little but showed an upward trend. In the household characteristic variables, *Total_income* has a significant positive impact on rural HCE, while *Total_income square* has a significant negative effect. That means there is an inverted "U"-shaped relationship between family income and HCE, again confirming the EKC hypothesis. *Family_size* positively affects HCE and is significant at 1%. *Age* significantly negatively affects HCE, while *Junior* and *Secondary* and *Higher* all significantly positively affect HCE. The largest influence coefficient is *Higher*. Householders with risk preference have a greater probability of increasing HCE. Householders with risk aversion are more likely to have lower HCE. *LnGDP* did not pass the significance test. The empirical results show that the B and V pilot project has a role in improving rural HCE.

The ideal situation is that the individual characteristics of the treatment and control groups were the same before the pilot project. However, these groups did not fully meet this condition; therefore, there may be a selective bias. To alleviate this problem, we revisited the estimation analysis using the propensity score matching method (PSM) and the PSM-DID method of Heckman et al. (1997). Model 3 (column 4, **Table 3**) is the result of the PSM-DID model estimate. The interaction term (*Broadband*) is significant at 5%, and the coefficient size is very close to that of Model 2. In eliminating the impact of the characteristics of the householder and family, we once again confirm that the B and V pilot project has a role in increasing rural HCE. Although the research approach is different from those of previous studies, the conclusions that ICT contributes to CO_2 emissions are consistent with them (Danish M. A. et al., 2018; Shabani and Shahnazi, 2019).

Overall, the estimated results indicate that China is in the stage where the development of ICT is increasing rural HCE. Income is an important driver of CO_2 emissions over time (Dong et al., 2019). We found that different income levels of rural households have different contribution to CO_2 emissions. That is, when income reaches a certain level, it reduces CO_2 emissions.

4.3 Parallel Trend Test

Parallel trend is assumed to be a prerequisite for DID. If the parallel trend assumption is not satisfied, then the estimated policy effect is not a completely true policy effect. Time-series plots for both the treatment and control groups are used. We use data from 4 years (2011, 2013, 2015, 2017) to map the average HCE on the *y*-axis and years on the *x*-axis. According to **Figure 5**,

TABLE 5 | Results of threshold test.

Explained Variable	Null Hypothesis	Threshold Quantity	Interval	*p* Value	Numbers of BS
HCE	Single threshold	11.2300	[10.3050,11.8000]	0.0000***	300
	Double thresholds	16.1600	[16.0100,18.0800]	0.0167**	300
	Triple thresholds	23.0700	[22.9300,23.2100]	0.7500	300

*Note: 1. See **Table 1** for definitions of the Explained variables; 2. ***p < 0.01, **p < 0.05, and *p < 0.1.*

TABLE 6 | Results of threshold regression.

Variables	Model 6	Model 7
Interval 1 (*rbp* < 16.16)	0.7081***	0.5143***
	(15.0259)	(8.5128)
Interval 2 (16.16 < *rbp* < 31.32)	0.4441***	0.2916***
	(15.0051)	(6.9677)
Interval 3 (*rbp* > 31.32)	0.1778***	0.1497***
	(5.7354)	(4.7442)
Controls	No	Yes
Time fixed effect	Yes	Yes
Individual fixed effect	Yes	Yes
_cons	–0.936	–519.260***
N	19602	19602
R^2	0.02	0.07

*Note: 1. See **Table 1** for definitions of the variables(Controls variables:Family_size, Total_income, LnGDP; Definition of rbp see **Formula 5**); 2. ***p < 0.01, **p < 0.05, and *p < 0.1; 3. The values of T are in parentheses.*

we can judge the temporal trend between the treatment and control groups after the B and V pilot project year. There is no significant difference in the temporal trends before the B and V pilot project year, so the parallel trend test is passed.

4.4 Placebo Test

A placebo test is the use of a false policy occurrence time or experimental group to test whether a policy effect could be obtained. If the policy effect is still obtained, it shows that the estimated policy effect is not reliable. Guizhou and Chongqing are geographically adjacent to Yunnan and Sichuan, and the levels of economic development are similar. Therefore, this paper conducted a placebo test by changing the experimental groups, Guizhou and Chongqing, and two provincial administrative samples. The test results in **Table 4** show that the interaction terms do not pass the significance test, which indicates that estimated policy effect is reliable.

4.5 Further Studies

The EKC hypothesis suggests that the impact of income level on the environment is nonlinear. So, is there a non-linear relationship between the rural household broadband penetration and CO_2 emissions in China? The empirical findings suggest that there is an inverted "U"-shaped relationship between ICT development and CO_2 emissions (Higón et al., 2017). Some scholars revealed that threre was a threshold of external policies for economic resilience (Li Q. et al., 2016). We believe that the B and V pilot project period was the initial stage of rural household broadband penetration. Therefore, the impact of household broadband penetration on rural HCE does not have a simple linear relationship. In order to further verify the non-linear relationship between rural household broadband penetration level and HCE, we obtained two indicators from the *China Statistical Yearbook*: the total broadband access users (*abu*) and rural broadband access users (*rbu*) of provincial administrative units. Broadband penetration is generally measured by the number of broadband connections available (Koutroumpis, 2009), and this paper adopts the same approach. So, the rural household broadband penetration (*rbp*) is calculated as:

$$\text{rbp} = \frac{rbu}{abu} \tag{6}$$

Then, the relationship between *rbp* and HCE is determined by drawing from the panel threshold model proposed by Hansen (1999). The threshold variable is the rural household broadband penetration (*rbp*), and the control variables include *total_income*, *family_size*, and *LnGDP*. **Table 5** is the number of threshold test results, which show that the number of thresholds is two.

Based on the above analysis, considering the double threshold effect and combining the microscopic data of the CHFS surveys from 2013, 2015, and 2017, the threshold model is established as follows:

$$HCE_{it} = \mu_i + \beta_1' rbp_{it} \cdot I(rbp_{it} \le \gamma_1) + \beta_2' rbp_{it} \cdot I(\gamma_1 \le rbp_{it} \le \gamma_2) + \beta_3' rbp_{it} \cdot I(rbp_{it} > \gamma_2) + \beta_5 total\_income_{it} + \beta_6 family\_size_{it} + \beta_7 \ln GDP_{it} + \varepsilon_{it} \tag{7}$$

HCE_{it} is the CO_2 emissions of household i at time t. The individual intercept term μ_i represents the fixed-effect mode, and ε_{it} is the interference term. rbp_{it} is a threshold variable, β_1', β_2' and β_3' represent the influence of rbp_{it} on HCE_{it} of the threshold variable. $total\_income_{it}$, $family\_size_{it}$, and $\ln GDP_{it}$ are the other independent variables. **Table 6** presents the threshold regression results, which show that there is a nonlinear relationship between rural household broadband penetration and HCE. From **Table 5**, Models 6 and 7, the different proportions of rural broadband access have completely different effects on HCE. There is an obvious threshold effect and the promotion effect weakens rapidly. In **Table 5**, Model six shows that the double threshold values are 16.16, 31.32, and 31.32% without considering the control variables. In rural areas with a low rural household broadband penetration level (*rbp* < 16.16), to the next level (16.16 < *rbp* < 31.32), the coefficient of impact on HCE decreased from 0.7081 to 0.1778; all were significant at the 1% level. Model 7 (**Table 5**) suggests that the impact coefficient of rural household broadband penetration on HCE in rural areas decreased from 0.5143 to 0.1497 when considering control variables (all significant at 1%). This shows that in a low level of rural household broadband penetration, it significantly increases the rual HCE and, with further level, the impact of increase declines rapidly.

5 CONCLUSSION AND DISCUSSION

5.1 Conclusion

Whether ICT or broadband infrastructure can achieve a "win-win" between environmental conservation and economic development has captured much research attention. However, very few scholars have studied the impact of broadband infrastructure on rural HCE. We explore how broadband infrastructure affects rural HCE and examine the nonlinear relationship between household broadband penetration and rural HCE. We came to the following conclusions. 1) During the study period, B and V pilot project has a role in increasing rural HCE. We estimated an effect corresponding to an increase of approximately 1.7 MtC by the implementation of B and V in rural HCE. 2) Technology and income are both key drivers of HCE. Further, there was an inverted "U"-shaped relationship between family income and HCE, again confirming the EKC hypothesis. Different income levels of rural households have different contribution to CO_2 emissions. That is, when income reaches a certain level, it reduces CO_2 emissions. 3) In further verifying the nonlinear relationship between the rural household broadband penetration and HCE, we found a significant threshold effect between them. When the rural household broadband penetration is below 31.32%, it significantly increases HCE. The growth effect of rural household broadband penetration to HCE would be much weaker, if rural household broadband penetration goes above 31.32%.

Actually, the conclusions are helpful to clarify the implementation direction of the CO_2 mitigation strategies and digital villages strategy. First, improve rural household broadband penetration level, and cross the 31.32% threshold as soon as possible. Second, raising the income level of rural households can help achieve a "win-win" between environmental conservation and economic development. Third, improve the level of ICT application and develop rural industries.

5.2 Discussion

First, the B and V pilot project was taken as an external policy impact and the DID method was adopted for analysis. We found that different income levels of rural households have different contribution to CO_2 emissions. That is, when income reaches a certain level, it reduces CO_2 emissions. These results were consistent with those by Lutz (2019). However, expanding consumption and controlling greenhouse gas emissions are both long-term policy goals of the government, yet there may be some degree of incentive incompatibility between the two. Excessive pursuit of equity in household income distribution may increase CO_2 emissions generated by household consumption (Heerink et al., 2001). Thus, when the government formulates income redistribution policies, it also needs to consider the environmental externalities.

Second, the growth effect of B and V to rural HCE would be much weaker, if rural household broadband penetration goes above a threshold level. Earlier studies have also found a nonlinear relationship between household broadband penetration and CO_2 emissions (Higón et al., 2017; Li and Song, 2019). Considering China's situation, Internet technology is changing all aspects of rural life, such as its consumption model, consumption structure, and family income. In view of the situation that rural broadband construction has lagged that of urban areas for a long time (Liu and Wang, 2021), we should emphasize that promoting household broadband penetration in under-developed areas can raise them above the threshold. Developed areas can make good use of the Internet to reduce CO_2 emissions. Improving energy utilization efficiency and reducing the use of straw and coal in rural areas can also reduce CO_2 emissions.

Third, during the study period, B and V pilot project has a role in increasing rural HCE. Previous contributions tested for this association at a macro level (Li and Song, 2019). But what is important now is to take full advantage of the benefits brought by broadband infrastructure. Rural residents were more vulnerable to external shocks, such as climate change, because of their lack of nature and financial capital (Peng et al., 2018). To solve these problems, China has adopted a low-carbon economy to balance the relationship between CO_2 emissions and economic development (Zhang et al., 2011). With the help of the advantages of ICT, we will advocate for the dissemination of information related to low-carbon lifestyles to rural consumers via the Internet, improve their ability to judge the energy efficiency of electrical appliances, encourage them to buy low-carbon products, and improve the efficiency of resource utilization. ICT has also played a significant role in rural production and has helped reduce farming household cropland abandonment by 43.20% (Deng et al., 2019). Therefore, China is vigorously implementing the digital village strategy and expanding the application of ICT in rural areas.

Of course, the results of this paper only demonstrated a non-linear relationship between rural household broadband penetration and rural HCE. During the study period, there is no evidence that there is an inverted "U"-shaped relationship between the ICT and HCE. Therefore, the next step will be to add the latest data by expanding the time span of the study sample. We hope to demonstrate that when the rural household broadband penetration is at a higher level, the corresponding changes in rural HCE.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

PR proposed the research idea, developed the model and wrote the first manuscript draft. CN and XL collected data and performed the computations. FX and SZ revised them critically. All authors have made a substantial and intellectual contribution to this article and approved it for publication.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.818134/full#supplementary-material

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Climate Shocks and Farmers' Agricultural Productive Investment: Resisting Risk or Escaping Production?

*Ziming Zhou[1], Zhiming Yu[1] and Sihan Gao[2]**

[1] School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China, [2] Innovation and Talent Base for Income Distribution and Public Finance, Zhongnan University of Economics and Law, Wuhan, China

Climate shocks can increase uncertainty in agricultural production. Using data from the China Family Panel Studies (CFPS), this study examines the impact of climate shocks on farmers' productive investment and its mechanism of village public productive investment. The study found the following: (1) The impact of climate shocks have a significant impact on farmers' productive investment choices. Farmers who are greatly impacted by climate shocks have a significantly lower probability of increasing their total productive investment. (2) In terms of investment content, climate shocks will reduce farmers' investment in machinery (invest1) and investment in the cost of seeds, fertilizers and pesticides (invest3) and increase investment in agricultural productive services (invest2). (3) However, there is heterogeneity in the village climate characteristics and farmers' risk preferences in this result. (4) From the perspective of the transmission mechanism, village public production investment has a moderating effect between climate shocks and farmer agricultural production investment. For total investment and invest3, village public production investment will weaken the main effect of climate shock, significantly reduce the impact of climate shock, and alleviate the inhibitory effect of climate shocks on farmers' investment. Agricultural productive services (invest2) will strengthen the main effect of climate shocks and promote farmer households' agricultural productive service investment. The article finally concludes and discusses some policy implications.

Keywords: agricultural productive investment, risk perception, village public production investment, moderating effect, climate shocks

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****Correspondence:***
Sihan Gao
victoriagao@zuel.edu.cn

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INTRODUCTION

The first working report of the sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC) pointed out that climate change is extensive, rapid and intensifying. The frequency and intensity of extreme heat events, marine heat waves and heavy precipitation have increased significantly (IPCC, 2021), which is another reminder of the urgency of action on climate change. While some regions benefit from climate change (e.g., in mid-to-high latitudes, where warming increases crop yields), the vast majority will be adversely affected by climate change, especially for farmers who depend on agricultural income (Reynaud et al., 2017; Mera, 2018; Hu and Zheng, 2021). China is located in the monsoon climate zone with the fastest rate of environmental change in the world, and the climate conditions vary greatly from year to year. Intensified climate change will lead to high temperature, drought, heavy precipitation and other extreme weather and frequent occurrence of diseases and insect pests, which may directly lead to greater vulnerability of China's agriculture (Zhou et al., 2021). The reason is that agriculture relies heavily on natural climatic levels, and high temperatures or a lack of water can inhibit crop growth and reduce yields, especially extreme weather such as droughts and floods, which can even lead to failure of agricultural harvests (Bhuvaneswari et al., 2014).

In the long term, climate change will also affect irrigation resources, soil quality and the natural communities on which agricultural production depends (Araya et al., 2020). Melting polar glaciers are causing sea level rise and reducing the availability of cultivated land (Paul et al., 2010). This indirectly affects the price of food and the household income of farmers (Bandara and Cai, 2014). Nguyen et al. (2020) also further confirmed that climate shocks have a significant impact on household income, investment and poverty by using rural household survey data in northeastern Thailand and central Vietnam. Therefore, in this context, it is of great significance to study the impact of climate shocks on agricultural investment and explore the adaptive measures of farmers to cope with climate change, which are of great significance to the realization of various goals, such as stabilizing agricultural production, ensuring food security, and reducing poverty (FAO, 2012).

Becker (2010) believes that changes in the external environment have a profound impact on people's preferences and choices. The more severe the impact of climate risk is, the greater the uncertainty in agricultural production. To reduce the adverse impact of climate change and extreme weather on agricultural production and farmers' livelihoods, farmers will consciously and rationally take some adaptive measures to reduce the risk of shocks (Chen et al., 2014; Xu et al., 2017). Specifically, on the one hand, farmers will reduce the impact of climate change on agricultural production by increasing the level of mechanization, improving irrigation facilities, and changing crop varieties. As Belton et al. (2021) found, investment in agricultural mechanization facilitates more timely and efficient planting and harvesting, and these advantages help farmers to be more flexible in responding to risks in the context of labor shortages and changing climates. On the other hand, the use of agricultural machinery and the improvement of varieties are not only one of the ways to reduce climate risks through technological advantages but also a simple substitution of capital for agricultural labor under relative price constraints (Zhang et al., 2017). That is, under climate shock, the replacement of production factors such as labor, temperature, and precipitation by increasing agricultural input is also a rational choice for farmers to deal with climate change (Bhandari and Ghimire, 2016).

However, there are also views that climate shocks will prompt farmers to abandon agricultural production (Warner and Afifi, 2014; Cattaneo and Peri, 2016; Sheng and Yang, 2021). It has an inhibitory effect on farmers' agricultural investment. Based on opportunity cost theory (Hu X. et al., 2020; Geng and Luo, 2021), labor migration theory (Xu et al., 2020; Zeng et al., 2021) and the theory of comparative advantage (Hong and Luo, 2018; Hu W. et al., 2020), the formation mechanism of farmers' productive investment decision-making is analyzed. The logic of climate shocks reducing agricultural investment is that climate shocks will affect households through the income effect, which will gradually reduce farmers' dependence on agriculture, and the importance and expected returns of agricultural income will also decrease accordingly, thus prompting farmers to reduce agricultural investment. It can be seen that the existing conclusions on the impact of climate shocks on farmers' productive investment are inconsistent. The reason may be that there are differences in the research perspective and the definition of farmers' investment. Therefore, seemingly contradictory conclusions are drawn, and further discussion is necessary.

To respond to the above questions and explore farmers' adaptation behaviors to climate change, this study matched the macrolevel climate data with the microlevel peasant household data, focused on the impact of climate shock on agricultural productive investment, and investigated the internal logic, mechanism of action and heterogeneity of this impact. Thus, the impact of climate change on productive investment in agriculture can be estimated more reliably. It should be emphasized that although our research is based on Chinese data, its conclusions may have a certain reference for other developing countries in terms of coping with the impact of climate risks on agriculture, especially those countries in sub-Saharan Africa.

DATA AND METHODS

Data

This study applies two databases. The first is the farmer household survey data at the micro level. The data come from the China Family Panel Studies (CFPS) of Peking University. CFPS covers 25 provinces (municipalities and autonomous regions) in mainland China and adopts a three-stage unequal probability cluster sampling design. The data used in this article are mainly from CFPS2018 released in 2020, and only samples who live in rural areas and are still engaged in agricultural production in that year are retained. To obtain more comprehensive farmer household information, our research combined CFPS2016, CFPS2014, and CFPS2012 data with CFPS2018 data[1]. Only the information of rural households and members who participated in the four questionnaires was retained to obtain sample community information, cultivated land information and changes in agricultural investment. After processing, 23 provinces (cities/autonomous regions), 109 counties (districts), 243 villages, and a total of 2,799 valid samples were obtained.

The second is macrolevel climate data. The data come from the 2014, 2015, and 2016 "China Environmental Statistical Yearbook" and "China Statistical Yearbook." The main variables used are the provincial GDP and economic losses caused by extreme weather after earthquake disasters, including droughts, floods, and low temperatures, freezing, storms, marine disasters,

[1]This article uses cross-sectional data, and the purpose of merging is to fill in missing values.

etc. Compared with previous studies, the data coverage of this article is wider and more representative at the national level.

Variables

Explained Variable

Taking into account the above literature and data availability, this study focuses on three types of agricultural productive investment. The first is fixed investment that is not directly related to land. This study uses the added value of the total value of various types of agricultural machinery owned by farmers in that year. The second is the investment in agricultural productive services, including hire labor, hire livestock, machine rental, etc. This study uses the total value of the investment in hire labor and hire machinery. The third is investment in basic agricultural means of production with liquidity directly related to land, including seeds, fertilizers and pesticides. The total amount of the three types of investment is taken as the total scale of agricultural investment. In addition, Chinese farmers generally have diversified planting (Lu and Hu, 2015). In addition, some production investments (such as fixed assets) have difficulty accurately corresponding to the production of each crop, so this article does not distinguish between crop types. At the same time, considering that the household is the basic unit of agricultural production and management, the agricultural productive investment and other variables in this article are all taken as the statistical unit of the household, and the data are standardized.

Core Explanatory Variables

Climate Shock Index

The National Meteorological Administration lists floods, droughts, freezing disasters (mainly frost disasters) and wind disasters as the most important meteorological disasters, and the National Bureau of Statistics Poverty Monitoring Survey also lists and counts these disasters separately. There is a strong correlation between climate shocks and economic losses (Wasko et al., 2021). Considering the rationality and possibility of research needs and existing data, this article refers to the method of the disaster intensity index[2] and Xu et al. (2021). The amount of damage caused by natural disasters accounts for the proportion of GDP to measure the impact of climate shocks throughout the year (In order to facilitate the calculation, this article processes this ratio by $\times 100$). Using relative value rather than absolute value indicators is conducive to measuring the impact of disaster losses on different regions according to local conditions. Of course, this article will also use the absolute loss value of climate shocks to test the robustness of the relationship between climate shocks and agricultural productive investment.

Control Variables

To improve the reliability of the fitted regression, this study introduces a series of control variables with reference to the existing literature. It mainly includes 13 control variables in three dimensions (**Table 1**): family demographic characteristics, family asset characteristics, and village characteristics. (1) Family demographic characteristics: This study selects four variables: family size, the number of household laborers, average age and average education level. (2) Family asset characteristics: on the one hand, considering whether to invest in agricultural production, a critical factor is the investment ability of the household (Huang and Ji, 2012). Therefore, this study uses the characteristics of farmers' household assets to represent the wealth level and economic ability of farmers. Specifically, it includes the value of financial assets, non-mortgage financial liabilities, per capita annual household income, and whether government subsidies are received. On the other hand, the scale of land management is a key variable affecting production investment. A larger management area means that farmers need to invest more liquidity assets (Hong, 2019; Yang and Ji, 2021). Therefore, this study also takes into account two factors, the scale of self-owned land and the scale of contracted land, which can reflect the characteristics of land assets. (3) Village characteristics: The terrain will affect the investment behavior of farmers by affecting the difficulty of farming, and the traffic situation will affect the investment behavior of farmers by affecting the acquisition of production materials. Therefore, this study refers to Qian and Qian (2018) to introduce the variables of village topography, traffic conditions and infrastructure at the village level. In addition, to control the possible influence of regional-level factors, this study controls the province fixed effect. The definitions of the key variables are displayed in **Table 1**.

Model

To analyze the impact of climate shocks on farmers' productive investment, the benchmark model is set as follows:

$$\begin{aligned} Investment_i = {} & \alpha_0 + a_1 CS_i + a_2 Family_i + a_3 Asset_i + a_4 Village_i \\ & + \delta_1 P + \varepsilon_i \end{aligned} \tag{1}$$

where $Investment_i$ indicates the agricultural production investment of farmers' households, CS_i is the Climate Shock Index, $Family_i$ is family demographic characteristics, $Asset_i$ is family asset characteristics, $Village_i$ is village characteristics, P is the province dummy variable to control the possible impact of regional-level factors, and ε_i is a random disturbance term. The main concern of this study is the coefficient of a_1, the impact of the climate shock index on the investment of farmers. To further examine whether there are differences in investment types due to climate shocks, this study will use Equation (1) to examine the impact of climate risk shocks on different investment types (Invest1, Invest2, and Invest3).

$$\begin{aligned} Investment_i = {} & \beta_0 + \beta_1 CS_i + \beta_2 \cdot CS_i \cdot Vinvest_i + \beta_3 Vinvest_i \\ & + \beta_4 Control + \delta_2 P + \varepsilon_i \end{aligned} \tag{2}$$

As an external risk-resistant factor, village productive investment can moderate the relationship between climate shocks and farmers' productive investment (**Figure 1**). Drawing on the research method of Wen et al. (2005). On the basis of Equation (1), this study introduces the interaction term between

[2]"14th Five-Year" National Emergency System Planning http://www.gov.cn/zhengce/content/2022-02/14/content_5673424.htm?spm=C73544894212.P59511941341.0.0.

TABLE 1 | Variable definition.

Variable	Variable definition	Mean
Invest1	Increased cost of agricultural machinery (yuan)	−0.010
Invest2	The cost of agricultural productive services (yuan)	0.097
Invest3	The cost of seeds, fertilizers and pesticides (yuan)	0.134
Invest total	Total agricultural productive investment (yuan)	0.319
CS	Climate shock index × 100	0.757
Family size	Family size	1.299
Num_labor	Number of household labor (15 < age < 60)	2.068
Avg_age	Average age of family members	3.837
Avg_edu	Average education level of family members (average years of schooling)	6.232
Ln_assets	The value of financial assets (yuan)	6.957
Ln_debt	The value of non-mortgage financial liabilities (yuan)	2.520
Ln_income	Per capita annual household income (yuan)	8.742
Allowance	Whether government subsidies are received (yes = 1, no = 0)	0.725
Land	The scale of self-owned land (mu)	12.214
Ln_rent	The scale of contracted land (yuan)	0.992
Ln_distance	The distance from county seat (the time it takes to travel normally)	0.329
Ln_infra	Amount of infrastructure investment (yuan)	0.355
Terrain	Hills = 1, Mountains = 2, Plains = 3, Others = 0	1.862

the climate shock index and village-level productive investment $Vinvest_i$, examines its moderating effect β_2 on the impact of climate shock on farmer agricultural productive investment, and constructs the moderating effect Model (2).

RESULTS

Descriptive Statistics

Table 2 shows the measurement results of the climate shock index in each province from 2014 to 2016. Taking 2016 as an example, it can be seen that the top five climate shock indexes are: Shanghai (0.001), Tianjin (0.020), Beijing (0.065), Shandong (0.107), and Guangxi (0.150). It is mainly the provinces with small actual losses caused by climate shocks or strong anti-risk ability caused by high GDP. Fujian (1.644), Hebei (1.930), Hainan (1.955), Anhui (2.311), and Hubei (2.564) are in the bottom five. The above provinces are mainly caused by high disaster losses, but the actual loss value of Hainan is not high. It is due to its low GDP and weak anti-risk ability. From the 2014 to 2016 data, it can be seen that there are differences in the climate shock index in different years. Some provinces, such as Hainan, even showed

TABLE 2 | Climate shock index by province (2014–2016).

Province	2014	2015	2016	Province	2014	2015	2016
Shanghai	0.000	0.014	0.001	Qinghai	0.404	0.496	0.665
Tianjin	0.008	0.000	0.020	Jilin	0.849	0.582	0.668
Beijing	0.049	0.006	0.065	Shanxi	0.398	0.809	0.833
Shandong	0.138	0.128	0.107	Hunan	0.764	0.438	0.841
Guangxi	1.223	0.289	0.150	Yunnan	0.763	0.963	0.924
Jiangsu	0.022	0.121	0.156	Inner mongolia	0.636	0.618	0.992
Guangdong	0.497	0.433	0.182	Heilongjiang	0.371	0.262	1.043
Liaoning	0.592	0.227	0.206	Gansu	1.090	0.907	1.243
Sichuan	0.584	0.433	0.233	Xizang	0.206	0.407	1.311
Chongqing	0.691	0.140	0.269	Guizhou	2.107	0.642	1.472
Henan	0.340	0.119	0.308	Fujian	0.189	0.728	1.644
Zhejiang	0.144	0.532	0.354	Hebei	0.459	0.361	1.930
Shanxi	0.528	0.403	0.404	Hainan	5.068	0.384	1.955
Ningxia	0.603	0.285	0.549	Anhui	0.141	0.540	2.311
Jiangxi	0.463	0.417	0.573	Hubei	0.248	0.278	2.564
Xinjiang	1.128	1.671	0.595				

significant differences in 2014 (5.068) and 2015 (0.384), which fully demonstrates the climate shock is uncertain.

Figure 2 shows the average level of the climate shock index from 2014 to 2016. It can be seen that Hainan has the highest average climate shock index, reaching 2.469, mainly due to the high value in 2014 (see **Table 3**). In addition, the provinces with high average climate shock index (0.75–1.40) are mostly concentrated in the northwest region (Xinjiang and Gansu), the southwest region (Yunnan and Guizhou), the central region (Hubei and Anhui), and Hebei and Fujian. Shandong and Jiangsu, which are major agricultural provinces, have low climate shock indices, which fully shows that climate shocks vary among provinces in China. Therefore, analyzing the impact of different climate shocks on farmers' investment behavior is of great significance for interregional resource allocation and policy formulation to combat climate change.

Are Climate Shocks Affecting Agricultural Productive Investment?

First, the OLS method is used to estimate Model (1) to examine whether the impact of climate shocks on agricultural productive investment exists (**Table 3**). Among them, Column (1) only considers the impact of the climate shock index on the agricultural productive investment of farmers; Columns (2–4) gradually control for family demographic characteristics, family asset characteristics and village characteristics. As expected, the coefficients of the climate shock index are all significantly

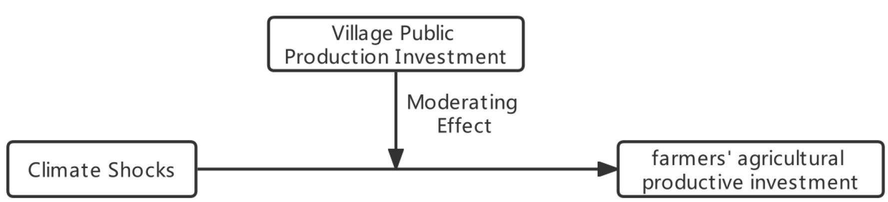

FIGURE 1 | Climate shocks, village public production investment, and farmers' agricultural productive investment.

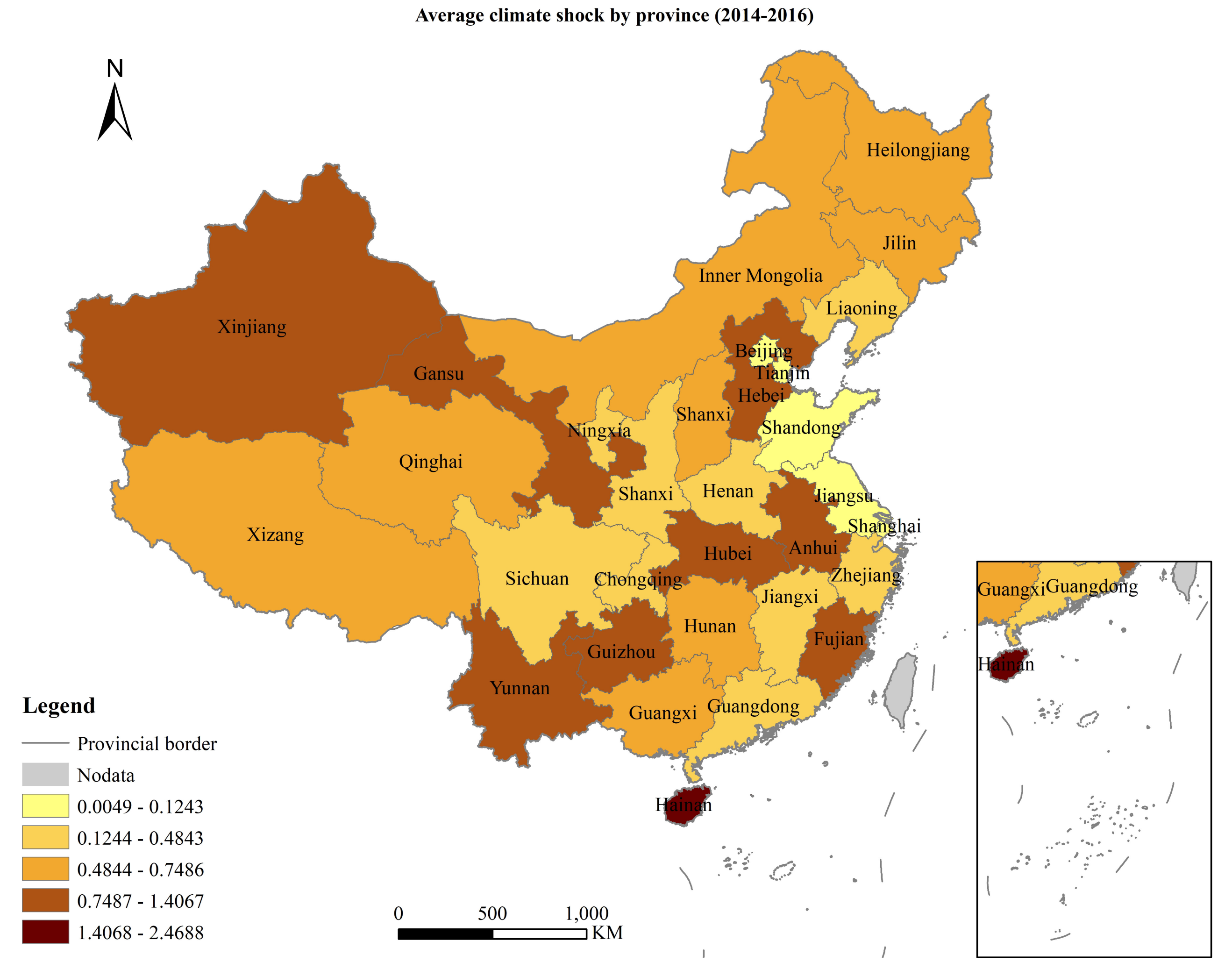

FIGURE 2 | Average climate shock by province (2014–2016).

negative in all regressions. This shows that, based on the benchmark model, the climate shock significantly reduces the total agricultural productive investment of farmers.

Among the control variables, family size and average education level in household demographic characteristics have significant promoting effects on agricultural productive investment. The larger the family size and the higher the average level of education, the greater the probability that farmers will invest in agricultural production. Among the characteristics of household assets, the value of household financial assets and non-mortgage financial liabilities have a significant role in promoting agricultural productive investment. It should be noted that the impact of the scale of family-owned land on agricultural productive investment is positive but not significant, but this is also expected. Under the household contract responsibility system policy, except for large-scale farms, there is little difference in the area of land owned by farmers (Xu and Zhang, 2016). In contrast, the impact of the scale of contracted land on agricultural productive investment of farmers is significantly positive because it is theoretically believed that the larger the scale of land, the more likely farmers are to increase capital investment to increase returns to scale (Xin and Qin, 2005). Therefore, the increase in the contracted land area will naturally encourage farmers to increase investment in agricultural mechanization and seed fertilizers (Li et al., 2021). Among village characteristics, the level of village infrastructure has a negative effect on agricultural investment, which may be due to the crowding-out effect of government investment on farmer investment. If the government's investment increases, the willingness of farmers to invest will decrease (Chu and Mo, 2011).

Are There Category Differences in the Impact of Climate Shocks on Agricultural Productive Investment?

The above estimates suggest that climate shocks can have an impact on agricultural productive investment. In this section, we examine whether there are differences in the impact of climate shocks on different types of productive investment. **Table 4** shows that climate shocks reduce farmers' investment in machinery (invest1), increase investment in agricultural productive services (invest2), and reduce investment in the cost of seeds, fertilizers and pesticides (invest3). What is different from the results in **Table 4** is the promotion effect of climate shocks on investment in agricultural productive services. This may be because farmers only make agricultural investments when they expect returns (Beekman and Bulte, 2012). In production practice, as the demander of agricultural machinery operations, there are mainly two ways for farmers to operate agricultural machinery. One is the self-service of self-purchased agricultural machinery. The second is the outsourcing method of leasing agricultural machinery. Compared with investment in productive services, investment in agricultural machinery has higher sunk costs and a long break-even period (Qiu et al., 2021). In particular, climate shock is not conducive to the survival of small farmers. Agricultural machinery has the characteristics of high investment costs, high technical thresholds and long payback periods, which reduce farmers' willingness to invest (Hong et al., 2020). In recent years, to meet the needs of small-scale farmers for agricultural machinery, specialized agricultural machinery service organizations have emerged in large numbers in rural areas, and many labor-intensive production links have been outsourced and mechanized. Therefore, farmers under climate shock are more inclined to increase investment in agricultural productive services. This is consistent with the existing research conclusions and in line with the actual situation of current agricultural production.

Robustness Tests

Climate shock is relatively exogenous to farmers' productive investment, which alleviates the endogenous problem of core explanatory variables to a certain extent. Therefore, to ensure the reliability of the above regression results, further robustness tests are carried out from the following three aspects. First, referring to the practice of Crinò and Ogliari (2015), to address the potential measurement error problem and prevent outliers from biasing the core results, this article performs bilateral truncation on the 1% quantile of the climate shock index. The results are shown in **Table 5**. The impact of the core explanatory variable climate shock index on agricultural productive investment remains unchanged and still significant.

Another concern is that there are certain differences in the impact of climate shocks on farmers' behavior in different years, which may lead to differences in the impact of agricultural productive investment. Therefore, to further test the robustness of the research conclusions, this study selects the average value of the climate shock index (2014, 2015, and 2016) as the core explanatory variable, and the regression results are shown in **Table 6**. After replacing the core explanatory variables, the influence coefficients of the climate shock index on invest1 (agricultural machinery investment), invest2 (agricultural productive services investment), and invest3 (the investment of seeds, fertilizers, and pesticides) have slightly increased, but the direction of influence is consistent with **Table 3** and remains significant. This further confirms the robustness of the results of the impact of climate shocks on agricultural productive investment.

The climate shock index set in the benchmark model in this article is a relative variable, and for provinces with large differences in climatic conditions and GDP, it may not fully reflect the real situation of the level of climate shock. To further exclude possible interference, this study uses the economic loss value caused by the actual climate shock instead of the climate shock index for the robustness test. From **Table 7**, it can be found that after replacing this core explanatory variable, the influence coefficients of the climate shock index on invest1 (agricultural machinery investment), invest2 (agricultural productive services investment), and invest3 (the investment of seeds, fertilizers, and pesticides) are slightly reduced but still significant, which further confirms the robustness of the conclusions of this article.

Heterogeneity Analysis

Heterogeneity of Village

Will climate shocks in disaster-prone regions have a greater impact on productive investment? To confirm the above judgments, this article divides the overall sample into two subsamples, the climate safe area and the climate non-safe area, according to whether the village where the farmer is located in the CFPS questionnaire is an area with frequent natural disasters. Using the benchmark model, the above two subsamples are fitted and regressed, and the results are shown in **Table 8**. For farmers in climate-insecure areas, the coefficients of the impact of climate shocks on invest total (Total agricultural productive investment), invest1 (agricultural machinery investment), and invest3 (the investment of seeds, fertilizers, and pesticides) are still negative, which is consistent with the benchmark regression. However, for farmers in climate-safe areas, climate shocks will not have a significant impact on their agricultural productive investment. This also fully illustrates a problem. With the aggravation of climate change, it is necessary to pay more attention to the productive investment of farmers in climate-insecure areas with frequent natural disasters.

Heterogeneity of Risk Appetite

Classical economic theory believes that risk appetite will affect investment decisions. Therefore, this part focuses on examining the impact of farmers' risk attitude heterogeneity on agricultural productive investment. This study uses the behavior and mental state part of the CFPS2018 questionnaire to evaluate farmers' risk attitudes. The value of the risk attitude variable from 1 to 6 represents the increasing degree of risk preference of residents. If the variable value of risk attitude is greater than or equal to 4, it is classified as a risk-loving farmer; otherwise, it is classified as a risk-averse farmer. **Table 9** shows that for risk-averse farmers, the coefficients of the impact of climate shocks on invest total (Total agricultural productive investment), invest1 (agricultural machinery investment), and invest3 (the investment of seeds, fertilizers, and pesticides) are still negative, which is consistent with the benchmark regression. However, the negative impact of

TABLE 3 | Regression results of the benchmark model between climate shocks and farmers' agricultural investment.

	(1)	(2)	(3)	(4)
	Invest total	**Invest total**	**Invest total**	**Invest total**
CS	−0.0765* (0.0404)	−0.0853** (0.0417)	−0.1396*** (0.0446)	−0.0924* (0.0508)
Family size		0.0883*** (0.0287)	0.0898*** (0.0262)	0.0902*** (0.0266)
Num_labor		0.0108 (0.0115)	0.0011 (0.0116)	0.0010 (0.0117)
Avg_age		0.0480 (0.0903)	0.1250 (0.0821)	0.1144 (0.0815)
Avg_edu		0.0146*** (0.0035)	0.0143*** (0.0034)	0.0130*** (0.0034)
Ln_debt			0.0120** (0.0049)	0.0119** (0.0049)
Ln_assets			0.0078* (0.0041)	0.0076* (0.0042)
Ln_income			−0.0069 (0.0197)	−0.0077 (0.0195)
Allowance			−0.0393 (0.0336)	−0.0406 (0.0336)
Land			0.0002 (0.0003)	0.0004 (0.0003)
Ln_rent			0.0658*** (0.0111)	0.0655*** (0.0110)
Ln_distance				−0.0011 (0.0156)
Ln_infra				−0.0285* (0.0148)
Constant	0.3920*** (0.0008)	−0.0130 (0.3826)	−0.2649 (0.3794)	−0.2017 (0.3713)
Observations	2832.0000	2826.0000	2799.0000	2799.0000
R^2	0.0630	0.0746	0.1500	0.1566

*Standard errors of estimated coefficients are in parentheses. Significance relationships are shown as indicated by the p-values: *p < 0.10, **p < 0.05, ***p < 0.01. The other tables are the same.*

TABLE 4 | Impact of climate shocks on different types of productive investment.

	(1)	(2)	(3)	(4)	(5)	(6)
	Invest1	**Invest1**	**Invest2**	**Invest2**	**Invest3**	**Invest3**
CS	−0.0176*** (0.0064)	−0.0263*** (0.0082)	0.0570*** (0.0183)	0.0443* (0.0254)	−0.0639*** (0.0164)	−0.0675*** (0.0211)
Other control variables	NO	YES	NO	YES	NO	YES
Province-fixed effects	YES	YES	YES	YES	YES	YES
Observations	2799	2799	2799	2799	2799	2799
R^2	0.0125	0.0237	0.0164	0.0692	0.0909	0.1884

*To save space, this study will no longer report the regression results of other control variables, and readers who need it can ask the author for it. Standard errors of estimated coefficients are in parentheses. Significance relationships are shown as indicated by the p-values: *p < 0.10, **p < 0.05, ***p < 0.01.*

TABLE 5 | Robustness test 1: Bilateral truncation on the 1% quantile of the climate shock index.

	(1)	(2)	(3)	(4)	(5)	(6)
	Invest1	**Invest1**	**Invest2**	**Invest2**	**Invest3**	**Invest3**
CS	−0.0190*** (0.0069)	−0.0283*** (0.0088)	0.0613*** (0.0200)	0.0477* (0.0273)	−0.0688*** (0.0177)	−0.0726*** (0.0228)
Other control variables	NO	YES	NO	YES	NO	YES
Province-fixed effects	YES	YES	YES	YES	YES	YES
Observations	2799	2799	2799	2799	2799	2799
R^2	0.0125	0.0237	0.0164	0.0692	0.0909	0.1884

*Standard errors of estimated coefficients are in parentheses. Significance relationships are shown as indicated by the p-values: *p < 0.10, **p < 0.05, ***p < 0.01.*

climate shocks on agricultural investment is no longer significant for risk-loving farmers.

DISCUSSION

Village public production investment mainly includes investment in farmland water conservancy infrastructure, rural roads and public agricultural product storage and processing equipment. In addition to farmersŠ investment, village public production investment is also of great significance to improving farmersŠ income and enhancing the ability of agriculture to resist risks (Huang et al., 2006; Shibao et al., 2019). Therefore, this study will examine whether "village public production investment" can have a buffering effect under climate shocks; see Equation (2). This study selects "Last year, in your village's total financial expenditure, how much was used for production investment (agricultural water conservancy, etc.)" as the measure

TABLE 6 | Robustness test II: Replace the core explanatory variable with the average value of the climate shock index in the past 3 years.

	(1)	(2)	(3)	(4)	(5)	(6)
	Invest1	**Invest1**	**Invest2**	**Invest2**	**Invest3**	**Invest3**
Average CS	−0.0177*** (0.0064)	−0.0301*** (0.0093)	0.0570*** (0.0183)	0.0506* (0.0290)	−0.0640*** (0.0164)	−0.0771*** (0.0242)
Other control variables	NO	YES	NO	YES	NO	YES
Province-fixed effects	YES	YES	YES	YES	YES	YES
Observations	2799	2799	2799	2799	2799	2799
R^2	0.0125	0.0237	0.0164	0.0692	0.0909	0.1884

*Standard errors of estimated coefficients are in parentheses. Significance relationships are shown as indicated by the p-values: *p < 0.10, **p < 0.05, ***p < 0.01.*

TABLE 7 | Robustness test 3: Using actual disaster losses instead of the climate shock index.

	(1)	(2)	(3)	(4)	(5)	(6)
	Invest1	**Invest1**	**Invest2**	**Invest2**	**Invest3**	**Invest3**
Economic loss	−0.0067*** (0.0024)	−0.0100*** (0.0031)	0.0217*** (0.0070)	0.0169* (0.0096)	−0.0243*** (0.0063)	−0.0257*** (0.0080)
Other control variables	NO	YES	NO	YES	NO	YES
Province-fixed effects	YES	YES	YES	YES	YES	YES
Observations	2799	2799	2799	2799	2799	2799
R^2	0.0125	0.0237	0.0164	0.0692	0.0909	0.1884

*Standard errors of estimated coefficients are in parentheses. Significance relationships are shown as indicated by the p-values: *p < 0.10, **p < 0.05, ***p < 0.01.*

TABLE 8 | Climate shocks and farmers' productive investment: Heterogeneity of village.

	Invest total	Invest1	Invest2	Invest3
		Climate insecure zone (*N* = 2186)		
CS	−0.1255** (0.0534)	−0.0206** (0.0089)	0.0394 (0.0302)	−0.0835*** (0.0198)
[-1.2pt] Other control variables	YES	YES	YES	YES
R^2	0.1639	0.0292	0.0771	0.1993
		Climate safe zone (*N* = 605)		
CS	0.0868 (0.1218)	0.0476 (0.0306)	0.0665 (0.0486)	0.0207 (0.0514)
Other control variables	YES	YES	YES	YES
R^2	0.1532	0.0615	0.0631	0.1725

*Standard errors of estimated coefficients are in parentheses. Significance relationships are shown as indicated by the p-values: *p < 0.10, **p < 0.05, ***p < 0.01.*

TABLE 9 | Climate shocks and farmers' productive investment: Heterogeneity of risk attitudes.

	Invest total	Invest1	Invest2	Invest3
		Risk-averse farmers (*N* = 2290)		
CS	−0.0946* (0.0547)	−0.0251*** (0.0082)	0.0469 (0.0305)	−0.0697*** (0.0207)
Other control variables	YES	YES	YES	YES
R^2	0.1509	0.0303	0.0697	0.1813
		Risk-loving farmers (*N* = 605)		
CS	−0.1174 (0.1418)	0.0315 (0.0340)	−0.0196 (0.0616)	−0.0557 (0.0636)
Other control variables	YES	YES	YES	YES
R^2	0.2583	0.0497	0.1644	0.2806

of the village's public production investment. **Table 10** shows the regression estimation results. Column (1) shows that the coefficient of interaction between climate shocks and village public production investment variables is significantly positive, indicating that village public production investment can indeed alleviate the adverse impact of natural disasters on farmers' productive investment and has a certain incentive effect on farmers' investment.

Specifically, for invest total (Total agricultural productive investment) and invest3 (the investment of seeds, fertilizers, and pesticides), the coefficient of the cross term of climate shock and village public production investment is negative, and the sign is the same as that of the core explanatory variable climate shock coefficient, indicating that village public production investment will significantly weaken the main effect of climate shocks on investment impacts. For invest2 (agricultural productive services

TABLE 10 | Climate shocks and village public production investment: Moderating effects of village-level infrastructure investment.

	(1)	(2)	(3)	(4)
	Invest total	**Invest1**	**Invest2**	**Invest3**
CS	−0.0558 (0.0672)	−0.0276*** (0.0090)	0.0639** (0.0286)	−0.0555* (0.0295)
CS × village investment	0.0007*** (0.0003)	−0.0000 (0.0001)	0.0004*** (0.0001)	0.0002** (0.0001)
Village investment	−0.0012*** (0.0004)	0.0000 (0.0001)	−0.0006*** (0.0002)	−0.0004** (0.0002)
Other control variables	YES	YES	YES	YES
Province-fixed effects	YES	YES	YES	YES
N	2799	2799	2799	2799
R^2	0.1560	0.0237	0.0690	0.1875

*Standard errors of estimated coefficients are in parentheses. Significance relationships are shown as indicated by the p-values: *p < 0.10, **p < 0.05, ***p < 0.01.*

investment), the coefficient of the multiplication term is positive, and the sign of the core explanatory variable climate shock coefficient is the same, which will significantly strengthen the main effect of promoting investment. A possible explanation is that investment in village public production is external, and investment in village public production will reduce the production cost of farmers. In other words, if the investment in the village's public production builds a new reservoir in the village, farmers can obtain irrigation water by simply increasing the field irrigation facilities, and then the phenomenon of "coinvestment" will appear and exert the "crowding-in effect (Cremades et al., 2015)."

CONCLUSION AND RECOMMENDATIONS

This article comprehensively reviews the theoretical mechanism of climate shock on agricultural productive investment and conducts empirical analysis and mechanism discussion based on nationally representative CFPS data. The study found the following: (1) Climate shocks have a significant impact on farmers' productive investment choices. Farmers who are greatly impacted by climate risks have a significantly lower probability of increasing their total investment (Total agricultural productive investment). In terms of investment content, climate shocks will reduce farmers' investment in invest1 (agricultural machinery investment) and invest3 (the investment of seeds, fertilizers, and pesticides) and increase farmers' investment in invest2 (agricultural productive services investment). An important reason for the current academic debate about climate shocks promoting or inhibiting farmers' productive investment is that they ignore the differences in investment types. (2) The impact of climate shocks on farmers' productive investment shows a certain degree of heterogeneity, and farmers in climate-insecure areas and risk-averse farmers are more susceptible to climate risk shocks. (3) From the perspective of the impact mechanism, investment in village public production has a moderating effect on the relationship between climate shocks and agricultural productive investment. Specifically, for invest2 (agricultural productive services investment), village public production investment will strengthen the main effect of climate shocks and enhance the promotion of farmer investment; for invest3 (the investment of seeds, fertilizers, and pesticides), village public production investment will weaken the main effect of climate shock and ease the inhibitory effect on investment.

Based on the above findings, this article draws the following implications. First, for government departments, it is necessary to assess climate risks in a timely manner and reduce carbon emissions and to pay attention to the decision-making behaviors affected by changes in the sentiment of agricultural investors caused by climate shocks. This focus needs to pay attention to the impact of farmers' demand for productive services in the context of climate shocks and provide microcredit support to meet farmers' investment needs in times of crisis (Yagura, 2020). At the same time, promote the establishment of a service outsourcing system that supports the diversified production needs of farmers, and guides the effective connection of supply and demand through the construction of relevant mechanisms and platforms, reduces transaction costs, and alleviates the dilemma of the lack of service outsourcing supply. Second, for villages with frequent large-scale natural disasters, accelerate the process of marketization of rural land transfer, optimize the allocation of rural production factors and resources, and opportunities such as non-agricultural employment are provided to increase the income of farmers, to alleviate the inhibitory effect of climate shocks on agricultural productive investment. The most important thing is that reducing risks can lead to higher investment (Karlan et al., 2014). It is necessary to pay attention to the corresponding infrastructure construction for rural disaster prevention and resilience and to strengthen the coverage ratio of agricultural insurance (Xu et al., 2019), fundamentally improving farmers' security level under climate shocks.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: http://www.isss.pku.edu.cn/cfps/.

AUTHOR CONTRIBUTIONS

ZZ drafted and wrote the first draft of the manuscript. All authors reviewed and revised the manuscript, agreed to be accountable for all aspects of the work, read, and approved the final manuscript.

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Effect of Natural Hazards on the Income and Sense of Subjective Well-Being of Rural Residents: Evidence From Rural China

Lei Huang[1,2]*

[1] College of Tourism and Urban Rural Planning, Chengdu University of Technology, Chengdu, China, [2] College of Architecture and Environment, Sichuan University, Chengdu, China

China is a country that experiences severe natural hazards. In comparison to urban residents, farmers in rural areas of China are more susceptible to these natural hazards, whose impact is multidimensional; however, existing research has mainly focused on the household level. Based on China Household Finance Survey (CHFS) data in 2019, a total of 17,900 farmer households have been chosen to discuss the influences of natural hazards on the rural income and subjective well-being from the individual perspective and the family perspective; further, regional differences within the sphere of influence have been analyzed. Empirical results demonstrate that (1) the farmer household income is a factor that affects subjective well-being, but does not play a decisive role. (2) From the perspective of spatial differences and laws, subjective well-being and the income of farmers vary significantly. The subjective well-being in North China (NC) is the highest, while the subjective well-being in the Central South (CS) is the lowest. The distribution trend of rural income is high in Southeast China (SE) and low in Northwest China (NW). (3) Natural hazards can lower the subjective well-being [Mean ATT (average treatment effect) = –0.1040] and income (Mean ATT = –0.1715) of farmers significantly. Moreover, the influences of natural hazards on subjective well-being are lower than that on income. Therefore, it is imperative to ascertain the impact of natural hazards on farmers' subjective well-being and household income. Further, the government should consider regional differences and the different affected groups, and also strengthen the farmers' ability to cope with hazards and their post-hazard recovery ability during the implementation of hazard rescue.

Keywords: natural hazards, household income, subjective well-being, propensity score matching, China

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Edited by:
Shaoquan Liu,
Institute of Mountain Hazards and Environment (CAS), China

Reviewed by:
Yongsheng Wang,
Institute of Geographic Sciences and Natural Resources Research (CAS), China
Jing Tan,
Southwestern University of Finance and Economics, China

Correspondence:
Lei Huang
huanglei1@cdut.edu.cn

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INTRODUCTION

Natural hazards and disasters have significant influences on human society, leading to casualties, economic losses, and environmental damages (Chen et al., 2020). With increases in the frequency and severity of global natural hazards, they have become one of the most concerning global problems. According to Mori et al. (2021), the annual global deaths caused by natural hazards are about 60,000, which accounts for 0.1% of the total global annual deaths. This leads to annual economic losses of about 8.66–43.3 billion dollars.

Owing to global climatic changes and its unique geographical environment, China is influenced by significant natural hazards. Recently, frequent natural hazards have influenced production, life, and social development to a large extent. China's Ministry of Emergency Management has found that natural hazards have claimed 107 million victims, 162,000 house collapses, 11,739,000 ha of affected crop area, and 334.02 billion yuan of direct economic losses in 2021. It is important to note that, in comparison to urban areas, rural areas are faced with greater threats of natural hazards due to the poor living and geographic conditions, along with the weak ability of residents to defend themselves against hazards.

Natural hazards refer to abnormal phenomena that occur in nature. In this study, natural hazards include various meteorological hazards and geological hazards, such as earthquakes, floods, landslides, debris flow, and typhoons. Existing studies on natural hazards mainly focus on a single type of hazard (Kind et al., 2017). The research content mainly includes causes and spatial-temporal evolutions of natural hazards, risk assessment and avoidance, influences, and response analysis (Lohmann et al., 2019; Palanca-Tan, 2020). Researchers have carried out relatively in-depth and systematic studies on the influences of natural hazards, primarily from multiple aspects like the economy, agriculture, industry, and income gap. However, there are few empirical studies on the influences of natural hazards on individuals and households of farmers in China. In particular, studies on subjective well-being are still very few (Wang et al., 2000). The income of rural residents is an important and intuitive index to measure the influences of hazards from the economic perspective. Nevertheless, subjective well-being can reflect the influences of natural hazards on individuals more comprehensively (Berlemann and Eurich, 2021). This is because subjective well-being is a subjective evaluation of the life satisfaction of individuals affected by hazards (Diener et al., 2013), and is affected by a variety of factors (Helliwell, 2003). Therefore, it is also necessary to discuss the subjective well-being of farmers, in addition to the relationship between rural household income and natural hazards.

In summary, it is imperative to understand the influences of natural hazards in China, which witnesses the frequent occurrence of natural hazards. For this reason, this study focuses on the national macroscopic scale. Based on the China Household Finance Survey (CHFS) data of 17,900 farmer households in 29 provinces in China, regional differences in the subjective well-being and income of Chinese farmers were analyzed. Next, the influences of natural hazards on the subjective well-being and income of peasants were quantified by propensity score matching (PSM) based on the idea of quasi-natural experimentation. This study not only empirically analyzes natural hazards in rural areas, but also provides a valuable reference for the implementation of hazard rescue and decision-making on post-hazard development.

LITERATURE REVIEW AND HYPOTHESES

Income and Natural Hazards

Income has always been an important economic concern, and is studied as an important multidisciplinary individual/family characteristic. Through a literature review, it is found that studies on income mainly focus on income inequality (the income gap) (Butler et al., 2020), income distribution (Kind et al., 2017), and factors influencing income (Kan et al., 2006; Westmore, 2018). Specifically, the major factors influencing income include human capital, social capital, resource endowment, policy institutions, and natural hazards (Ward and Shively, 2015; Kumar, 2019). Additionally, rural residents' income is often associated with the urban–rural gap, livelihood capital, livelihood risk, and poverty (Wu et al., 2015; Liu et al., 2020).

At present, academia has focused its efforts on the relationships between hazards and the affected subject: human society. Some studies on natural hazards and income issues have originated in the west, and after Kunreuther (1997) proposed the concept of "hazard economics", related studies have received extensive research attention. Existing studies mainly analyze the influences of hazards on economics from the macroscopic economy scale and microscopic individual scale. In terms of the economy, scholars focus on the influences of natural hazards and their influences on national economic growth. For example, based on the hurricane damage index built using panel data in the United States, Strobl (2011) found that hurricanes decreased the annual economic growth rate of a county by 0.45%, on average. Nevertheless, state-scale calculations have demonstrated that hurricanes may not affect national economic growth. However, Murlidharan and Shah (2022) pointed out that hazards have significantly negative influences on national economic growth in the short-term, but such influences weaken gradually with the passage of time. In terms of individuals, researchers mainly focus on the economic impact of natural hazards on people (including individuals and families) on the micro-level. Palanca-Tan (2020) carried out a case study in a fishing village in the Philippines, determining that extreme climate first affected the fishing industry, influencing the household income of fishermen and finally intensifying the vulnerability of families. Coffman and Noy (2012) pointed out, through an empirical study of the DID model, that natural hazards have significant long-term influences on income, and the practical per capita income differs by about 112–267 dollars from those in neighboring counties. Some researchers believe that natural hazards lower the income in the short-term, but not the long-term. It is worth noting that Belasen and Polachek (2008) investigated employment and income variations between hurricane-affected counties and unaffected counties. They found that the income of directly affected counties increased by 4.35%, while that of neighboring counties decreased by 4.5%, on average.

In addition to the abovementioned hazards, studies on the relationship between natural hazards and income have been carried out for common hazard types, such as earthquakes (Wei et al., 2017), landslides (Mertens et al., 2016), floods (Mottaleb et al., 2013), and droughts (Arouri et al., 2015). Generally speaking, the influences of natural hazards on the income of rural residents are generally consistent. That is, in the short-term, natural hazards decrease the income significantly, but the influence weakens as time goes on. Further, the income level might exceed the level before the hazard after a period of time. However, the exposure degree to natural hazards leads to differences in the natural environment of affected regions. Further, different hazard prevention abilities of individuals lead to varying influences of these hazards on individuals and families (Clark et al., 1998). Based on the above theoretical analysis, a hypothesis is proposed:

H1: Natural hazards have significantly negative influences on farmer household income.

Subjective Well-Being and Natural Hazards

With continued social development, subjective well-being is attracting the attention of more and more scholars and policymakers. It has become a multidisciplinary research topic, involving the economy, psychology, and sociology. Nevertheless, the concept of subjective well-being is quite controversial, with no consensus being reached yet. Most people believe that subjective well-being is a positive and intrinsic psychological state with strong subjective emotions (Tsou and Liu, 2001). Diener et al. (1999) believed that subjective well-being is an extensive category, including the general judgment of people's emotional responses and life satisfaction. Some studies often use the terms subjective well-being and life satisfaction interchangeably, although some believe that they are not completely consistent (Berlemann, 2016). For the purposes of this study, the two terms are synonyms, referring to a residents' cognition and evaluation regarding their actual quality of life based on subjective emotion.

Studies on subjective well-being focus on the influencing factors. Existing studies have proven that factors influencing subjective well-being mainly comprise personal characteristics, including age, gender, educational background, health conditions, marriage status, and income (Clark, 2018; Frey and Stutzer, 2002); family characteristics, such as fixed assets, housing conditions, and family expenditure (Zhang et al., 2018; Lohmann et al., 2019); social development, including the unemployment rate, social fairness, and income inequality (Oishi et al., 2011; Dell'Anno and Amendola, 2015); the natural environment, including climatic changes and environmental pollution (Cuñado and de Gracia, 2013; Zhang et al., 2017); and policy institutions, such as policy beliefs, public services, political freedoms, and democratic rights (Frey and Stutzer, 2002; Helliwell, 2006). In addition to the abovementioned factors, social relations, material welfare, neighborhood location, etc., also affect subjective well-being (Rafael et al., 2003; Stevenson and Wolfers, 2008). With continued research in this field, the scale has shifted from microscopic individuals to macroscopic regions, especially focusing on the spatial differences and causes of residents' happiness in different regions and geographical backgrounds. Based on Gallup data in the United States, Rentfrow et al. (2009) carried out a correlation analysis on the relationships between the economy, education, and careers with subjective well-being at the state-scale. Based on 28 provinces (cities and municipalities) in China, Zhang et al. (2018) found that housing conditions have positive influences on the general satisfaction of residents. Eren and Aşıcı (2017) concluded—from urban-level analysis—that there are significant differences in subjective well-being in different cities.

It is important to note that, due to the comprehensive and systematic effects of hazards, some scholars have introduced the concept of subjective well-being into their studies. The influences of natural hazards on human society can be divided into two types: direct and indirect (Berlemann, 2016). Direct influences refer to damage to houses, raw materials, and resources caused by natural hazards. Indirect influences refer to secondary influences after damage to physical infrastructure (Cavallo and Noy, 2011). However, the effects of natural hazards on happiness are mainly indirect. Based on questionnaire data on influences of the Nepal earthquake in 2015, Sapkota (2018) found that subjective well-being has a significantly negative correlation with the degree of experienced damage. However, a cross-sectional survey in Germany in 2012 found that flood experiences may not influence subjective well-being (Osberghaus and Kühling, 2016). Based on survey data on survivals from the Philippines typhoon, Hamama-Raz et al. (2017) found that individual resources could facilitate a feeling of subjective well-being after natural hazards. Additionally, researchers have investigated some natural hazards, such as hurricanes (Berlemann, 2016), droughts (Carroll et al., 2009), forest fires (Ambrey et al., 2017), etc., mainly focusing on America, Japan, Germany, and some countries in South and Southeast Asia (Goebel et al., 2013; Lohmann et al., 2019). Few studies have been conducted in China (Wang et al., 2000). To the best of our knowledge, this study is the first demonstration of the subjective well-being of Chinese farmers under the influences of various natural hazards.

H2: Natural hazards can lower the subjective well-being of farmers.

DATA AND METHODS

Data Source

All data in this study was obtained from the CHFS, issued by the Research Center of Southwestern University of Finance and Economics[1]. This data includes the general demographic features, financial status, assets, income, consumption, employment, insurance, and other family information. In 2019, CHFS data samples covered 29 provinces (except Xinjiang, Tibet, Hong Kong, Macao, and Taiwan). It collected the information of 107,008 family members from 34,643 households. Herein, based on the research objective, the CHFS data were processed as follows: firstly, heads of household samples in the individual variable databases were screened out and correspond to the family variable database one by one (both individual variable database and family variable database contain ID numbers, so samples are matched by ID numbers here). Secondly, eliminate all non-rural households in the sample of head of household screened out in the previous step; Then, to make the empirical results more accurate, all rural samples with missing dependent variables and explanatory variables were deleted. Thirdly, missing samples, in terms of the dependent variables and explanatory variables, were deleted. Finally, the study obtained a valid sample

[1] https://chfs.swufe.edu.cn/

of 17,900 households nationwide, including those affected and unaffected by natural hazards.

Variable Definition and Descriptive Statistics

Dependent Variables

In this study, the dependent variables include subjective well-being and income. The subjective well-being index is assessed based on the responses of heads of households to the question: "generally speaking, do you feel happy now?" Subjective well-being used the five-point Likert scale, where values of 1–5 reflect very unhappy to very happy states. The levels account for 1.23, 4.21, 26.70, 41.52, and 26.34% of the population, respectively. The mean subjective well-being of respondents was 3.875, which was between Moderate and Subjective well-being. Household income refers to the total household income of respondents in the last year, comprising income from wages, income from agricultural production and management, income from industrial business, income from properties, and transfer income. The annual average income of all respondent households was 52,170.57 yuan.

Explanatory Variables

According to the abovementioned theoretical analysis and research hypothesis, the core explanatory variable is whether respondents and their families have been affected by natural hazards from 2014 to 2019. In the questionnaire, interviewers determined whether respondents and their families have been affected by natural hazards through the following question: "Did your family have been affected by natural hazards since 2014?" If respondents answered "Yes," the value was recorded as 1; otherwise, it was recorded as 0.

Control Variables

Existing empirical studies have demonstrated that subjective well-being and the income of farmers are influenced by multiple factors (Frey and Stutzer, 2002). Since these factors are of the individual level and household level, respectively, the control variables in this study are mainly personal features and family features of the heads of households, including the education level, health condition, age, communication tools, household size, working conditions, fixed assets, fund demand, and food expenses. Specific variable selection and descriptive statistics are listed in **Table 1**.

Comparative Analysis of the Characteristics of Farmers and Their Families in Samples

The t-test results of dependent variables and control variables before matching are listed in **Table 2**. When other economic conditions of respondents are not controlled, the subjective well-being gap between farmers affected by natural hazards and the rest of the farmers was –0.133, and the mean farmer household income difference was –0.291, both of which pass the significance test at a 1% level. This reveals that the subjective well-being and income of farmers affected by natural hazards were lower than those of other farmers. Additionally, the statistical results also demonstrated that individuals with a lower education degree, poorer physical health, and worse communication tools were affected more by natural hazards. Farmer households with more family members, fewer fixed assets, and those that require capital support for production and management are more easily affected by natural hazards. Through a comparison of mean values, we found that there are significant differences in individual and family features between farmers affected by natural hazards and those unaffected. However, the goal of our study is to understand the specific influences of natural hazards on the subjective well-being and income of farmers. As a result, it is necessary to further prove the aforementioned influences by using the precise metering method.

Methods

To prove whether there are significant relationships between natural hazards and subjective well-being and income, differences in the subjective well-being and income caused by other factors need to be eliminated first. PSM is a method that can overcome the selection bias problem and make the treatment effect evaluation more effective. This is a concept from quasi-natural experimentation, and is a nonlinear estimation method proposed by Rosenbaum and Rubin (1982), mainly used for post-event balance treatment of covariate elements in the experimental group and for balance treatment of covariate elements, similar to randomization. The specific step involves conducting propensity value matching by using the "propensity score, PS" as the distance function and eliminating the influences of variable "confusion" through phenomenon causality, which is gained by controlling the PS. Hence, the causal efficiency of the explanatory variables on the outcome variables can be ensured.

In the present study, farmers affected by natural hazards were determined as the treatment group (HAZ = 1), and farmers unaffected by natural hazards were used as the control group (HAZ = 0). By matching members with similar individual features between the treatment group and the control group, the differences in the subjective well-being and household income between the two groups were further analyzed. A total of nine factors of individual features and family features of the heads of households were chosen as the control variables. Nearest neighbor matching (k = 4), kernel matching, radius matching (r = 0.01), and local linear regression matching were used. The matching was completed by using the "psmatch2" command in STATA/MP 16. The specific algorithm used is as follows:

(1) The conditional probability fitting values of the influences of natural hazards on farmers were calculated using the Logit model, also known as the PS. The probability model was:

$$P(X_i) = P_r[D = 1|X_i] = \frac{\exp(\beta X_i)}{1 + \exp(\beta X_i)} \tag{1}$$

where, D is the treatment variable. When D = 1, farmers have been affected by natural hazards; if D = 0, farmers have not been affected by natural hazards. X_i represents the observable individual and family features (control variables) of farmer households.

TABLE 1 | Descriptive statistics of the variables used in this study.

Variable	Definition and measurement	Mean	SD
Dependent variables			
Subjective well-being (SWB)	Overall, do you feel happy now (1 = very unhappy–5 = very happy)	3.875	0.891
Household income (INC)	In the past year, the total income of your family is (1 = 0–10000 yuan 2 = 10000–30000 yuan 3 = 30000–50000 yuan 4 = 50000–80000 yuan 5 = more than 80000 yuan)	2.860	1.366
Explanatory variables			
Natural hazards (HAZ)	Has your home been affected by any natural hazards since 2014 (1 = yes 0 = no)	0.073	0.260
Control variables			
Education level (EDU)	The education level of the head of the household (1 = no schooling 2 = primary school 3 = junior high school 4 = high school 5 = technical secondary school/vocational high school 6 = junior college/higher vocational 7 = undergraduate 8 = postgraduate)	2.719	1.128
Health condition (HEA)	Health conditions of the head of the household (1 = very poor–5 = very good)	2.823	1.038
Age (AGE)	The age of the head of the household (1 = 16–25 years old 2 = 25–40 years old 3 = 40–50 years old 4 = 50–60 years old 5 = 60–70 years old 6 = over 70 years old)	4.116	1.232
Communication tool (COM)	Type of mobile phone currently used by the head of the household (1 = smart phone 2 = non-smart phone 3 = no mobile phone)	1.408	0.555
Household size (HOU)	The number of family members (number)	3.289	1.641
Work status (WOR)	Whether a member of your family has a job (1 = yes 2 = no)	1.214	0.410
Fixed assets (ASS)	How many cars does your family have (number of cars)	0.234	0.475
Fund demand (DEM)	Whether your home needs funds for production and operation (1 = yes 2 = no)	1.940	0.238
Food expenses (EXP)	What was the average monthly food bill for your family last year (yuan) (logarithm value)	2.933	0.419

(2) The treatment group and the control group were matched according to their PSs. Since different matching methods applied different matching values and weights, the matching results could differ. Therefore, four matching methods, including nearest neighbor matching (k = 4), radius matching (r = 0.01), kernel matching, and local linear regression matching were applied. In this section, nearest neighbor matching (k = 4) was chosen. The calculation method can be formalized as

$$C(P_i) = \min||P_i - P_j|| \quad (2)$$

where, P_i and P_j are PS values of the i^{th} "treatment group" and j^{th} "control group," respectively. C(P) refers to the neighborhood relationship between i and j.

(3) The influences of natural hazards on the subjective well-being and income of farmers were calculated. This is the mean treatment effect (average treatment effect, ATT):

$$\begin{aligned} ATT &= E\left(Y_i - Y_j \mid T_i = 1\right) \\ &= E\left(Y_i \mid T_i = 1, P(X_i)\right) - E(Y_j|T_j = 0, P(X_j)) \quad (3) \end{aligned}$$

where, Y is the outcome variable, indicating subjective well-being and income in this study. Other variables and parameters, such as i and j, have the same meanings as above.

RESULTS

Regional Differences in the Subjective Well-Being and Income of Farmers

Regional differences in the subjective well-being and household income of farmers are quite prominent. To ascertain more spatial distribution characteristics of subjective well-being and income, we will analyze the distribution pattern of the subjective well-being and income in six administrative regions based on the mean value (**Figure 1**). The mean subjective well-being of farmers is shown in **Figure 1A**, at is 3.875, which lies between *Moderate* and *Subjective well-being*. The subjective well-being in NE, NC, and EC is higher than the national mean level. Specifically, the subjective well-being score of NC is the highest, reaching 3.97. Furthermore, there are three regions below the national level, among which CS (SWB = 3.81) is the lowest and SW (SWB = 3.86) is relatively the highest.

TABLE 2 | Differences between farmers who have been affected by natural hazards and those unaffected.

Variable	Treatment group (*n* = 1303)		Control group (*n* = 16597)		
	Mean	SD	Mean	SD	*t*-test
SWB	3.752	0.993	3.885	0.882	5.183***
INC	2.606	1.288	2.879	1.371	6.957***
EDU	2.582	0.986	2.730	1.137	4.575***
HEA	2.959	1.012	3.194	1.038	7.859***
AGE	4.104	1.132	4.117	1.240	0.392
COM	1.451	0.566	1.404	0.554	–2.917**
HOU	3.497	1.789	3.273	1.627	–4.743***
WOR	1.166	0.372	1.218	0.413	4.393***
ASS	0.167	0.412	0.240	0.479	5.338***
DEM	1.912	0.283	1.942	0.234	4.321***
EXP	2.917	0.409	2.935	0.420	1.423

*The t-test represents whether the differences between the treatment group and the control group are significant; ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% levels, respectively; SD = standard deviation.*

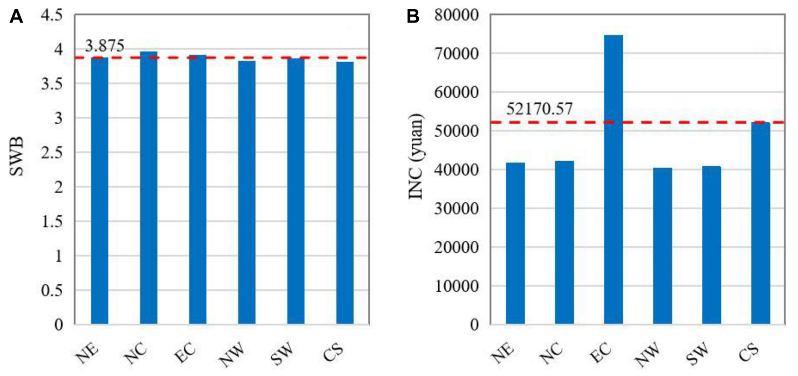

FIGURE 1 | Regional differences in farmers' subjective well-being and income: **(A)** Subjective well-being; **(B)** Income (yuan).

This distribution can be attributed to three factors, including economic factors, environmental factors and political factors. The economy of NC is relatively developed, and the income of rural residents is high and from a wide range of sources. More importantly, this region is close to the political center of China (Beijing), and its social recognition is high. Therefore, subjective well-being is higher than other regions. However, the CS is an area with rapid economic development and large-scale factories, so as to attract a large number of migrant workers came to the region. And result in a high population density in the region, which in turn leads to negative impacts such as deterioration of the living environment and traffic congestion (Luo et al., 2016). In addition, the income and quality of life of local farmers did not improve, so their subjective well-being has decreased.

The regional distribution of farmer household income is shown in **Figure 1B**. Among the six administrative regions, EC has the highest average household income—at 74556.73 yuan—and it is the only region where farmer household income is higher than the national average (INC = 52,170.57 yuan). Generally speaking, farmer household income is consistent with the regional economic development level, i.e., EC is the most developed region in China. EC has not only good natural conditions and infrastructure, but also has a higher average wave level than other regions. Hence, farmer household income in EC is far higher than that in other regions and the national average. Additionally, the farmer household income levels significantly differ among NE, NC, NW, and SW, at 41647.77 yuan, 42111.01 yuan, 40277.17 yuan, and 40572.95 yuan, respectively.

TABLE 3 | Estimation results of the Logit models.

HAZ	Coefficient	SE	z
EDU	–0.082*	0.0319	–2.58
HEA	–0.225***	0.0311	7.23
AGE	–0.059*	0.0311	–1.89
COM	0.133**	0.0619	2.14
HOU	0.097***	0.0189	5.13
WOR	–0.468***	0.0844	–5.55
ASS	–0.375***	0.0779	–4.80
DEM	–0.252**	0.1088	–2.31
EXP	0.147	0.0791	0.19
_cons	–2.184***	0.3855	–5.67
Obs	17099		
LR $\chi^2(9)$	181.52		
Pseudo R^2	0.0203		
Log likelihood	–4369.5294		

****, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively. Table shows the result of nearest neighbor matching (k = 4).*

Effects of Natural Hazards on the Subjective Well-Being and Income of Farmers

Estimation of Propensity Score

To match the treatment group and the control group, the probability of farmers being influenced by natural hazards was estimated by using the Logit model, which was taken as the PS value. The estimation results of PS are shown in **Table 3**. It can be seen from the regression results of the Logit model that the education background (EDU = –0.082), physical condition (HEA = –0.225), age (AGE = –0.059), working conditions (WOR = –0.468), fixed assets (ASS = –0.375), and capital demands (DEM = –0.252) can affect the influence of natural hazards on farmers and their families significantly. In other words, these factors all can lower the probability of farmers being affected by natural hazards. In contrast, communication tools (COM = 0.133), family size (HOU = 0.097), and food expenses (EXP = 0.147) could increase the probability of farmers and their families being affected by natural hazards. Generally speaking, older farmers, with a lower education background and poorer physical condition, are more easily affected by these hazards. This is primarily because this group of individuals has little knowledge regarding hazard prevention and alleviation. Thus, they cannot avoid hazards well and their post-hazard recovery is relatively weak. Additionally, families that have more family members, lower fixed assets, and poor working conditions are more easily affected by natural hazards.

Matching Effect Analysis

The effectiveness of the PSM method depends on two prerequisites. One is the balance test and the other is the common

TABLE 4 | Balance test results of propensity score matching (PSM).

Variable	Unmatched Matched	Mean Treated	Mean Control	%Bias	% Reduction | bias|	t-test t	t-test $p > t$
EDU	U	2.5871	2.7452	–14.8	97.8	–4.76	0.000
	M	2.5868	2.5833	0.3		0.09	0.930
HEA	U	3.045	2.7927	24.7	99.7	8.30	0.000
	M	3.0442	3.0435	0.1		0.02	0.986
AGE	U	4.0851	4.098	–1.1	5.8	–0.36	0.772
	M	4.0852	4.0973	–1.0		–0.26	0.792
COM	U	1.445	1.3971	8.6	77.6	2.95	0.003
	M	1.4445	1.4338	1.9		0.48	0.632
HOU	U	3.498	3.282	12.7	77.2	4.49	0.000
	M	3.492	3.4427	2.9		0.70	0.482
WOR	U	1.1606	1.2134	–13.6	69.9	–4.41	0.000
	M	1.1608	1.1449	4.1		1.10	0.271
ASS	U	0.16707	0.24423	–17.1	93.8	–5.48	0.000
	M	0.1672	0.16245	1.1		0.29	0.771
DEM	U	1.9116	1.9437	–12.4	71.0	–4.63	0.000
	M	1.9124	1.9217	–3.6		–0.84	0.401
EXP	U	2.9187	2.9369	–4.4	85.3	–1.48	0.139
	M	2.9183	2.9156	0.6		0.16	0.870

support test. Since test results of different matching methods are mostly consistent, only the robustness test results of nearest neighbor matching ($K = 4$) are shown in this section.

The balance test requires that the treatment group and control group have no systematic differences in terms of the matching variables after the completion of matching. Rosenbaum (1985) tested the balance before and after matching by using the standardized bias. In other words, whether the balance passes the test is mainly determined by the covariate deviation changes and t-statistical significance level changes before and after matching (Caliendo and Scheel-Kopeinig, 2008). It can be seen from **Table 4** that the standardized bias of all covariates is smaller than 5% after matching, and the t-test statistics of most control variables before matching are significant. Moreover, all P values of the t-test statistics for all control variables after matching are higher than 0.2, indicating that control variables are insignificant after matching. Therefore, matching significantly reduced the difference in the distribution of explanatory variables between the treatment group and the control group, and the overall matching quality was good.

The kernel density diagram (**Figure 2**) shows the density distribution fitting conditions of the P-score (calculated using Equation 1) before and after matching between the treatment group and the control group. In this study, the common support domain was tested by plotting the kernel density. If the common support domain is too narrow, samples beyond the common support domain cannot be matched effectively, leading to sample loss. Otherwise, the matching effect is relatively good if the common support domain increases after matching. The kernel density diagrams of subjective well-being and income are shown in **Figures 2A,B**, respectively. It is clear that the PS probability density distributions of two groups after matching differ significantly. In other words, there is significant coverage between the two groups, and the PS probability distribution of the two groups has gradually become consistent. This reveals that the chosen matching variables and matching method in this study are reasonable and can lower differences in the explanatory variable distribution between two groups to a certain extent, facilitating decreases in the biased error of sample selection.

Average Treatment Effect

Estimation based on multiple matching methods can increase the robustness and reliability of the results. Therefore, different matching methods were used in this section to estimate the ATT of natural hazards on the subjective well-being and income of farmers, including nearest neighbor matching ($k = 4$), radius matching ($r = 0.01$), kernel matching, and local linear regression matching. The ATT results of the treatment group after matching using different matching methods are shown in **Table 5**.

Although the calculated results of different matching methods differ slightly, their general trends are consistent. Firstly, the influences of natural hazards on the subjective well-being of farmers were analyzed. It can be seen from **Table 5** that the mean ATT = –0.1040, indicating that natural hazards have significantly negative effects on the subjective well-being of farmers. In other words, under the same conditions, the subjective well-being of the treatment group is 0.1040 lower than that of the control group. Hence, H1 is verified. Similarly, the household income of the treatment group is lower than that of the control group. This means that natural hazards can decrease the household income (Mean ATT = –0.1715) of farmers significantly. Therefore, H2 is verified. Therefore, we found, through PSM, that natural hazards have a significant negative relationship with farmers' subjective well-being and income. It is important to note that the influences of natural hazards on subjective well-being are smaller than those on income ($0.104 < 0.1714$). This is mainly because, in comparison to income, the influences of natural hazards on subjective well-being are not direct. Additionally, there are many influencing factors on the subjective well-being, which can relieve the influences of hazards to some extent.

DISCUSSION

In 2021, the number of people affected and economic losses caused by natural hazards in China decreased by 31 million and 36.13 billion yuan, respectively, compared to the previous year (data source: Ministry of Emergency Management). However, China is a country that suffers from the most severe hazards. As a result, it is necessary to obtain a more systematic and comprehensive understanding of the natural hazards to alleviate their effects. This study found that the distributions of the subjective well-being and income of farmers differ significantly among different regions. However, natural hazards have significantly negative influences on subjective well-being and income. This is consistent with the research results of Mertens et al. (2016) and Lohmann et al. (2019). Nevertheless, some scholars have also pointed out that the influences of natural hazards on income decreased significantly in the short-term (Mu and Chen, 2016); however, rural income may exceed the

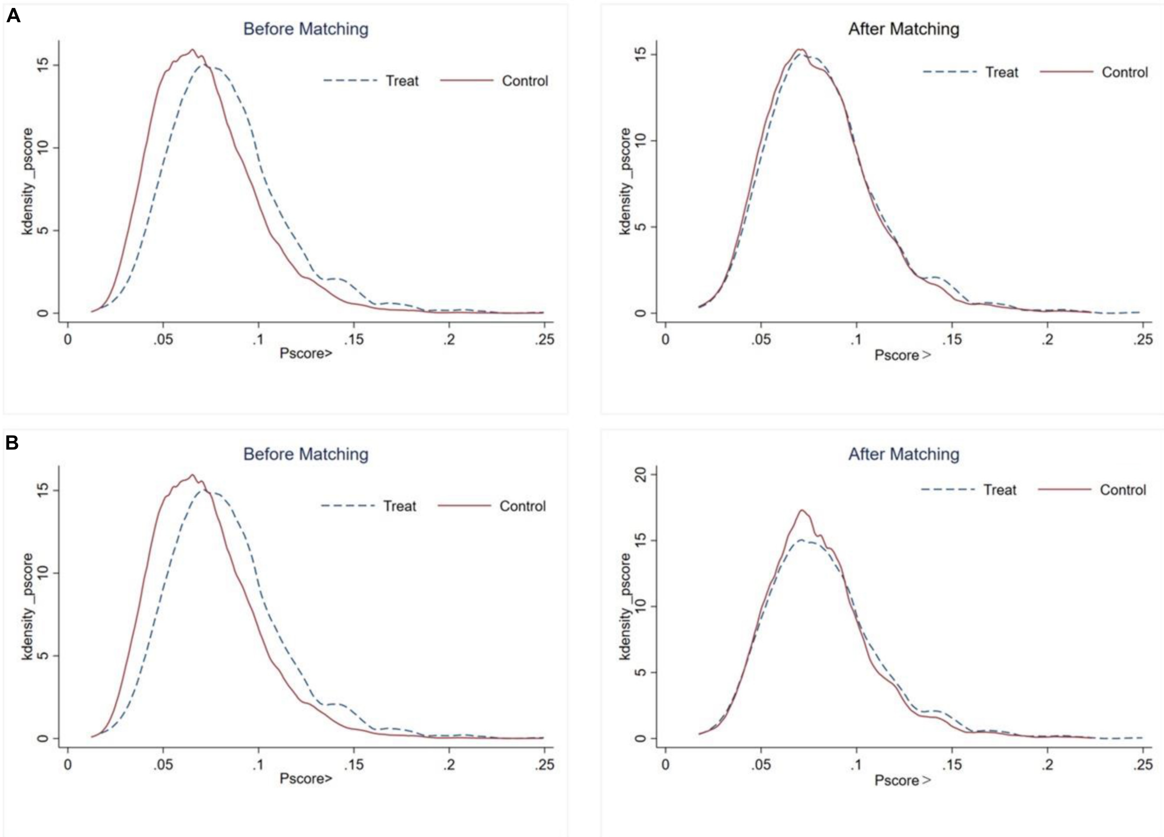

FIGURE 2 | Kernel density distribution of natural hazards before and after matching: **(A)** Subjective well-being; **(B)** Income. The solid line represents rural residents who have received the indicated intervention. —The dashed line represents rural residents who have not received the indicated intervention.

TABLE 5 | Comparisons of average treatment effect (ATT).

Matching method	Dependent variables	Subjective well-being	Household income
Nearest neighbor matching (*k* = 4)	ATT	–0.0922**	–0.1539***
	T-stat	–3.01	–3.56
Radius matching (*r* = 0.01)	ATT	–0.0956**	–0.1526***
	T-stat	–3.01	–3.56
Kernel matching	ATT	–0.1232***	–0.2099***
	T-stat	–4.25	–5.48
Local linear regression matching	ATT	–0.1050***	–0.1697***
	T-stat	–2.93	–3.41
	Mean ATT	–0.1040	–0.1715

*Significance is obtained using the bootstrap test, where ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively; Mean ATT is the average value of ATT obtained by the four matching methods.*

level before hazards in the long-term. This is because farmers recombine their productive asset inventories, and infrastructure in affected areas is rebuilt and sometimes improved, reducing transaction costs (Gignoux and Menendez, 2014). Additionally, post-hazard rebuilding can provide more jobs, and these regions can obtain economic support. Therefore, a farmer's income will be recovered and can even increase.

Natural hazards affect people in a variety of ways. People who become homeless, lose income, lose jobs, or get injured owing to natural hazards could have low subjective well-being because their living conditions have changed greatly. Moreover, natural hazards could influence subjective well-being indirectly through people's perceptions of hazard risks. Cui and Han (2019) found—through an empirical study—that risk perception of earthquakes includes perceiving the probability of earthquakes in the future, which influences an individual's subjective well-being. Further, natural hazards can affect farmers' income through direct and indirect channels. Direct influences include decreased incomes as a response to decreases in the agricultural output due to natural hazards, while indirect influences include income reduction caused by hindered transportation of agricultural produce owing to damaged infrastructure (e.g., highways). Hence, it is believed that natural hazards can influence the subjective well-being of individuals and household income through direct and indirect channels.

The relationship between income and subjective well-being is an important research topic in the field of economics. Early studies can be dated back to Easterlin (1974), who found that subjective well-being may not continue to increase with increases in income. Subsequent researchers called this phenomenon the "Easterlin paradox". However, some studies found that economic or income growth would promote continuous improvements in subjective well-being (Diener et al., 2012). Generally speaking, such positive influences exhibited a decreasing trend. It is important to note that some researchers have found that there is a negative correlation between subjective well-being and per capita GDP (Deaton and Stone, 2013). The empirical results of this study indicate that income has a certain positive impact on subjective well-being, but the degree of this impact varies with time, the region, and the individual. It can be seen from **Figures 1A,B** that the regional average income and subjective well-being do not have the same trend. This reflects that the region with the highest average income may not have the highest average subjective well-being. For example, CS has a relatively higher average income, but its average subjective well-being is the lowest of all six administrative regions, at only 3.81. Therefore, income is a factor that influences subjective well-being, but does not play a decisive role in it.

Furthermore, although subjective well-being is highly related to income, income is not the only factor that influences subjective well-being; it is also influenced by individual characteristics, social relations, the external environment, policy systems, etc. Moreover, natural hazards influence subjective well-being indirectly, but directly influence income. As a result, natural hazards influence subjective well-being less than income. This might be because many factors influence subjective well-being, including income, which relieves some influences of hazards on subjective well-being; in contrast, the influences of natural hazards on income are more direct.

Natural hazards can influence the subjective well-being and household income of farmers significantly. The two factors are part of the individual level and household level, respectively. Therefore, the government has to consider farmer victims at different levels during hazard rescue and when formulating post-hazard recovery policies. They must provide employment and psychological counseling to individuals, house repair and rebuilding, material assistance at the household level, etc. Moreover, the government should increase hazard prevention measures, including safety education and general engineering measures. Some studies have found that preventive measures not only strengthen the hazard risk perception of farmers, but also are conducive to preventing decreases in subjective well-being caused by anxiety regarding future natural hazards (Berlemann, 2016). In addition, hazard prevention measures can reduce the loss of life and property.

CONCLUSION

Natural hazards can have significant influences on the social economy owing to the uncertainty, uncontrollability, and difficulties associated with their prediction. Based on micro-data, this study got rid of small-scale research and focused on macro scale to quantify the impact of natural hazards on rural residents' subjective well-being and family income from individual and household levels. Moreover, the method of this study is also separated from the traditional regression analysis, and PSM method is used to reduce the result bias caused by sample selection, so as to get more accurate quantitative results.

The results demonstrate that (1) the average subjective well-being of farmers in China is 3.875. Farmers in NC have the highest subjective well-being and farmers in CS have the lowest subjective well-being. (2) The household income of farmers in China exhibit obvious regional differences. It is generally high in the southeast and low in the northwest. (3) Natural hazards can lower the subjective well-being (Mean ATT = −0.1040) and income (Mean ATT = −0.1715) of farmers significantly, and natural hazards influence subjective well-being less than income.

Almost all countries have experienced the influences of various types of natural hazards, such as climate change. Rural areas are facing greater threats due to their exposure and vulnerability. This study also has some limitations. On the one hand, CHFS is not obtained through stratified sampling, and there may be regional imbalance in the sample data; on the other hand, the large difference in the number of control group and treatment group in the sample may not be conducive to matching (the matching effect is found to meet the requirements through testing). However, this study reveals the relationship of natural hazards with the subjective well-being and income of farmers in rural areas in China. This not only helps fill this research gap in China, but also provides a theoretical reference to deepen our understanding of natural hazards. In addition, the study of SWB can also provide more direct suggestions for the government's policy design to improve residents' happiness and sense of gain. We know that income will affect people's subjective well-being, and to improve the well-being of rural residents, we should start from the aspects of land cultivation and industry. The government should actively explore local characteristics, drive the development of relevant industries, increase employment and income, and constantly strengthen ecological restoration and disaster prevention. More importantly, during hazard rescue, the government shall not only pay attention to the practical situation, but also consider issues from the individual and family perspectives, aiming to help farmers return to their normal lives and stabilize the regional development.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

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Climate Change Adaptation: A Study of Digital Financial Inclusion and Consumption Among Rural Residents in China

Chunyan He[1], Weisong Qiu[2] and Junlin Yu[3]*

[1]School of Economics, Xihua University, Chengdu, China, [2]Tailong Finance School, Zhejiang Gongshang University, Hangzhou, China, [3]School of Business Administration, Yonsei University, Seoul, South Korea

Climate change impacts agricultural production negatively. Therefore, rural residents experience large income and consumption fluctuations when dealing with climate change risks. However, little is known about whether digital financial inclusion can help rural residents improve their ability to resist climate change. This study uses the Peking University Digital Financial Inclusion Index of China and China Household Finance Survey data, together with historical temperature data from major cities, to study the impact of digital financial inclusion on Chinese rural residents' consumption in response to climate change. The results suggest that digital financial inclusion significantly promotes rural households' total consumption and consumption upgrades. Heterogeneity analyses also show that digital financial inclusion predominantly affects low-income households, low-asset households, and households living in China's central and western regions. The instrumental variable and control function methods were used for robustness, and our main conclusions are robust and reliable. Although climate change reduces rural residents' consumption and increases their risks, digital finance inclusion significantly mitigates this negative effect. The government can increase the usage depth of digital financial inclusion in rural areas by promoting the construction of digital financial inclusion facilities. The government should strive to deepen the impact of digital financial inclusion on rural household income and consumption to further improve their ability to resist climate risks.

Keywords: climate change adaptation, digital financial inclusion, rural, consumption, China household finance survey

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Jiancheng Wang,
Sun Yat-sen University, China

****Correspondence:***
Weisong Qiu
qiuweisong1992@163.com

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1 INTRODUCTION

Extreme weather conditions such as high temperatures, heatwaves, droughts, floods, hurricanes, and cold waves have extensive impacts on human health, agriculture, the economy, and natural ecosystems. Climate change has increased the frequency and severity of natural disasters (Aldunce et al., 2015). Additionally, it can also affect the economic growth rate (Babiker 2005), prolong poverty, and create new poverty predicaments (De Pryck Kari, 2021). According to the "2019 Global Climate Risk Index Report", since 1998, 526,000 people have died from extreme weather conditions worldwide, and the direct economic loss has reached 3.47 trillion US dollars. The more vulnerable individuals, groups, classes, or regions are, the more easily they are affected by environmental shocks brought about by climate change (Bohle et al., 1994). Vulnerable groups, such

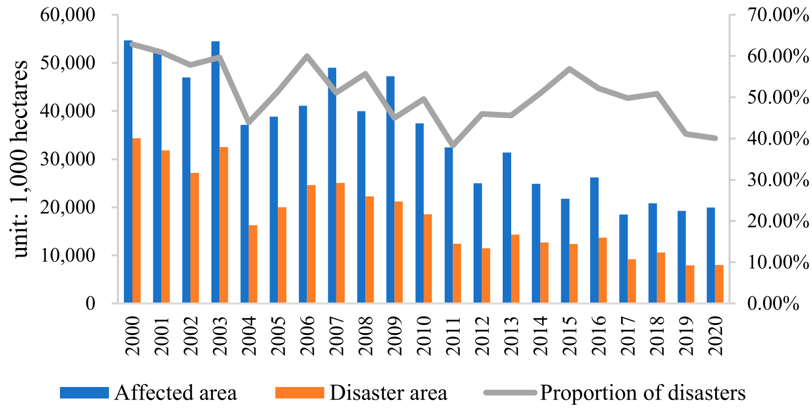

FIGURE 1 | The affected area, disaster area, and the proportion of disasters in China from 2000 to 2020 (Data source: National Bureau of Statistics of China).

as rural women, children, and herdsmen, have limited access to land, employment, and public services, and their ability to cope with climate change risks is also weaker (Paavola 2008; Maccini and Yang 2009). Harsh environmental conditions are often associated with low incomes, low consumption, and high savings (Zhang et al., 2021). Furthermore, the economic impacts of climate change are more pronounced in developing countries, with relatively few measures to address environmental challenges (Jury 2002; Thurlow et al., 2012).

Financial inclusion can help remove and overcome barriers to access to low-cost, fair, and secure formal financial services for certain social groups and individuals (Chakravarty and Pal 2013).Financial inclusion is a mechanism that ensures that vulnerable groups have access to timely and adequate financial services (storage, borrowing, insurance, payments, etc.) at affordable costs. Countries with a high population proportion without access to formal financial services exhibit higher levels of poverty and inequality (Bhanot et al., 2012).

Financial saving products can improve savings safety, smooth consumption for rural residents, help them achieve good asset management, and ensure sustainable development. In a state of sustainable development, traders and farmers can increase their savings, which can be translated into more investment and output and higher household consumption. Generally, people borrow money for business, to buy land or a house, to send children to school, or to respond to emergencies. Therefore, access to credit can provide adequate financial support for rural residents and is more effective than private borrowing in helping to alleviate poverty, increase household assets and consumption, and increase the child enrolment rate. People may use savings and credit to resist sudden shocks. However, as a financial product, insurance can spread risk by expanding risk-sharing groups. Farmers with agricultural insurance plant crops with higher risks but higher returns and invest more in planting to achieve higher yields (Demirgüç-Kunt et al., 2020). In this virtuous circle, rural residents can increase their income, improve their ability to resist climate change risks, and have more disposable income to achieve consumption.

Agricultural insurance is an important mechanism to effectively reduce the uncontrollable economic losses caused by climate change disasters. Additionally, it is a vital measure for farmers to stabilize their incomes and prevent the catastrophic effects of natural disasters. Agricultural insurance helps risk-averse people avoid the negative effects of extreme natural disasters. Effective risk reduction and loss management strategies, such as agricultural crop insurance, allow farmers to take huge risks without encountering difficulties; such strategies also improve their ability to resist risks, protect their continuous investment in agricultural production, encourage them to invest in high-input and high-yield crops, increase agricultural added value, and increase household income and consumption (Raju and Chand 2007). Credit can enhance farmers' ability to minimize and manage risks. For example, suppose official institutional credit can improve credit flexibility, adapt credit to diversified market demands, and provide a variety of repayment methods in arid and non-arid regions. In that case, it can help farmers improve their risk-resistance ability (Jodha 1981). Moreover, credit for small-scale farmers can improve credit availability and increase the proportion of small-scale farmers in overall credit by increasing inputs, output, and employment—effectively improving social equity and efficiency (Mishra 1994).

Figure 1 shows that, although the affected and the disaster areas decrease yearly, China's proportion of disaster-affected crops is always above 40%. This suggests that the proportion of crops affected by extreme climate change has a greater impact on rural residents. **Figure 2** shows the per capita disposable income and consumption of Chinese rural residents. The graph shows that in years with a high proportion of disasters, the annual growth rate of disposable income has a downward trend, indicating a positive relationship between the proportion of crops affected by disasters and the income of rural residents.

Although the per capita disposable income and consumption of rural residents shown in **Figure 2** are increasing yearly, the annual growth rate of the per capita disposable income of rural residents shows great fluctuation. Combined with the proportion of per capita disposable income spent on rural residents'

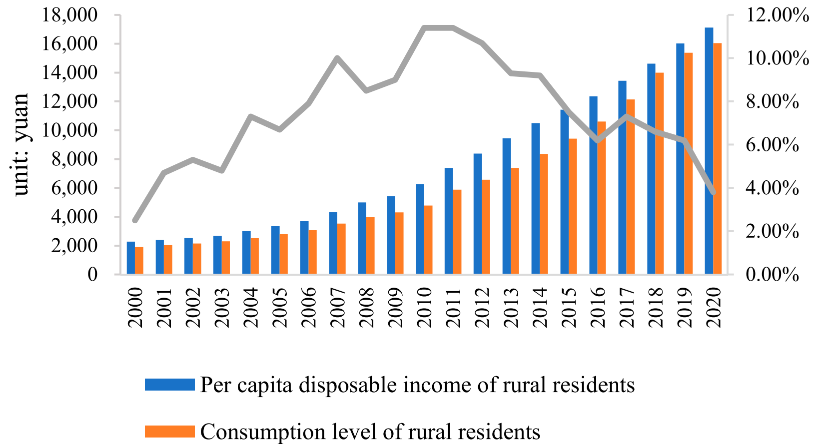

FIGURE 2 | Per capita disposable income and consumption of rural residents in China from 2000 to 2020 (Data source: National Bureau of Statistics of China).

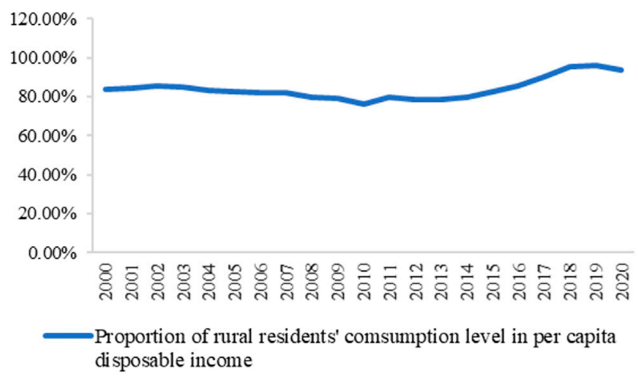

FIGURE 3 | Proportion of rural residents' consumption in per capita disposable income from 2000 to 2020 (Data source: National Bureau of Statistics of China).

consumption (shown in **Figure 3**), the statistical results show that in years with a low growth rate of disposable income and a high proportion of disasters, the proportion of consumption by rural residents gradually increased. Therefore, to ensure that rural residents' income and consumption can be matched during times with declining annual disposable income growth rate, rural residents gradually reduce consumption in the later stage to avoid the risk of a subsequent reduction in agricultural production income caused by possible climate change. It can be considered that climate change may negatively impact rural residents' consumption in China.

Digital financial inclusion is developing rapidly and continuously in China. However, the existing literature pays little attention to promoting rural residents' consumption under climate change. It is practical to study whether digital financial inclusion can promote the growth and upgrade of rural residents' consumption in China, thereby reducing the negative impact of climate change. This study could help reduce poverty caused by climate change and promote rural revitalization in developing countries. We use Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), China Household Financial Survey (CHFS) data, and temperature data for major cities to empirically analyze the impact of digital financial inclusion on consumption by China's rural residents for a new climate change adaptation strategy. The other contributions of this study are as follows. 1) Compared with the case study on the impact of digital financial inclusion on residents' consumption in the existing literature, this study is specifically concerned with its impact on rural residents' consumption and consumption upgrading, which could provide a new strategy for alleviating rural poverty in developing countries. 2) Climate change will further exacerbate the poverty and vulnerability of vulnerable groups, reduce welfare, and affect the regional economic growth. Combining natural data and micro-survey data, this study tested whether digital finance inclusion mitigates the negative effect of climate change on rural residents' consumption, which has not been covered in the existing literature.

The rest of this paper is organized as follows: **Section 2** is a literature review. **Section 3** contains the theoretical analysis. **Section 4** presents the data sources and empirical methods used. **Section 5** reports the empirical results, and **section 6** summarizes the conclusions and proposed implications for promoting the growth and upgrading of rural residents' consumption and reducing the negative impact of climate change.

2 LITERATURE REVIEW

2.1 Climate Change and Rural Residents' Consumption

The ecological environment will always deeply affect economic growth and regional sustainable development (Zeraibi et al., 2020; Ahmad et al., 2021a). Greenhouse gases emitted by anthropogenic activities exacerbate climate change, and extreme climate events are occurring more frequently worldwide. As a result, climate change will continuously slow the global economic growth rate by 0.28% per year (Carleton and Hsiang 2016). Furthermore, Ciscar et al. (2011) showed that climate change could halve European residents' annual wealth growth rate by 2080 if the economic damage caused by climate change is sustained. Climate change has a huge impact on agricultural industries that depend on rainfall, which can cause instability in rural residents' consumption. Poverty is related to consumption and vulnerability. Poor rural households are especially vulnerable when facing income risks, which may restrain farmers' agricultural investment and lead to a poverty trap (Karlan et al., 2014). Chen et al. (2020) found that an increase in the instability of agricultural income caused by climate change would further accelerate the decrease in farmers' disposable incomes and force them to reduce their non-subsistence consumption. Regarding production input, rural residents will change crop varieties and increase investment in climate disaster prevention according to their climate change forecasts. Ultimately, this manifests as an increase in agricultural production costs and total input, reducing farmers' net income and consumption (Offiong and Ita 2012). From the perspective of output, climate change manifests as changes in light conditions, heat sources, water resources, and so on, all of which change soil conditions. Changes in soil and other potential land productivity factors will ultimately be reflected in the yield and quality of crops (Gershon and Mbajekwe 2020), affecting farmers' income and consumption patterns. Overall, the effects of climate change continue to reduce individual income and consumption (Skjeflo 2013).

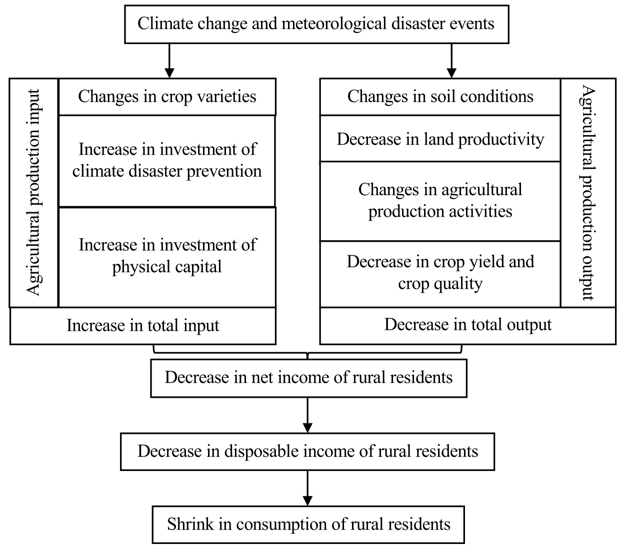

FIGURE 4 | Theoretical framework of the impact of climate change on the consumption of rural residents.

2.2 Digital Financial Inclusion and Consumption

Financial development plays an important role in economic growth in China (Ahmad et al., 2021b; Shehzad et al., 2021). Rural financial development can improve rural resource allocation efficiency and promote income growth among rural residents (Adetiloye 2012; Peng et al., 2021). Galor and Moav (2006) found that credit capital was an important factor in smoothing consumption and alleviating poverty. Financial support to farmers from rural commercial banks and the rural financial market can significantly increase farming income (Attipoe et al., 2020). This is because such support leads to an increase in the use of fertilizers and tractors, which in turn results in higher agricultural productivity and strengthens rural resident income growth. Rural financial development was instrumental in accelerating the transformation of rural industries (Peng et al., 2021).

Regarding credit capital, digital financial inclusion can help the commercial banking system establish a more comprehensive data sharing system and a big data credit risk prevention system. A clearer and more comprehensive data-sharing system can also provide commercial banks with deeper market information. Thus, commercial banks can provide more credit service levels regarding credit support for rural residents, and they can make more accurate and detailed plans and arrangements to help smooth rural residents' consumption patterns and achieve better asset management, thereby promoting rural residents' consumption (Wang and Fu 2022; Ma and Li 2021). From the perspective of transaction costs, the convenience of digital financial inclusion can help rural residents save on the cost of long-distance payment, make it easier for residents in remote areas to obtain credit support, and increase payment security (Ji et al., 2021). Additionally, digital financial inclusion enables consumers to meet more diversified consumption needs at lower circulation costs for goods and services. It enables rural residents to access higher-level consumption, upgrading rural residents' consumption. Moreover, digital financial inclusion can reach rural residents in remote areas that lack financial support, such as credit services (Zhou et al., 2020). Credit services can alleviate the instability of rural residents' income caused by climate change and ensure that they can maintain their lives and carry out continuous agricultural production and operations, improving their ability to resist future risks (Wang and He 2020). Ultimately, credit services promote high-quality investment in agricultural production, increase family income, and promote consumption growth (Wang and Liu 2016).

The existing research primarily focuses on the impact of digital financial inclusion on economic growth. Some literature has recognized the relationship between digital financial inclusion and climate change. For example, Shehzad et al., 2021 found that negative shocks in the use of digital financial inclusion cause an upsurge in the level of CO_2 emissions based on quarterly data from Pakistan. However, there is no direct evidence between digital financial inclusion and farmers' ability to minimize the risks of climate change. To fill this gap, this study uses the Peking University Digital Financial Inclusion Index of China and China Household Finance Survey data, together with historical temperature data from major cities, to study the impact of digital financial inclusion on Chinese rural residents' consumption in response to climate change.

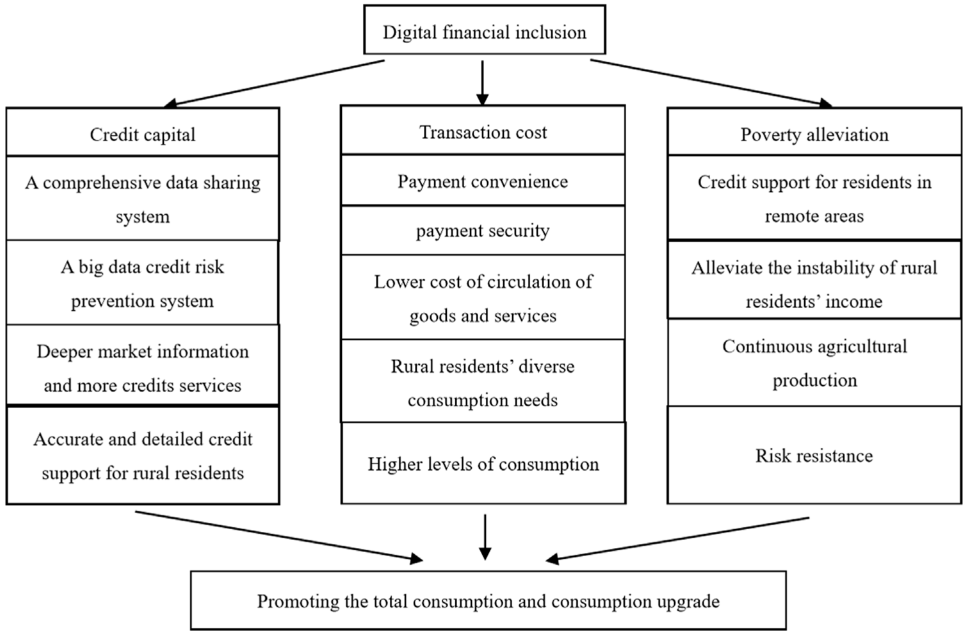

FIGURE 5 | Theoretical framework of how digital financial inclusion affects consumption.

3 THEORETICAL FRAMEWORK

Extreme climate change, such as extremely high temperatures, low temperatures, and droughts, increases agricultural production risk. The most significant manifestation is a sharp drop in crop yields, which increases the volatility of farmers' income and leads rural residents to reduce their consumption level to avoid future income instability caused by climate change risks. Additionally, the disposable income of rural residents, who mainly focus on agricultural production, is lower than that of urban residents. Meteorological catastrophic events caused by extreme climate change directly damage the physical capital of rural residents, increase the input of physical capital, and further lead to a decrease in income and a consumption decline. climate change also affects agricultural output, agricultural income, and farmers' consumption by affecting agricultural production activities. For example, global warming has led to a continuous northward shift of the isotherm in China. This is reflected in the changes in the planting areas of heat-tolerant crops. However, the economic value differs by crop, leading to changes in farmers' incomes and further affecting their consumption habits. **Figure 4** shows the theoretical framework of this study.

Regarding the increased volatility of rural residents' incomes caused by climate change, digital financial inclusion provides rural residents with advantages in terms of digital payments, credit, and insurance options, which directly stimulates the growth of rural residents' consumption (Karlan and Zinman 2010). Additionally, digital financial inclusion can help rural residents better manage their assets, smooth their consumption patterns (Gross and Souleles 2002), improve their risk resilience, and indirectly increase their income levels. As a result, it promotes rural residents' consumption growth. According to the theory of mental accounts, the convenience of payment provided by digital financial inclusion can reduce rural residents' sensitivity to price when they consume (Soman 2001), reduce psychological losses that are high under cash transaction conditions, and improve their willingness to pay, which can also promote rural household consumption (Prelec and Simester 2001). The theoretical mechanism of the impact of digital financial inclusion on rural residents' consumption is reflected in the following three aspects (**Figure 5**).

4 MATERIALS AND METHODS

4.1 Data

This study adopts the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), produced by a joint research team from the Peking University Digital Finance Research Center and Ant Technology Group to measure China's digital finance development. The Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) includes coverage breadth, usage depth, and digitization level. Usage depth involves sub-indexes such as payment, credit, insurance, investment, and money funds (Li et al., 2020). This study adopted the aggregate index, coverage breadth, and usage depth from the PKU-DFIIC system for empirical research.

Microdata on Chinese rural residents were obtained from the China Household Finance Survey (CHFS). The CHFS was the first nationwide survey program on Chinese household financial micro-issues. The investigated subject mainly includes housing

TABLE 1 | Descriptive statistics.

2015–2019 Variable type	Variable name	Variable definition	Obs	Mean	Std. Dev.
Explained variables	*con*	Total rural household consumption	23,306	50,158.61	56,983.29
	per_con	Per capita consumption	23,306	15,540.94	22,542.86
	deve_con	Consumption for rural household life development	23,306	11,234.56	22,256.31
	per_deve_con	Per capita living development consumption	23,306	3,472.26	8,832.11
Core explanatory variables	*dig*	Aggregate index of PKU-DFIIC	22,681	215.20	36.62
	cov	Coverage breadth index of PKU-DFIIC	22,681	202.03	39.15
	dep	Usage depth index of PKU-DFIIC	22,681	212.15	51.06
Head of household Characteristics	*gender*	Gender (Male: 1)	23,306	0.89	0.31
	age	Age (year); *age2*: square of age	23,306	51.56	8.42
	edu	Educational background (Bachelor's degree and above: 1)	23,287	0.02	0.13
	marri	Marital status (Married: 1)	23,302	0.92	0.28
	health	(Healthy: 1)	23,284	0.77	0.42
	job	(Having a job: 1)	23,276	0.87	0.34
	soin	Whether to participate in social medical insurance (Yes: 1)	23,255	0.96	0.20
Family characteristics	*familynum*	Number of family members	23,306	3.99	1.83
	inc	Total annual household income (yuan)	23,306	48,047.59	53,068.39
	asset	Family asset (yuan)	23,306	428,,059.10	1,142,081.00
Regional characteristics	*loan_gdp*	Financial loan balance ratio to GDP	20,598	1.80	1.43
	internet	Number of Internet broadband access users (10,000 households)	20,598	182.38	207.71
	phone	Number of mobile phone users at the end of the year (10,000 households)	20,598	749.01	764.30
	st_gdp	Ratio of primary and secondary industries to GDP	20,598	89.12	12.22
	per_gdp	GDP per capita	20,598	59,640.27	34,461.13

assets and financial wealth, liabilities and credit constraints, income and consumption, social security and insurance, intergenerational transfers, demographics, employment, and payment habits. The CHFS provides high-quality micro-household financial data for academic research and government decisions. CHFS data fill the gaps in the micro-field of household finances in China and have a profound impact on academic research, industrial development, and policy formulation. The CHFS has conducted five rounds of large-scale household interviews nationwide in 2011, 2013, 2015, 2017, and 2019, involving more than 40,000 Chinese households.

4.2 Variables

With the popularization of digital financial products such as digital payments, credit, and insurance, digital financial services have continued to improve. Therefore, to study the impact of the development of digital financial inclusion on rural household consumption, this study constructs the following panel fixed effect model to reflect the relationship between digital financial inclusion and rural household consumption. The panel fixed effect model was adopted to control rural households' unobservable factors. These may simultaneously affect the development of digital financial inclusion and some other unobservable factors that will not change with family consumption over a short-term period. Moreover, panel fixed effect data can also solve the problem of missing variables (individual heterogeneity) to a certain extent and reduce the endogeneity of the model.

Rural household consumption is the explained variable. This study used the sample households' total consumption expenditure and per capita consumption expenditure in the three rounds of surveys in 2015, 2017, and 2019. The sample data include household consumption expenditures on food, tobacco and alcohol, clothing, housing, daily necessities, transportation, communications, education, culture, entertainment, medical care, and other services. In the analysis process, we further focus on exploring changes in life development consumption, including education, culture, entertainment, and medical security.

The core explanatory variables are the aggregate index, coverage breadth, and usage depth index from the PKU-DFIIC. This study uses an aggregate index to measure the development of digital financial inclusion in China. Additionally, the coverage breadth and usage depth indices were used for specific research and analysis.

The control variables are sorted into three main categories: 1) Variables representing the personal characteristics of the household head—including gender, age, education, marital status, health, work status, and participation in social medical insurance—are used to control the impact of household head's characteristics on household consumption. 2) Family characteristic variables—including the number of family members, annual family income, and total family assets—are used to measure the overall resource status of the family. 3) Regional characteristic variables—including the level of traditional financial development, number of users with Internet broadband access, number of mobile phone users at the end of the year, regional industrial structure, and per capita GDP—are used to control the impact of household location on household consumption (**Table 1**).

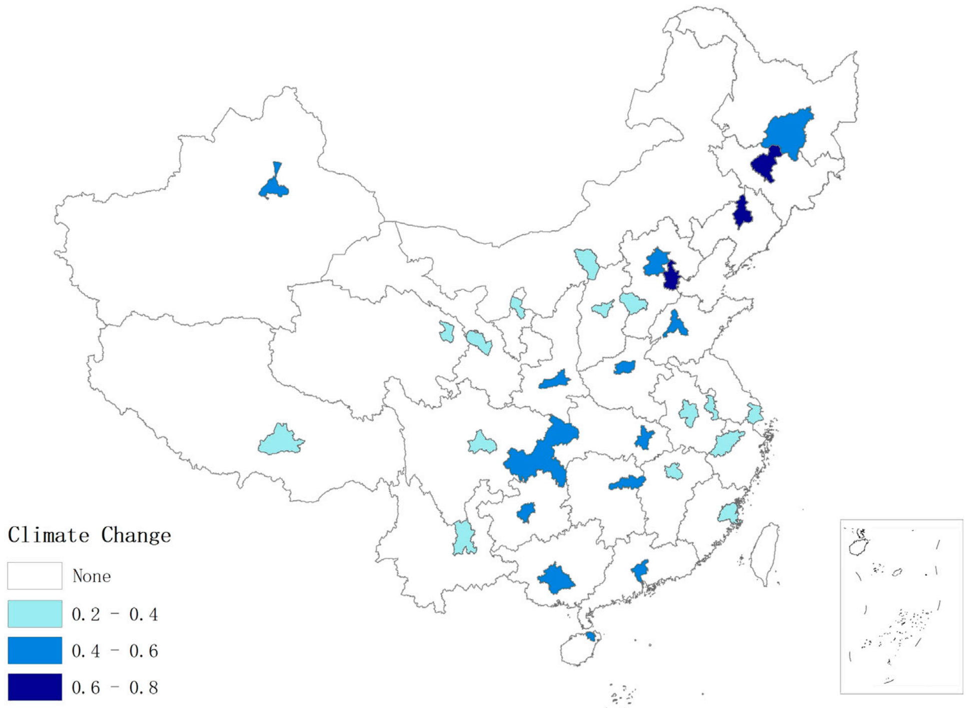

FIGURE 6 | Standard deviation of the average temperature in provincial capital cities and municipalities.

4.3 Benchmark Model

First, we test the impact of digital financial inclusion on rural residents' consumption. The benchmark regressions are as follows.

$$Lncon_{ict} = \alpha_0 + \alpha_1 Lndig_{ict} + \alpha_2 Per_{ict} + \alpha_3 Hou_{ict} + \alpha_4 Cit_{ict} + \theta^1_{ct} + \varepsilon_{ict} \tag{1}$$

$$Lnper\_con_{ict} = \beta_0 + \beta_1 Lndig_{ict} + \beta_2 Per_{ict} + \beta_3 Hou_{ict} + \beta_4 Cit_{ict} + \theta^2_{ct} + \mu_{ict} \tag{2}$$

$$Lndeve_{ict} = \gamma_0 + \gamma_1 Lndig_{ict} + \gamma_2 Per_{ict} + \gamma_3 Hou_{ict} + \gamma_4 Cit_{ict} + \theta^3_{ct} + \sigma_{ict} \tag{3}$$

$$Lnper\_deve\_con_{ict} = \lambda_0 + \lambda_1 Lndig_{ict} + \lambda_2 Per_{ict} + \lambda_3 Hou_{ict} + \lambda_4 Cit_{ict} + \theta^4_{ct} + \zeta_{ict} \tag{4}$$

The subscripts *i,c* represent the *ith* household in city *c*, and *t* represents time. The explained variable con_{ict} is the total consumption of the *ith* rural household in city *c* in year *t*. Household consumption refers to all the expenditures for household consumption needs and is divided into eight categories: food, tobacco and alcohol, clothing, housing, articles and services for daily use, transportation and communication, education, culture and entertainment, medical care, and other services. per_con_{ict} is the per capita consumption, and $deve_{ict}$ is the household's life development consumption. Life development consumption mainly includes education, culture, entertainment consumption, and health care consumption, which can represent the upgrading of the consumption structure. $per\_deve\_con_{ict}$ is the per capita life development consumption. The core explanatory variables, $dig_{ict}, cov_{ict}, dep_{ict}$, are the aggregate digital financial inclusion index, coverage breadth index, and usage depth index of city *c* in year *t*, respectively. These are used to measure the digital financial inclusion development level in the region. The control variables, $Per_{ict}, Hou_{ict}, Cit_{ict}$, are the head of household characteristics vector, family characteristics vector, and regional features vector, respectively. These are used to control the influence of other factors, except for digital financial inclusion on household consumption. $\alpha_0, \beta_0, \gamma_0, \lambda_0$ are constant terms; $\theta^1_{ct}, \theta^2_{ct}, \theta^3_{ct}, \theta^4_{ct}$ are the fixed effects; and ε_{ict}、μ_{ict}、σ_{ict}、ζ_{ict} are random error terms. **Table 1** shows the descriptive statistics.

4.4 Control Function Method

The study further addresses multiple concurrent endogeneity problems, such as sample selection bias and potential omitted variable bias in the estimation results. It also applies the control function (CF) method (Ebbes et al., 2011; Petrin and Train 2010; Wooldridge 2015; Sibande et al., 2017) for estimating the aggregate digital financial inclusion index with a lag of one order as an instrumental variable. The CF method directly introduces the residual term of the first-stage regression as an

TABLE 2 | Impact of digital financial inclusion on rural residents' consumption.

	(1) *lg_con*	(2) *lg_per_con*	(3) *lg_deve*	(4) *lg_per_deve_con*
lg_dig	0.597*** (0.061)	0.523*** (0.063)	0.708*** (0.131)	0.636*** (0.131)
gender	0.053* (0.029)	0.065** (0.029)	0.083 (0.062)	0.095 (0.062)
age	−0.021 (0.015)	−0.031** (0.015)	−0.099*** (0.032)	−0.109*** (0.032)
age2	0.000 (0.000)	0.000* (0.000)	0.001*** (0.000)	0.001*** (0.000)
edu	0.088 (0.074)	0.085 (0.076)	−0.011 (0.159)	−0.015 (0.160)
marri	0.098** (0.044)	0.085* (0.045)	0.221** (0.093)	0.208** (0.093)
health	0.005 (0.020)	0.004 (0.021)	−0.228*** (0.044)	−0.228*** (0.044)
job	−0.023 (0.022)	−0.030 (0.023)	−0.107** (0.048)	−0.114** (0.048)
soin	−0.051 (0.036)	−0.047 (0.037)	−0.122 (0.076)	−0.118 (0.077)
familynum	0.056*** (0.006)	−0.243*** (0.006)	0.112*** (0.012)	−0.187*** (0.012)
lg_inc	0.024*** (0.003)	0.027*** (0.003)	0.013* (0.007)	0.016** (0.007)
lg_asset	0.112*** (0.007)	0.111*** (0.007)	0.072*** (0.015)	0.070*** (0.015)
loan_gdp	−0.036*** (0.005)	−0.027*** (0.005)	−0.055*** (0.011)	−0.046*** (0.011)
lg_internet	0.070** (0.031)	0.048 (0.032)	0.185*** (0.066)	0.162** (0.066)
lg_phone	−0.070*** (0.024)	−0.054** (0.024)	−0.135*** (0.051)	−0.118** (0.051)
st_gdp	−0.001 (0.001)	−0.000 (0.001)	−0.002 (0.002)	−0.001 (0.002)
lg_pergdp	0.011** (0.006)	0.004 (0.006)	0.025** (0.012)	0.018 (0.012)
Constant	6.073*** (0.474)	6.673*** (0.485)	5.312*** (1.014)	5.897*** (1.016)
Fixed effect	Yes	Yes	Yes	Yes
Observations	20,443	20,443	20,443	20,443
Within R^2	0.104	0.207	0.042	0.046

Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

additional regression term into the original equation. The regression residuals of the first stage can capture the "missing variables" that cause endogeneity problems in the original model.

The first stage regression of this model is:

$$Lndig_{ict} = \alpha_0 + \alpha_1 Lndig_{ict-1} + \alpha_2 Per_{ict} + \alpha_3 Hou_{ict} + \alpha_4 Cit_{ict} + \mu_{ict}$$

$$dia_{jt} = \gamma_0 + \gamma_1 riv_{jt} + \gamma_2 Z_{ijt} + \nu_{ijt}$$

$Lndig_{ict-1}$ is an instrumental variable, digital financial inclusion index with a lag of one order. Add the residual of the first stage regression, $\widehat{\mu_{ict}} = Lndig_{ict} - \widehat{Lndig}_{ict}$, directly to the original model:

$$Lncon_{ict} = \gamma_0 + \gamma_1 Lndig_{ict} + \gamma_2 \widehat{\mu_{ict}} + \gamma_3 Per_{ict} + \gamma_4 Hou_{ict} + \gamma_5 Cit_{ict} + \varepsilon_{ict}$$

The regression residuals, $\widehat{\mu_{ict}}$, can be incorporated into the original model to control the "missing variables" that cause endogeneity problems, so that the endogeneity problem can be alleviated, and we can judge whether the original model has an endogeneity problem by testing the significance of the $\widehat{\mu_{ict}}$ coefficient γ_2.

4.5 Climate-Digital Financial Inclusion–Consumption Link Model

Climate variations range from the freezing Mongolian Plateau to the mild Sichuan Basin in China. Zhang et al. (2021) found that a harsh climate in a region could reduce consumption. This section tests whether digital finance inclusion could attenuate the negative effects of climate change on rural residents' consumption. Among all the climate factors, temperature is a good measure for climate change (Ji et al., 2014). Therefore, the standard deviation of the monthly average temperature over 11 years was used to measure climate change (Zhang et al., 2021). Our analysis focused on cross-sectional variability, and a coverage period of 11 years provided a sufficient description of a particular region's climate.

We used data from the National Bureau of Statistics of China for 2009–2019. This dataset reports the monthly temperatures in China's 32 major cities (including all provincial capital cities and municipalities). The monthly temperature is denoted as $T^m_{c,t}$ (m = January, February, . . . , December; t = 2009, 2010, . . ., 2019; c = Beijing, Tianjin, Shijiazhuang, Taiyuan, Hohhot, Shenyang, Changchun, Harbin, Shanghai, Nanjing, Hangzhou, Hefei, Fuzhou, Nanchang, Jinan, Zhengzhou, Wuhan, Changsha, Guangzhou, Nanning, Haikou, Chongqing, Chengdu, Guiyang, Kunming, Lhasa, Xi'an, Lanzhou, Xining, and Yinchuan). For each city in each year, the average value of temperature was calculated as $\bar{T}_{c,t} = \frac{1}{N}\sum_m T^m_{c,t}$, where $N = 12$. Climate change, as the long-term temperature variations over 11 years, can be calculated as follows:

$$climate_c = \text{STD}\left(\bar{T}_{c,2009}, \bar{T}_{c,2010}, \ldots, \bar{T}_{c,2019}\right)$$

The function $STD\,(\cdot)$ denotes the standard deviation of the variables in brackets.

A high variable value for a city indicates greater climate change. **Figure 6** shows a map of the temperature variations in the 32 sample cities. More comfortable living is expected in areas with less climate variation.

Combining climate change data and China Household Financial Survey data from 2019, the climate–digital financial inclusion–consumption link model is designed as follows:

TABLE 3 | Impact of digital finance coverage breadth and usage depth on rural residents' consumption.

	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	lg_con	*lg_per_con*	*lg_deve*	*lg_per_deve_con*	*lg_con*	*lg_per_con*	*lg_deve*	*lg_per_deve_con*
lg_cov	0.731***	0.596***	1.021***	0.885***	—	—	—	—
	(0.063)	(0.064)	(0.134)	(0.135)	—	—	—	—
lg_dep	—	—	—	—	0.201***	0.208***	0.172**	0.181**
	—	—	—	—	(0.037)	(0.037)	(0.078)	(0.078)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,443	20,443	20,443	20,443	20,443	20,443	20,443	20,443
Within R^2	0.109	0.209	0.046	0.048	0.097	0.203	0.040	0.044

*Notes: Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1*

$$Lncon_{ic} = \alpha_0' + \alpha_1' climate_c + \alpha_2' Per_{ic} + \alpha_3' Hou_{ic} + \alpha_4' Cit_{ic} + \varepsilon_{ic}' \quad (5)$$

$$Lncon_{ic} = \alpha_0'' + \alpha_1'' climate_c + \beta_1'' Lndig_{ic} + \lambda_1'' climate_c * Lndig_{ic} + \alpha_2'' Per_{ic} + \alpha_3'' Hou_{ic} + \alpha_4'' Cit_{ic} + \varepsilon_{ict}'' \quad (6)$$

where $climate_c * Lndig_{ic}$ represents the interaction term between climate change and digital financial inclusion.

5 RESULTS AND DISCUSSION

5.1 Impact of Digital Finance Inclusion on Rural Residents' Consumption

The basic regression examines and explains the impact of digital financial inclusion on rural residents' consumption from different perspectives. To control for variables that vary across households but not over time, fixed effects models based on three-period panel data are applied. Models (1)–(4) in **Table 2** analyze the impact of digital financial rural residents' consumption growth. The regression results show that digital financial inclusion significantly promotes rural residents' total and per capita consumption. Moreover, digital financial inclusion can also effectively promote the life development of rural residents. For every 1% increase in the level of digital financial inclusion, the total consumption, per capita consumption, life development consumption, and per capita life development consumption will increase 0.597%, 0.523%, 0.708%, and 0.636%, respectively. We also tested the impact using random effects models and obtained similar results. Overall, digital financial inclusion can promote the growth of rural residents' consumption and upgrade their consumption.

In **Table 3**, models (5)–(8) explore the relationship between the breadth of digital finance coverage and rural residents' consumption. According to the regression results, the coverage breadth of digital financial inclusion can significantly promote rural residents' overall and per capita consumption. Compared to the usage depth of digital financial inclusion in models (9)–(12), the promotion effect from coverage breadth is more obvious. The significant impact of digital finance coverage breadth suggests that digital financial inclusion can effectively reach underdeveloped rural areas that are currently difficult for the traditional financial system to reach. Digital finance can overcome the time and space limitations of the traditional financial system and provide more convenient and comprehensive financial services for financially underserved areas (Ozili 2018). However, areas with insufficient financial services are often remote rural areas with frequent climate disasters. To reduce income volatility caused by the impact of climate change on future agricultural production, rural residents in these areas are often inclined to reduce current consumption and increase savings. This situation is called precautionary savings (Omar and Inaba 2020). Digital financial inclusion provides diversified Internet insurance services. It broadens the risk avoidance channels for residents in remote areas and helps them prevent risks more efficiently, reducing precautionary savings and further ensuring the continued growth of rural residents' consumption. Increasing the coverage breadth of digital financial inclusion can also improve life-development-related consumption among rural residents more efficiently, and it can promote consumption upgrades. The mechanism by which digital finance coverage promotes rural residents' consumption can be analyzed from two aspects: 1) By covering remote areas, digital financial inclusion provides more diverse consumption methods for rural households with fewer choices in life development consumption, thereby promoting their pursuit of higher-level consumption. 2) The wide coverage of digital financial inclusion provides a strong financial guarantee to rural families who lack financial support, ensuring income stability for more disposable income, investing more in high-level consumption, and promoting consumption upgrading. Additionally, improving rural residents' living development consumption can help them improve their education level and non-agricultural employment as well as increase their income channels. This leads to both increased and upgraded consumption among rural residents.

The usage depth of digital financial inclusion also has a significant impact on promoting rural residents' consumption. Still, its consumption promotion effect on rural residents is lower than that of the aggregate digital financial inclusion index and the coverage breadth index. This result suggests that when China promotes the development of digital financial inclusion, it will

TABLE 4 | Robustness checks: Instrumental Variable method.

	(13) *lg_dig*	(14) *lg_con*	(15) *lg_per_con*	(16) *lg_deve*	(17) *lg_per_deve_con*
lg_dig_s	0.709*** (0.002)	—	—	—	—
lg_dig	—	0.666*** (0.063)	0.557*** (0.064)	0.822*** (0.134)	0.713*** (0.134)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	20,443	20,443	20,443	20,443	20,443
R^2	0.982	—	—	—	—

*Notes: Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1*

TABLE 5 | Robustness checks: Control Function method.

	(18) *lg_con*	(19) *lg_per_con*	(20) *lg_deve*	(21) *lg_per_deve_con*
lg_dig	0.803*** (0.044)	0.814*** (0.044)	1.024*** (0.090)	1.035*** (0.090)
Controls	Yes	Yes	Yes	Yes
Observations	20,443	20,443	20,443	20,443
R^2	0.289	0.326	0.104	0.068

*Notes: The standard errors for the CF estimates are based on 1000 bootstrap replications. Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1*

reach a stage where the aggregate and coverage of digital financial inclusion is relatively mature. In that case, the government should focus more on developing the usage depth of digital financial inclusion. Therefore, more attention needs to be given to quality digital financial inclusion.

5.2 Robustness Checks

5.2.1 Instrumental Variable Method

Econometric models (1)–(12) may have insurmountable endogeneity problems. Changes in rural residents' consumption and the development of digital financial inclusion may be simultaneously affected by a series of other unobservable factors. This leads to biased regression coefficient estimates for digital financial inclusion. To avoid the endogeneity problem in measurement identification, we use the aggregate digital financial inclusion index with a lag of one order as an instrumental variable for estimation. The regression results based on the instrumental variable method in **Table 4** show that the estimated coefficients are significant and positively correlate with the explanatory variables of interest. The weak instrumental variables test results also show that weak instrumental variables are unlikely. The estimation results suggest that after considering the endogeneity problem, the development of digital financial inclusion still significantly promotes rural residents' consumption. Additionally, it can also significantly promote the consumption of life development, such as for education, culture, entertainment, and medical security, among rural residents, which is conducive to consumption upgrading. All the results were robust.

5.2.2 Control Function Method

The study further addresses multiple concurrent endogeneity problems, such as sample selection bias and potential omitted variable bias, in the estimation results. It also applies the control function method for estimating the aggregate digital financial inclusion index with a lag of one order as an instrumental variable. As a result, the endogeneity problem can be alleviated. **Table 5** reports results consistent with the benchmark regression results.

5.3 Heterogeneity Analysis

Regarding heterogeneity, all sample households are divided into two groups according to annual household income: high-income group (*lowin* = 0) and low-income group (*lowin* = 1), and then further subdivided into two groups according to total household assets: high-asset group (*lowas* = 0) and low-asset group (*lowas* = 1). Moreover, according to geographical location, the sample is divided into households in the eastern region (*east* = 1) and those in the central and western regions (*east* = 0). The multiplication (*diglowin*) of the aggregate digital financial inclusion index and low-income rural households, the multiplication (*diglowas*) of the aggregate digital financial inclusion index, low-asset rural households, and the multiplication (digeast) of the aggregate digital financial inclusion index and eastern rural households were introduced into the regressions. **Tables 6**, **7** report the results. Results (22)–(29) show that, compared with high-income and high-asset households, digital financial inclusion has a greater role in promoting the consumption of low-income and low-asset households. This indicates that digital financial inclusion can improve rural residents' resilience to the risks brought about by climate change, especially for vulnerable groups in rural areas. Results (30)–(33) show that digital financial inclusion can especially promote rural residents' consumption in central and western China, where the impact of climate change on agricultural production is more serious, and the economy is more undeveloped. Heterogeneous results indicate that digital financial inclusion can reduce the risk of poverty caused by climate change and is more conducive to helping disadvantaged groups who find it more difficult to obtain financial support.

TABLE 6 | Heterogeneous analysis: rural households of different incomes and assets.

	(22) *lg_con*	(23) *lg_per_con*	(24) *lg_deve*	(25) *lg_per_deve_con*	(26) *lg_con*	(27) *lg_per_con*	(28) *lg_deve*	(29) *lg_per_deve_con*
lg_dig	0.578*** (0.061)	0.502*** (0.062)	0.706*** (0.131)	0.631*** (0.131)	0.578*** (0.061)	0.503*** (0.063)	0.696*** (0.131)	0.622*** (0.132)
diglowin	0.026*** (0.003)	0.029*** (0.003)	0.003 (0.007)	0.006 (0.007)	—	—	—	—
diglowas	—	—	—	—	0.022*** (0.004)	0.022*** (0.004)	0.014 (0.009)	0.015 (0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,443	20,443	20,443	20,443	20,443	20,443	20,443	20,443
Within R^2	0.111	0.214	0.042	0.046	0.107	0.210	0.043	0.046

Notes: Standard errors in parentheses. ***p < *0.01,* **p < *0.05,* *p < *0.1*

TABLE 7 | Heterogeneous analysis: rural households of different regions.

	(30) *lg_con*	(31) *lg_per_con*	(32) *lg_deve*	(33) *lg_per_deve_con*
lg_dig	0.620*** (0.070)	0.554*** (0.071)	0.844*** (0.149)	0.778*** (0.150)
digeast	−0.055 (0.080)	−0.075 (0.082)	−0.324* (0.171)	−0.340** (0.171)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	20,443	20,443	20,443	20,443
Within R^2	0.104	0.207	0.043	0.046

Notes: Standard errors in parentheses. ***p < *0.01,* **p < *0.05,* *p < *0.1*

TABLE 8 | Moderating effect of digital finance.

	(34) *lg_con*	(35) *lg_per_con*	(36) *lg_con*	(37) *lg_per_con*
climate	−0.670*** (0.207)	−0.718*** (0.208)	−1.199** (0.580)	−1.134* (0.581)
lg_dig	—	—	2.536*** (0.875)	2.505*** (0.874)
*climate * lg_dig*	—	—	0.404* (0.223)	0.370* (0.223)
Controls	Yes	Yes	Yes	Yes
Observations	1,503	1,503	1,503	1,503
R^2	0.275	0.193	0.356	0.280

Notes: Standard errors in parentheses. ***p < *0.01,* **p < *0.05,* *p < *0.1*

5.4 Impact of Digital Financial Inclusion on Climate Change Adaption

In the climate–consumption link, our main interest is the impact of climate change on rural residents' consumption at the household level. Combining city-level climate change with household survey data in 2019, we perform regressions based on **Eqs 5**, **6**. The main empirical findings are presented in **Table 8**. The first two models (models 34 and 35) study the impacts of climate change on consumption, whereas models 36 and 37 report results for the impacts of multiplication (*climate * lg_dig*) of climate change and the aggregate digital financial inclusion index. The results for models 34 and 35 are statistically significant at the 1% level, and the coefficients are all negative, which indicates that higher climate change in a city with one standard deviation is associated with a reduction in rural household consumption. Rural residents who live in areas with harsh weather conditions have low sensitivity to utility from consumption and thus have a low propensity to consume. With all other factors being equal, households in areas with harsh weather conditions or regions with high-temperature changes tend to consume less. Models 34 and 35 show that the coefficients of the multiplication variable are all positive and statistically significant at the 10% level. This indicates that, although climate change will reduce rural residents' consumption and increase their risks, digital finance inclusion mitigates this negative effect significantly, further verifying the role of digital finance in moderating climate change.

6 CONCLUSIONS AND IMPLICATIONS

Extreme weather conditions caused by climate change directly and negatively impact agricultural production. As the main source of agricultural production, rural residents are more affected by the reduction of income, lack of financial support, and consumption restrictions due to climate change (Harvey et al., 2014). This study explores the role of digital financial inclusion in promoting consumption among China's rural residents to determine the mechanism for promoting their consumption under climate change risk. In the empirical analysis, this study uses data from the Peking University Digital Financial Inclusion Index of China and the China Household Finance Survey (CHFS) to perform benchmark regression. The study concludes that the development of digital financial inclusion can provide rural residents with more accurate financial services, such as credit and insurance, and help them smooth their consumption patterns. It can also enhance their ability to resist climate change risks and reduce the negative impact of climate change, thereby promoting rural residents' consumption and complete consumption upgrades. Specifically, digital financial inclusion promotes rural residents' consumption by increasing the coverage breadth and usage depth (especially coverage) of digital finance in rural areas.

The results of the heterogeneity analysis show that the development of digital financial inclusion can enhance the ability of low-income and low-asset rural families to cope with climate change risks, thereby increasing their consumption. The results also show that the development of digital financial inclusion can reduce the poverty risk caused by climate change. Therefore, digital financial inclusion plays a certain role in alleviating poverty. From the perspective of regional development, digital financial inclusion can significantly promote rural residents' consumption in China's central and western regions. Additionally, it enhances the ability of central and western rural residents to resist climate risks. It also helps narrow the poverty gap between regions and aids in forming better regional economic development.

Finally, we further verified the role of digital finance in moderating climate change and found that, although climate change reduces rural residents' consumption and increases their risks, digital finance will mitigate this negative effect significantly by combining climate change data from major cities and China Household Financial Survey data from 2019.

This study offers policy implications from a bottom-up perspective. First, the results show that households suffer significant welfare losses owing to climate variation. These variations can cause a reluctance to consume among rural residents, negatively impacting the macroeconomy. Hence, policy support is required in regions with harsh weather conditions. Second, the long-term effects of cultural elements indicate that the behavioral consequences of climate variation can have long-lasting effects and are thus difficult to change. Therefore, to promote digital financial inclusion and consumption upgrades among rural households, the government should pay close attention to the digital-finance usage depth in rural areas and promote the construction of digital financial inclusion facilities. In so doing, it can strive for digital financial inclusion to have a deeper impact on rural household incomes and consumption, which can further improve their ability to withstand climate risks. Our specific recommendations are as follows: 1) The rural information infrastructure is quite different in developing countries such as China. In some rural areas, as internet infrastructure is poor, power supplies unstable, and logistics networks underdeveloped, rural digital finance and e-commerce development is restricted. Therefore, it is necessary to strengthen mobile communication networks in rural areas to increase network coverage and provide a safe, convenient, and cost-effective network environment. 2) In most developing countries, the majority of rural residents lack basic financial and internet knowledge. Therefore, financial institutions need to promote mobile and online payments in rural areas. Digital finance and agricultural supply chains need to be explored as well, and e-commerce companies need to be encouraged to improve rural area e-commerce systems. 3) Because of the imbalances in China's rural populations, the left-behind elderly, children, and other groups have poor knowledge of digital financial risk prevention and control. Therefore, small financial service institutions, such as local rural commercial banks, village banks, and loan companies, need to strengthen their internal institutions to prevent information leakage and protect the rights and interests of their customers. Relevant departments also need to develop financial products that meet the wealth management needs of rural residents.

The limitations of this study are as follows: 1) Since the consumption data of rural residents comes from micro-surveys, we use three-period panel data. Because we use short panel data instead of long time series data, it is difficult to use advanced modeling techniques such as CS-ARDL to conduct empirical research. 2) Due to the difficulty in obtaining long-term average temperature data for each city, which can be calculated by using data released by each weather station, we were only able to use the official data on major cities published by the National Bureau of Statistics, resulting in the temperature data only covering some cities and reducing the sample size. These could be well addressed in future research.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

Conceptualization, CH and WQ; methodology, CH; software, CH; formal analysis, WQ; data curation, JY; writing—original draft preparation, CH; writing—review and editing, CH and JY; visualization, JY; supervision, WQ; funding acquisition, CH. All authors have read and agreed to the published version of the manuscript.

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The Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity: Evidence From China

Qiang Gao[1], Changming Cheng[1,2], Guanglin Sun[3,4] and Jianfeng Li[5]*

[1] College of Economics and Management, Nanjing Forestry University, Nanjing, China, [2] School of Economics and Management, Chuzhou University, Chuzhou, China, [3] School of Finance, Nanjing University of Finance and Economics, Nanjing, China, [4] Institute of Industrial Economics, Chinese Academy of Social Sciences, Beijing, China, [5] College of Economics and Management, China Jiliang University, Hangzhou, China

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Peng Jiquan,
Jiangxi University of Finance and Economics, China

***Correspondence:**
Jianfeng Li
fengzhongfeifan@foxmail.com

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This manuscript applies the GML model with unexpected output to measure agricultural green total factor productivity (GTFP) in 30 provinces in China from 2011 to 2019. We explore the effect and mechanism of digital inclusive finance (DIF) on agricultural green total factor productivity. Our empirical results show that during the sample period, China's agricultural green total factor productivity has shown an increasing trend. Digital inclusive finance mainly promotes agricultural GTFP by improving green technology level. The coverage rate, the application rate and the digitalization rate of digital inclusive finance all generate positive effects on agricultural green total factor productivity, among which the coverage rate contributes the most. Besides, the positive effect of digital inclusive finance in the eastern coastal areas is more significant than in other areas. The analysis of the mechanism shows that digital inclusive finance can indirectly help improve agricultural green total factor productivity through motivating agricultural technology innovation and industrial structure optimization. The research results of this manuscript are extremely meaningful for better implement DIF-related policies, and promote the green development of agriculture.

Keywords: agricultural green total factor productivity, digital inclusive finance, Tobit model, mechanism, China

INTRODUCTION

Since the Economic Reform and opening-up, China's agricultural economy has been rapidly growing, which is now called the world-known "China Miracle". During 1978 to 2020, the average annual growth of China's agricultural gross domestic product (GDP) is at 4.6%. During the same period 2003 to 2021, China's total grain output has increased from 430 million tons to 680 million tons, maintaining a continuous growth for 18 years. However, China's high speed agricultural economic growth at the cost of high investment and heavy pollution inevitably lead to excessive waste of resources and deterioration of the biological environment (Su et al., 2020). Taking carbon emissions as an example, China's agricultural carbon emissions account for 17% of world's carbon emissions, but this share for the U.S. and the world's average level is only at 7 and 11%, respectively (Huang et al., 2019). In fact, China has become the largest source of agricultural carbon emissions in the world. Agricultural development faces dual pressures of low production efficiency and heavy environmental pollution (Fang et al., 2021).

In this context, the report of the 19th National Congress of the Communist Party of China proposed to promote the development of environmentally friendly agriculture and improve the total factor productivity. In 2022, China's "No. 1 Document" further emphasizes the importance of development of environmental efficient agriculture. Previous studies have confirmed that implementing sustainable development strategies and improving agricultural green total factor productivity is an effective way to achieve agricultural green development (Wu et al., 2020). Agricultural green total factor productivity, i.e., agricultural environmental efficiency and agricultural ecological efficiency, measures agricultural total factor productivity under the consideration of resources and environment. The acceleration of agricultural green total factor productivity growth is inseparable from supports provided by financial services (Zeng et al., 2021).

Under the traditional financial service framework, the cost and risk of providing financial services to agriculture and rural areas is high, therefore discouraging financial institutions from entering the industry, and by consequence creating obstacles for farmers to receive external financings. Zhang et al. (2015) shows that due to the constraints of cost, risk and technology, traditional finance fails to provide strong support for the green development of China's economy. Therefore, it is urgent to accelerate the pace of financial model reform and innovation to improve the availability of agricultural financial services (Cao et al., 2021). Incorporating new technologies such as artificial intelligence and big data (Awan et al., 2021), digital financial inclusion emerges in responding the demand. Digital inclusive finance overcomes high costs and information asymmetry in traditional rural financial transactions, it is also able to improve the financial availability in remote areas and for vulnerable groups, thus playing an important role in alleviating the shortage of funds in the agricultural sector and promoting high-quality agricultural development (Xing, 2021). The 49th "Statistical Report on Internet Development in China" shows that the number of rural netizens in China has reached 284 million, and the Internet penetration rate in rural areas has reached to 57.6% up to December 2021. Through network terminals such as mobile phones, groups excluded from the formal financial system have access to financial services (Gomber et al., 2018). Practice shows that digital financial inclusion promotes the optimal allocation of financial resources, which has a significant positive impact on rural development and agricultural production (Ahmed and Huo, 2021; Cao et al., 2021). Hence, it is of great significance to explore the relationship between the digital inclusive finance and agricultural green total factor productivity for realizing the sustainable development of China's agriculture.

Previous research has mainly focused on the effect of agricultural trade (Zhao et al., 2018), industrial agglomeration (Wu et al., 2020), agricultural insurance (Carter et al., 2016), and farmer household characteristics (Adnan et al., 2018) and other factors on agricultural green total factor productivity, nevertheless, little attention has been paid to the relationship between digital inclusive finance and agricultural green total factor productivity. Romer's endogenous growth theory points out that financial development would affect total factor productivity through resource allocation and technological progression (Romer, 1986). Subsequently, some studies have shown that digital inclusive finance can promote green economic development (Siek and Sutanto, 2019) and green total factor productivity growth (Li et al., 2021). However, previous studies have controversial conclusions at the level of agricultural research. Hu et al. (2021) argue that inclusive finance supports the transformation of agricultural production by providing loans to improve agricultural total factor productivity. Li (2021) and Sun et al. (2022) found that digital inclusive finance increases the supply of financial services, thereby promoting changes in agricultural production methods, quality and efficiency, and leads to promoting agricultural green total factor productivity. However, Matthews (2019) pointed out that the short-term effect of digital financial inclusion on agricultural and rural economies is limited. In the absence of mature digital inclusive finance development systems and regulatory mechanisms, it may bring new risks to the development of the agricultural sector. Digital inclusive finance is profit-seeking like other types of capital. The narrow profit-seeking space in rural areas, technical threshold of digital inclusive finance, the lack of financial infrastructure in rural areas and financial knowledge of rural people make digital inclusive finance significantly less active in rural areas (Xing, 2021).

The existing literature mainly focuses on the impact of digital financial inclusion on the agricultural economy, while few studies focus on the impact of agro-ecology, and fewer studies comprehensively consider the economic and ecological effects. Most of the existing literature examines and verifies the relationship between the two, and lacks sufficient analysis of the transmission path, so it is difficult to identify the internal mechanism of digital inclusive finance affecting agricultural green total factor productivity. In general, the impact of digital inclusive finance on agricultural green total factor productivity is still a relatively new topic. Can digital inclusive finance promote the improvement of agricultural green total factor productivity? If so, what is its mechanism of action? These questions require in-depth research by the academic community to give convincing answers. The main objective of this study is to measure agricultural green total factor productivity using the GML model that introduces undesired output based on the panel data of 30 provinces in China from 2011 to 2019. Then empirically investigate the effect of digital inclusive finance on agricultural green total factor productivity, as well as its internal mechanism.

The contributions of this study to the existing literature are as follows: First, this study incorporates both economic and ecological effects into the research framework to explore comprehensively the effect of digital inclusive finance. The existing literature focuses on the effect of digital inclusive finance on the agricultural economy, while little attention is paid to the effect on agroecology, and the simultaneous impact on economic and ecological effects. Second, this study uses the mediation effect model to explore the impact mechanism of digital inclusive finance on agricultural green total factor productivity. Previous studies are difficult to give a clear explanation on the internal affecting mechanism of digital inclusive finance on the agricultural green total factor productivity, for focusing on verifying the relationship between the two, rather than analyzing the transmission path. Third, this study examines the relationship between digital inclusive finance and agricultural green TFP from three perspectives: sub-index, sub-dimension, and sub-region, in order to investigate the heterogeneity of the impact of digital inclusive finance.

The rest of this article is organized as follows. Section "Theoretical Analysis and Research Hypothesis" introduces the theoretical framework. Section "Theoretical Analysis and Research Hypothesis" describes the data and models. Section "Materials and Methods" reports empirical results including heterogeneity analysis, endogeneity problem and mechanism analysis. Section "Conclusion and Policy Implications" concludes.

THEORETICAL ANALYSIS AND RESEARCH HYPOTHESIS

The Direct Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity

The small and scattered demand for agricultural capital, the difficulty in collecting credit information make it difficult for the agricultural sector to obtain support from traditional finance institutions. Digital inclusive finance relying on digital technology can greatly improve the efficiency of capital matching and the availability of financial services in the agricultural sector under the condition of low-cost, thereby promoting the improvement of agricultural green total factor productivity (Sun et al., 2022). Specifically, the impact of digital inclusive finance on agricultural green total factor productivity is mainly reflected in the following three aspects: First, digital inclusive finance lowers the entry difficulty to obtain financial services. Digital inclusive finance provides low-cost and high-efficiency access to funds for rural areas with relatively weak economic foundations, and helps alleviate insufficient financial supply and financial exclusion in rural areas. Adequate capital supply can improve the application of agricultural machineries and equipment, advanced technology, etc., which lays the foundation for large-scale and intensive development. Second, digital inclusive finance can facilitate the application of green technology. By leveraging its technological advantages, digital inclusive finance can accurately invest funds in green farming fields such as green farming, agricultural machinery and equipment, pollution prevention, which will improve the scale and efficiency of green agricultural output. Third, digital inclusive finance helps diversify risks. By building a risk control system based on big data, digital inclusive finance can effectively improve the financial literacy and risk awareness of farmers while reducing the systemic financial risks of financial institutions. At the same time, digital inclusive finance improves the resilience of the agricultural sector by promoting fintech and insurtech interconnectivity (such as "bank + insurance" loan), which in turn increases the acceptances of new technologies and green equipment (Visser et al., 2020), and can consequently improve agricultural green total factor productivity (Aung et al., 2019). Based on the above analysis, this study proposes the following hypotheses:

H1: Digital inclusive finance can promote the improvement of agricultural green total factor productivity.

The Indirect Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity

The development of digital inclusive finance can improve the level of agricultural technological innovation and promote the optimization of industrial structure, which would improve agricultural green total factor productivity.

The GTFP improvement is inseparable from technological progress especially green technology innovation (Sun et al., 2020; Wang H. et al., 2021). The inclusive nature of digital inclusive finance has eased the financial constraints of agriculture-related entities, making it possible to invest more R&D funds in the agricultural sector, thereby improving the level of regional agricultural technology innovation. Digital inclusive finance establishes a reliable credit reporting system through digital technology (Du et al., 2021), which effectively reduces the credit risk faced by the financial system when it provides inclusive financial services to farmers. This fundamentally elevates the financing constraints of agricultural-related entities' technology innovation (Gomber et al., 2018). Furthermore, the vigorous promotion of digital inclusive finance in China promotes the continuous improvement of rural digital infrastructure, which facilitates the promotion and application of advanced technologies and ultimately promotes the improvement of agricultural green total factor productivity (Zhang and Gao, 2018). Based on the above analysis, this study proposes the following hypotheses:

H2a: Agricultural technological innovation plays an intermediary role in the process of digital inclusive finance promoting the improvement of agricultural green total factor productivity.

As for the effect of industrial structure optimization. Digital inclusive finance reduces information asymmetry and transaction costs, thereby improving the efficiency of resource allocation and boosting the optimization and upgrading of the agricultural structure (Chava et al., 2013). The digital inclusive finance expands the coverage of financial services, enhances the application of financial services, promotes the green upgrade of the industrial structure, realizes the Pareto improvement of financial resources allocation, and finally achieves a win-win situation for output and for the environment (Liu and He, 2021; Zhou et al., 2021). The continuous optimization and upgrading of the agricultural structure have led to the expansion of the rural industries scale. The accompanying cluster effect and specialization effect not only reduce agricultural production costs and increase the additional value of products, but also bring huge structural and scale dividends, which will help improve agricultural green total factor productivity. Based on the above analysis, this study proposes the following hypotheses:

H2b: Industrial structural optimization plays an intermediary role in the process of digital inclusive finance promoting the improvement of agricultural green total factor productivity.

MATERIALS AND METHODS

Sample and Data Source

The data used in this manuscript consists of provincial statistics and the digital inclusive finance data. The statistical data of 30 provinces in China (excluding Hong Kong, Macau, Taiwan, and Tibet) are collected from the "China Statistical Yearbook", "China Rural Statistical Yearbook", "China Science and Technology Statistical Yearbook", "China's Population and Employment Statistical Yearbook", "Monthly Statistical Report on Import and Export of China's Agricultural Products" and Statistical Yearbooks of various provinces and cities. Data of digital inclusive finance comes from the China Digital inclusive finance Index released by the Digital Finance Research Center of Peking University (Guo et al., 2020). Therefore, our dataset is a balanced panel dataset of 30 provinces in China from 2011 to 2019.

Definition of Variables

Dependent Variables

The dependent variable in this manuscript is agricultural green total factor productivity (GTFP). Previous studies mainly apply two methods to measure green total factor productivity, first, the Malmquist-Luenberger (ML index) based on the directional distance function proposed by Chung and Fare (1997), second the Global Malmquist-Luenberger index (GML index) constructed by Oh (2010). However, compared with the ML index, the GML index can solve the defects of non-transitivity and no feasible solution perfectly. Therefore, this manuscript adopts the GML index to measure the agricultural green total productivity of various provinces of China. The specific model settings are as follows:

$$GML_t^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t\right) = \frac{1 + S_V^G\left(x^t, y^t, b^t\right)}{1 + S_V^G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \tag{1}$$

The GML values can be greater than 1, equal to 1 or less than 1, respectively, it represents the increase, the constant and the decrease of the level of agricultural green total factor productivity from the t to t + 1 period, respectively. As shown in equation (2), the GML index can be further decomposed into the product of Technical progress(GTC)and Technical efficiency(GEC), according to which we can examine the impact of GEC and GTC on productivity improvement.

$$\begin{aligned} & GML_t^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t\right) \\ & = \frac{1 + S_V^t\left(x^t, y^t, b^t; g\right)}{1 + S_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)} \\ & \times \left[\frac{\left[1 + S_V^G\left(x^t, y^t, b^t; g\right)\right] / \left[1 + S_V^t\left(x^t, y^t, b^t; g\right)\right]}{\left[1 + S_V^G\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)\right] / \left[1 + S_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)\right]}\right] \\ & = \frac{TE^{t+1}}{TE^t} \times \left[\frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}}\right] = GEC_t^{t+1} \times GTC_t^{t+1} \end{aligned} \tag{2}$$

According to Liu and Xin (2019), we took 2010 as the base period to convert the agricultural green total factor productivity index of each province into a cumulative productivity index. The variables in the measurement model of agricultural green total factor productivity include input, expected output and unexpected output. The specific indicators list as follows:

First, input indicators including labor, land and capital. Among them, we use the total number of agricultural employees to represent the labor factor. We choose the total sown area of crops to represent the land factor, for it can better reflect the situation of multiple cropping and intercropping, replanting and replanting, transplanting crops, comparing t with the arable land area index. The capital factor is represented by the amount of fertilizer use and the total mechanical power.

Second, the expected output indicators. The study selects the total agricultural output to represent the expected output. In order to exclude the impact of price factors, we converted the agricultural output value data into comparable data using 2010 as the base period.

Third, the unexpected output indicators. Non-point source pollution and carbon emissions are often used as proxies for undesired output in previous studies, and their measurement is still controversial (Sun et al., 2012). This manuscript selects carbon emissions as the undesired output because carbon emissions increase the global greenhouse effect, and the current agricultural carbon emission reduction play the essential part of environmentally friendly agriculture development. Carbon emissions are "real pollutants," which do not contain any nutrients such as nitrogen and phosphorus. Liu et al. (2021) and IPCC (2007) argue that most of the polluting behaviors of agricultural production generate greenhouse gases, so it is reasonable to treat carbon emissions as an undesired output. Li et al. (2011) and IPCC (2007) measured the total amount of agricultural carbon emissions by chemical fertilizers, pesticides, agricultural film, diesel oil, tillage and agricultural irrigation in the agricultural production process. And the coefficient of each carbon emission source is accurately estimated: fertilizer 0.8956 kg·kg-1; Chemical pesticide 4.9341 kg·kg-1; agricultural film 5.18 kg·kg-1; diesel oil used in agriculture 0.5927 kg·kg-1; tillage 312.6 kg km-2; irrigation 20.476 kg Cha-1.

Explanatory Variables

The core explanatory variable of this research is the development level of digital inclusive finance. This study selects the Peking University Digital Financial Inclusion Index as a proxy variable for digital inclusive finance. The index measures the development of digital inclusive finance from three dimensions: breadth of coverage (BREA), depth of use (DEP) and degree of digital support services (DIG) according to the principles of comprehensiveness, balance and comparability. Among them, the breadth of coverage (BREA) is mainly reflected by the number of electronic accounts, the depth of usage (DEP) is measured by the actual use of Internet financial services, and the level of digitalization (DIG) is closely related to convenience and cost. For the convenience of analysis, the digital inclusive finance index scores in this manuscript are divided by 100 with their raw data.

Mediating Variables

According to the above analysis, digital inclusive finance can indirectly affect agricultural green total factor productivity through agricultural technology innovation and industrial structure upgrading. Specifically, agricultural technology innovation (TEC) can be measured from the perspective of both input and output. However, the use of input indicators may overestimate the level of agricultural technology innovation due to the difficulty of fully converting inputs into outputs. Therefore, this manuscript selects the total number of patent applications in the agricultural sector to measure the level of agricultural technology innovation, whose data can be obtained from the CNKI patent database. According to Wang M.-X. et al. (2021), we constructed an industrial structure optimization index to measure the industrial structure level of 30 provinces, and its calculation formula is $isu = \sum_{i=1}^{3} I_i \times i = I_1 + 2 \times I_2 + 3 \times I_3$. Where, I_i represents the proportion of the output of the i-th industry of a province to the total output of the corresponding province. The value range of isu is $1 \leq isu \leq 3$. isu close to 1 indicates the current economic society is an agricultural society dominated by farming. On the contrary, isu close to 3 indicates that the economic society is entering a post-industrial knowledge economy society.

Control Variables

According to previous literatures (Li et al., 2020; Cao et al., 2021; Fang et al., 2021; Li, 2021), the control variables include the following: (1) Extent of disaster (EXT) measured by the proportion of the affected area of the sown area of crops. (2) Income structure (INS), measured by the ratio of urban and rural per capita disposable income. (3) Degree of economic openness (OPE), expressed by the ratio of the import and export volume of agricultural products to the total agricultural production value. (4) Average education level (EDU), expressed by the average years of education of rural residents. (5) Urbanization (URB), measured by the level of urbanization, which solves the dilemma of rural surplus labor and helps improve the efficiency of agricultural resource allocation (Yu et al., 2014), thereby promoting the growth of agricultural green total factor productivity. (6) Effective irrigation degree (WAT) and Industrialization (IND). The variable definitions and descriptive statistics of this study are shown in **Table 1**.

MODEL

The non-negative cumulative value of agricultural green total factor productivity and its decomposition index should be attributed to the restricted dependent variable. Therefore, the OLS estimation method will lead to large deviations in the results, thus this manuscript adopts the Tobit model setting as follows:

$$Y_{it} = \alpha_0 + \alpha_1 DIFT_{it} + \alpha_i X_{it} + \varepsilon_{it} \tag{3}$$

Where, $Y_{it}$is the accumulated GTFP, GTC and GEC for the i-th province in year t, $DIFT_{it}$ is the development level of digital inclusive finance, $X_{it}$are control variables, and ε_{it} is random disturbance term with distribution $\mu_i \sim (0, \sigma^2)$.

EMPIRICAL ANALYSIS

Agricultural Green Total Factor Productivity and Decomposition

Table 2 show China's agricultural green total factor productivity and its decomposition index calculated by GML index. Overall, the average annual growth rate of China's Agricultural green total factor productivity (GTFP), Technical progression (GTC) and Technical efficiency (GEC) are 2.0, 1.8, and 0.2% from 2011 to 2019, respectively. GTFP and GTC are both greater than 1, and generally exhibit an upward trend. Although the efficiency of green technology is generally greater than 1, it has been less than 1 in 5 years, and the overall trend is declining. The above analysis implies that the green technology progress is the main driving force of agricultural green TFP, while green technology efficiency is counterproductive.

From a geographical perspective, the average annual growth rates of agricultural green total factor productivity in the eastern, central and western regions are 2.4, 1.8, and 1.8%, respectively. The reason for the high growth of agricultural green total factor productivity in the eastern region is that the eastern regions have abundant resources, good economic foundation, preferential policies and relatively advanced technologies, which have a stronger impetus to promote agricultural transformation and upgrading, thereby promoting agricultural Green total factor productivity grew at a relatively rapid rate. As for the central and western regions, although agricultural development is relatively slower, with the increasingly application of technology introduction and policy support, agricultural green total factor productivity has also maintained growing.

The Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity

Benchmark Regression

Table 3 reports the estimated results of the impact of DIF on Agricultural GTFP. We run the LR test and the Wald test to

TABLE 1 | Variable definition and descriptive statistics.

Type	Variable name	Variable definition	Mean	SD	Min	Max
Dependent variables	Agricultural green total factor productivity (GTFP)	Accumulated value of agriculture green total factor productivity	1.433	0.704	0.086	5.022
	Technical progress (GTC)	Accumulated value of agricultural technology progress	1.523	0.865	0.144	6.760
	Technical efficiency (GEC)	Accumulated value of agricultural technical efficiency	0.994	0.326	0.202	3.992
Explanatory variables	Digital inclusive finance (DIF)	Score of digital inclusive finance (Original value/100)	2.034	0.916	0.183	4.103
	Breadth of coverage (BREA)	Score of breadth of coverage(Original value/100)	1.836	0.902	0.020	3.847
	Depth of usage (DEP)	Score of depth of usage(Original value/100)	1.980	0.914	0.068	4.399
	Level of digitalization (DIG)	Score of level of digitalization(Original value/100)	2.784	1.180	0.076	4.622
Instrumental variable	Internet penetration rate (INT)	Proportion of rural Internet users	0.502	0.121	0.242	0.787
Mediating variables	Agricultural technology innovation (TEC)	Agricultural patent applications	0.924	0.923	0.016	4.463
	Upgrading of industrial structure (ISU)	Industrial structure upgrading index	0.516	0.354	0.010	1.000
Control variables	Extent of disaster (EXT)	Affected area of crops	0.159	0.121	0.000	0.696
	Income structure (INS)	Proportion of urban and rural per capita disposable income	2.642	0.422	1.845	3.979
	Degree of economic openness (OPE)	Proportion of total import and export trade of agricultural products in agricultural GDP	0.335	0.914	0.004	6.071
	Average education level (EDU)	Average years of education in rural areas	7.818	0.617	5.909	9.941
	Urbanization (URB)	Urbanization level	0.577	0.124	0.344	0.942
	Effective irrigation degree (WAT)	Proportion of effective irrigation area in crop sowing area	0.438	0.178	0.172	1.234
	Industrialization (IND)	Proportion of industrial value-added in GDP	0.415	0.080	0.160	0.620

TABLE 2 | Provincial agricultural Green total factor productivity and its decomposition of China from 2011 to 2019.

Province	Region	GML	GTC	GEC	Province	Region	GML	GTC	GEC
Beijing	E	1.021	1.021	1.000	Hubei	C	1.014	1.014	1.000
Tianjin	E	1.036	1.012	1.024	Hunan	C	1.012	1.014	0.998
Hebei	E	1.016	1.017	0.999	Inner Mongolia	W	1.007	1.012	0.995
Liaoning	E	1.016	1.025	0.992	Guangxi	W	1.014	1.013	1.000
Shanghai	E	1.000	1.000	1.000	Chongqing	W	1.013	1.014	0.999
Jiangsu	E	1.030	1.030	1.000	Sichuan	W	1.018	1.015	1.003
Zhejiang	E	1.032	1.032	1.000	Guizhou	W	1.044	1.011	1.032
Fujian	E	1.028	1.028	1.000	Yunnan	W	1.014	1.010	1.004
Shandong	E	1.033	1.033	1.000	Shaanxi	W	1.011	1.011	1.001
Guangdong	E	1.025	1.025	1.000	Gansu	W	1.015	1.012	1.003
Hainan	E	1.028	1.028	1.000	Qinghai	W	1.038	1.038	1.000
Shanxi	C	1.015	1.014	1.000	Ningxia	W	1.011	1.008	1.002
Jilin	C	1.040	1.017	1.023	Xinjiang	W	1.013	1.022	0.992
Heilongjiang	C	1.015	1.013	1.015	East	–	1.024	1.023	1.001
Anhui	C	1.010	1.010	1.000	Central	–	1.018	1.015	1.003
Jiangxi	C	1.019	1.012	1.007	West	–	1.018	1.015	1.003
Henan	C	1.020	1.024	0.996	Average	–	1.020	1.018	1.002

The data in this table are dynamic values, that is, the change in efficiency from t to t + 1. The following regression uses cumulative values. E\C\W represents the east, central and west regions of China.

verify the model's fitness and the results show that our model fits well. Columns (1) to (3) of **Table 3** report the estimated results of the benchmark models without control variables, while columns (4) to (6) show the estimated results of the models with control variables. The results of the benchmark models manifest that DIF has a positive impact on agricultural GTFP. The results in columns (4) to (6) manifest that the coefficient of DIF is significantly positive, indicating that DIF still has a positive impact on agricultural GTFP after controlling for other variables. Thus, the hypothesis H1 is initially verified.

In addition, according to **Table 3**, we find that DIF had a significant positive effect on GTC, which is enhanced to a certain

TABLE 3 | Digital inclusive finance and Agricultural green total factor productivity.

	(1)	(2)	(3)	(4)	(5)	(6)
	GTFP	**GTC**	**GEC**	**GTFP**	**GTC**	**GEC**
DIF	0.436***	0.493***	0.024	0.469***	0.542***	−0.012
	(0.030)	(0.039)	(0.015)	(0.049)	(0.059)	(0.026)
EXT				−0.364	0.116	−0.205
				(0.275)	(0.363)	(0.148)
INS				0.578***	0.461**	0.052
				(0.190)	(0.223)	(0.094)
OPE				−0.166**	0−0.212**	−0.016
				(0.078)	(0.090)	(0.041)
EDU				0.209*	0.365***	0.030
				(0.116)	(0.133)	(0.066)
URB				0.419	−1.433*	1.220***
				(0.746)	(0.855)	(0.411)
IND				1.095	−0.073	0.212
				(0.861)	(0.952)	(0.479)
WAT				2.126***	2.064***	−0.138
				(0.531)	(0.463)	(0.239)
_cons	0.546***	0.520***	0.945***	−4.194***	−3.646	−0.046
	(0.091)	(0.121)	(0.055)	(1.353)	(1.535)	(0.724)
LR	68.65***	79.73***	133.90***	56.89***	31.90***	92.47***
Wald	205.86***	160.03***	2.52	274.46***	207.87***	17.06**
obs	270	270	270	270	270	270

*Standard errors in parenthesis. ***, **, and * represent the significance levels of 1, 5, and 10%, respectively. The table below is the same.*

TABLE 4 | The impact of various dimensions of DIF on agricultural GTFP.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
BREA	0.452***	0.504***				
	(0.031)	(0.052)				
DEP			0.457***	0.447***		
			(0.031)	(0.046)		
DIG					0.269***	0.206***
					(0.026)	(0.035)
Control variables	NO	YES	NO	YES	NO	YES
_cons	0.601***	−3.885***	0.527***	−2.933**	0.685***	−3.552**
	(0.087)	(1.341)	(0.091)	(1.238)	(0.105)	(1.517)
Wald	215.81***	286.11***	212.82***	267.79***	110.26***	173.92***
obs	270	270	270	270	270	270

extent after introduce control variables. While we did not find evidence for the impact of DIF on the GEC. Therefore, we can conclude that the improvement of agricultural GTFP by DIF is mainly through GTC. The specific reason is that digital inclusive finance has lowered the entry difficulty to obtain financings and provided sufficient financial support for the advancement of agricultural technology. The possible reason for the weak effect of digital inclusive finance on technical efficiency is the insufficient coverage and depth of digital inclusive finance in rural areas.

Heterogeneity Analysis

The Impact of Different Dimensions of Digital Inclusive Finance

In order to further clarify the internal mechanism of DIF affecting agricultural GTFP, we constructed regression models of the three dimensions of DIF and agricultural GTFP, the estimated results are shown in **Table 4**. Where columns (1), (3), and (5) are the estimated results of the benchmark models without control variables for breadth of coverage (BREA), depth of usage (DEP) and digital support services (DIG), respectively, while columns (2), (4) and Column (6) are the estimated results of the corresponding models with control variables. From the columns (1), (3), and (5) of **Table 4**, the Breadth of coverage, Depth of usage and Level of digitalization all have a significant positive impact on agricultural green total productivity at the 1% significant level. The results in columns (2), (4), and (6) of **Table 4** show that Breadth of coverage, Depth of usage and Level of digitalization all have a significant positive impact on agricultural green total productivity at the 1% significant level. Therefore, regardless of the introduction of control variables, the coefficients of Breadth of coverage, Depth of usage and Level of digitalization are significantly positive at the 1% significant

TABLE 5 | Regional differences in the impact of digital inclusive finance on agricultural green total factor productivity.

Variable	(1)	(2)	(3)	(4)	(5)
	Eastern Region	Central Region	Western Region	Coastal areas	Inland areas
DIF	0.720***	0.321***	0.064	0.727***	0.310***
	(0.075)	(0.043)	(0.106)	(0.084)	(0.048)
Control variables	YES	YES	YES	YES	YES
_cons	−4.421*	−2.617**	0.765	−6.565**	−0.943
	(2.570)	(1.046)	(1.565)	(2.829)	(1.237)
Wald	190.14***	153.09***	51.05***	190.52***	328.44***
obs	99	72	90	99	171

level, indicating that the results in **Table 4** are highly stable. It shows that Breadth of coverage, Depth of usage and Level of digitalization all have a significant improvement effect on agricultural green total productivity.

The above results show that: First, the wider the coverage of digital financial inclusion, the more plausible it covers the "long tail" customer group, i.e., digital financial inclusion can solve financing problems for rural areas with relatively lagging economies on a larger scale, thereby promoting the agricultural green total factor productivity. Second, continuous enhancement of the depth of the usage of digital inclusive finance has improved the financing of agricultural operators by providing more diverse financial products and services. Third, with the help of digital technologies such as big data and cloud computing, digital inclusive finance can effectively solve the problems of credit fragmentation and information asymmetry, laying a financial foundation for expanding financial coverage and utilization, and improving agricultural green total factor productivity.

Distinguishing Regional Development Levels

China's provinces have different characteristics in resource endowment, agricultural technology level, business scale and labor quality, in turn, it generates heterogeneity between regions in terms of effect of digital inclusive finance on agricultural green total factor productivity. Therefore, this manuscript first sets two regional division standards, the first one divides all provinces into eastern, central and western regions, the second divides all provinces into coastal areas and inland areas. We then investigate the heterogeneity of the effect of digital inclusive finance on agricultural GTFP according to the two types of regional division methods. Columns (1) $\sim$ (3) and (4) $\sim$ (5) of **Table 5** report the effects of DIF on agricultural GTFP under the first and second regional divisions, respectively.

The results in **Table 5** show that, except for the western region, digital inclusive finance in the eastern, central, coastal and interior regions all have a significant positive impact on agricultural green total factor productivity at the 1% significance level. Nevertheless, the effect of digital inclusive finance on agricultural total factor productivity in the eastern region is much larger than that in the central and western regions, and the effect of digital inclusive finance in the coastal region on improving GTFP is also much greater than that in the inland region. It can be explained by the fact that, on the one hand, high level of marketization in the eastern coastal areas help improve the efficiency of digital inclusive finance in the agricultural sector. Capital investment in the agricultural sector guided by digital inclusive finance can realize benefits through a profound market mechanism. On the other hand, the digital technology level in the eastern coastal areas is relatively more advanced, thereby an easier access to financing provided by a more developed digital inclusive finance is more likely to promote the progression of agricultural technology.

Endogeneity Discussion

Although previous discussion has been made from multiple perspectives such as sub-index, sub-dimension, and sub-region to ensure the robustness of the results, there may still be endogenous biases caused by reverse causality in the model. That is, when the level of GTFP increases, the agricultural sector takes the initiative to raise funds to achieve intensive operation and efficient use of resources, which will instead promote the development of digital inclusive finance. According to Cao et al. (2021), this study selects Internet penetration rate as an instrumental variable for DIF to conduct an endogeneity test. First the Internet penetration rate, as an infrastructure variable reflecting digital finance, is closely related to the development of digital inclusive finance and meets the correlation requirements of instrumental variables. Second, agricultural green total factor productivity mainly reflects the status of agricultural production and operation, so there is no direct correlation between the Internet penetration rate and agricultural green total factor productivity. Therefore, the instrumental variables selected in this manuscript satisfy the correlation and exogenous assumptions. The test results are shown in **Table 6**.

According to the results of IV-Tobit estimation, the Wald test rejects the null hypothesis of "$\alpha = 0$", suggesting that there are endogenous variables in the model. The estimation results of the first stage show that the coefficient of Internet penetration rate (INT) is significantly positive at the 1% significance level, and the F-value is 55.96, indicating no weak instrumental variable problem, i.e., the instrumental variable selection in this manuscript is effective. The second-stage Wald test results again reject the null hypothesis. The above analysis shows that the estimated value of the two-step method is close to the IV-Tobit, indicating the IV-Tobit regression is effective. After solving the endogenous problem, DIF still has a significant positive impact on agricultural GTFP, which indicates that the analysis results of the above regression are robust. Hypothesis H1 is verified again.

TABLE 6 | Endogeneity analysis.

Variable	First stage	Second stage
	DIF	**GTFP**
INT	0.071*** (0.005)	
DIF		0.296*** (0.068)
_cons	4.053*** (0.868)	−1.908** (0.849)
Control variables	YES	YES
F	55.96	
Wald		5.89**
obs	270	270

Analysis of the Mechanism

The empirical results have confirmed the development of digital inclusive finance can significantly promote agricultural green total factor productivity, however, its function mechanism is still unclear. In order to clarify the effect path of digital inclusive finance on agricultural green total factor productivity, we adopt the mediation effect model based on Baron and Kenny (1986) and Gomber et al. (2018) to analyze the mechanism effect of digital inclusive finance on agricultural green total factor productivity from the mediating role of agricultural technology innovation and upgrading of industrial structure. The results of the mediation effect test are shown in **Table 7**.

The Mediating Effect of Agricultural Technology Innovation

Table 7 (1) ∼ (2) shows the stepwise regression test results with agricultural technological innovation as the mediating variable. Column (1) shows that the coefficient of DIF is 0.384, which is significant at the 1% level, indicating that DIF has a promoting effect on technology innovation (TEC). The results in column (2) show that after incorporating TEC into the model, the coefficients of TEC and DIF are significantly positive, and the coefficient of DIF is smaller than that of the benchmark model, indicating that TEC only produces partial mediation effect. This also indicates that there is a mediating effect of DIF promotes agricultural GTFP through TEC, thus confirming the hypothesis H2a. Further calculations show that the mediating effect of TEC accounts for 9.34% of the total effect.

TABLE 7 | Mediating effect test.

Variable	(1)	(2)	(3)	(4)
	TEC	**GTFP**	**ISU**	**GTFP**
DIF	0.384*** (0.092)	0.466*** (0.084)	0.263*** (0.026)	0.386*** (0.098)
TEC		0.125** (0.058)		
ISU				0.486** (0.206)
Control variables	YES	YES	YES	YES
obs	270	270	270	270

The Intermediary Effect of Optimization of Industrial Structure

The coefficient of DIF in column (3) of **Table 7** is significantly positive at the level of 1%, indicating that DIF has significantly improved the industrial structure (ISU). Column (4) in **Table 7** shows that after incorporating ISU into the model, the coefficient of ISU is 0.486 at the 5% significance level. In other words, DIF can have a significant positive impact on agricultural GTFP by promoting the ISU, indicating the existence of the intermediary effect of ISU. Further calculation shows that the mediating effect of industrial structure upgrading accounts for 24.88% of the total effect. Thus, the hypothesis H2b is verified.

CONCLUSION AND POLICY IMPLICATIONS

Based on China's provincial panel data from 2011 to 2019, this manuscript applies the GML index to measure agricultural green total factor productivity considering undesired output. Furthermore, this study systematically investigates the impact and mechanism of digital inclusive finance on agricultural green total factor productivity. The main fundings are as follows: First, agricultural green total factor productivity mainly drove by green technology progress has shown a positive growth trend. Second, digital inclusive finance mainly promotes the improvement of agricultural green total factor productivity by promoting the progress of green technology. Third, the Breadth of coverage, Depth of usage, and Level of digitalization of digital financial inclusion have a positive effect on agricultural green total factor productivity, among which the Breadth of coverage has the strongest impellent effect. In addition, compared with other regions, the eastern coastal region has the greatest improvement effect by digital financial inclusion. Fourth, digital inclusive finance can indirectly promote the improvement of agricultural green total factor productivity by motivating Agricultural technology innovation and optimizing the industrial structure. The mediating effects of TEC and ISU on agricultural green total factor productivity are 9.34 and 24.88%, respectively.

The implications of this manuscript are as follows: First, the government should encourage and support private capital to participate in the rural financial field while increasing investments in digital inclusive finance in rural areas, strengthening the construction of digital inclusive financial infrastructure in rural areas, and effectively increasing the scale of financial development in rural areas. Second, local governments should accurately and orderly improve the development of digital inclusive finance according to their own resource endowments, agricultural economic development level and target positioning, while avoiding the "digital divide." Third, the government should establish a profound green development incentive mechanism to help integrate the development of digital inclusive finance and the agricultural industry, so that digital inclusive finance can comprehensively motivate technological innovation and structure optimization in agriculture.

We hope to expand this research in the future from the following aspects: First, with the development of database resources, more adequate empirical analysis can be carried out on the basis of larger-scale data in the future. Secondly, when examining the effect of digital inclusive finance on agricultural green total factor productivity, this manuscript's selection remains relatively narrow, which may contain latent variables that cause bias and insufficiency in the analysis of the mechanism. In the future, more dimensions should be taking into account. Finally, this manuscript mainly conducts empirical analysis from a macro perspective, and empirical analysis can be carried out from a micro perspective in the future.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

QG: responsible for the conception and structural design of the article. CC and GS: responsible for writing and revising the first draft of the manuscript. JL: responsible for the later revision of the manuscript. All authors contributed to the article and approved the submitted version.

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Analysis of Climatic Basis for the Change of Cultivated Land Area in Sanjiang Plain of China

Luyang Zhang[1], Zhaolin Wang[1], Shixuan E[1], Guoming Du[2] and Zhushu Chen[3]*

[1]School of Public Administration, Chongqing Technology and Business University, Chongqing, China, [2]School of Public Administration and Law, Northeast Agricultural University, Harbin, China, [3]Yiyang Tobacco Monopoly Administration, Yiyang, China

As the research area of this study, Sanjiang Plain is an important grain-producing area and commodity grain base in China, which plays an important role in China's food security and stability. From 2000 to 2015, the climatic conditions and cultivated land use in this region changed significantly. The climatic basis for the changes occurring to the regional cultivated land-use area was revealed using several analytical methods such as correlation coefficient and geographic detector. The findings are as follows: (1) The internal changes of cultivated land use were mainly from dry land changed to paddy field, and the area ratio of dry land to paddy field gradually decreased from 3.80:1 to 1.19: 1. (2) The average air temperature and precipitation during the tillage period were 18.05 °C and 428.25 mm, respectively. (3) The long-term increasing temperature trend promotes the transformation from dry land to paddy fields, but the increase in June precipitation inhibits it. (4) Regional hydrothermal climatic factors can go some way toward explaining the cultivated land-use spatial distribution. The trends of two factors are interlinked, and together explain the changes more effectively than when just considering individual factors.

Keywords: land use, cultivated land-use change, response analysis, hydrothermal climate change, Sanjiang Plain

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Li Peng,
Sichuan Normal University, China

Reviewed by:
Xiangjin Shen,
Northeast Institute of Geography and Agroecology (CAS), China
Xiaolan Wang,
Southwest University of Science and Technology, China

****Correspondence:***
Guoming Du
nmgdgm@126.com

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INTRODUCTION

Heated discussions between the United Nations Sustainable Development Goals (SDGs) and Nature-based Solutions (NbS) mean that climate change and its impact on food security have attracted the attention of several researchers, both in China and elsewhere (Khanal et al., 2018; Ali et al., 2020; Xu et al., 2020; Fujimori et al., 2022). The adaptability of agricultural production, cultivated land use, and layout to climate changes has become a hot topic. Although China's grain output has maintained sustained growth for many years, it is still difficult to balance long-term production and demand. According to the theory of crop growth dynamics, climatic conditions such as temperature and precipitation are the basic limiting conditions for crops to grow. Only in suitable climatic conditions can crops be cultivated and then developed into cultivated land. But does climate change have an impact on the change of cultivated land use? What is the impact of climate change on cultivated land-use change? These questions have not been answered, which is not conducive to the protection and rational utilization of cultivated land resources. Therefore, responding and adapting cultivated land use to climate changes and adjusting climate adaptive planting to ensure national food security and stability are vitally important.

According to the Third National Assessment Report on Climate Change, China's warming rate has exceeded the global average of 0.9–1.5°C/100a since 1900 (The third National Climate

Change Assessment Report writing committee, 2015). With the change of climate, planting systems and cultivated land layout in China vary in their regional climate adaptability, and the expansion of paddy fields in the cultivated land is prominent. Northeast China is a typical area of paddy field expansion among cultivated land (Ye et al., 2009; Li et al., 2020), and climate change is an important reason for the development of paddy fields in that area. However, the response characteristics of changed cultivated land use and distribution under different climatic factors and trends remain unclear, and the climatic basis for the change of both paddy field and dry land also needs more research. Most of the studies on the use of cultivated land in response to climate change have focused on the impact of climate change on food security and grain production potential (Du et al., 2018a; Purola et al., 2018; Xiao et al., 2021; Dasgupta and Robinson, 2022), the analysis of the factors driving cultivated land-use change (Shi and Shi, 2015; Cao et al., 2016; Shao et al., 2020; Wang et al., 2021), and the simulation of cultivated land-use change under different climate scenarios (Zhou et al., 2017; Duku et al., 2018; Strasser et al., 2019; Giuliani et al., 2022). However, there are relatively few studies on the impact of regional climate change on the internal change of cultivated land use and its distribution. In some studies, annual climate data were selected for analysis, as it is clearly unsuitable to use annual mean analysis for areas with large climate differences and a short farming period.

Sanjiang Plain became an important grain base in China after its transformation from "Great northern wilderness" to "Great northern warehouse." Since it is located in the northern part of the mid-temperate zone, the change in regional climate has been significant in recent years under the general environment of global warming (Liang et al., 2014). Temperature and precipitation are important limiting factors of regional crop planting. Since 2000, with regional and global climate warming, the suitable planting areas for crops shifting to the north has fostered the adjustment of regional cultivated land planting structures, increased planting area, and further increased grain output (Du et al., 2018b). Regional hydrothermal climate changes have a significant impact on cultivated land use. In the long run, the hysteresis of human activities in response to climate change is declining (Fang and Sheng, 2000), indicating that the hysteresis of the cultivated area in response to climate change has a decreasing trend. We selected the period 2000–2015 because the climate and cultivated land-use changes in the study area were significant. Using analytical methods, such as geographic detectors and correlation analysis, the climatic basic characteristics of the changes in the area of paddy fields and dry land were further clarified on the basis of understanding the changes in regional cultivated land use and internal structure, as well as the trend of hydrothermal and climate change during the farming period. This provides a basis for the adjustment of regional cultivated land planting structure and the guarantee of a stable food supply.

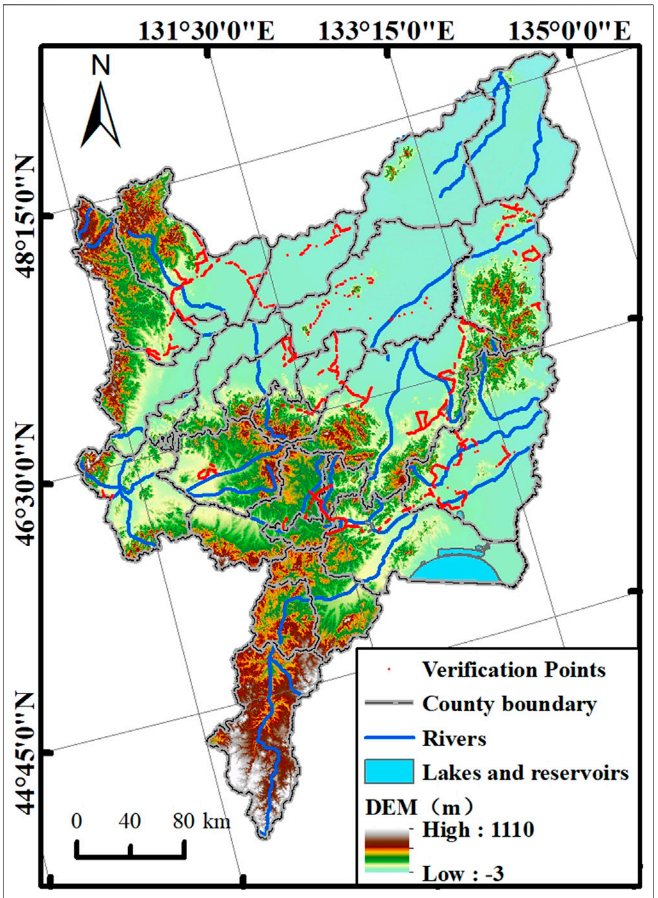

FIGURE 1 | Schematic diagram of the study area.

OVERVIEW OF THE STUDY AREA

Sanjiang Plain is located in the northeast of Heilongjiang Province. The elevation ranges from −3 to 1,110 m, with the north, north-east, and south-east lying low and the north-west and south high (**Figure 1**). It is located in the humid, semi-humid, and mid-temperate continental monsoon climate zone. Its average annual temperature is 1–4°C and average annual precipitation is 450–650 mm. Moreover, the soil is mainly meadow soil and swamp soil, with a high organic and nutrient content, which is ideal for agricultural cultivation in this important grain supply area. In 2015, cultivated land was the principal land use, followed by forest.

DATA SOURCES AND RESEARCH METHODS

Data Source and Pre-Processing

Cultivated Land-Use Data

Landsat TM images were used to visually interpret the changed areas in 2000, 2005, and 2015 based on the land-use data in 2010 using the ArcGIS platform. The 2010 land-use data were fully translated according to the “Remote Sensing Monitoring Data of China’s Land Use Status in 2010.” The data were released by the Resources and Environmental Science Data Center of the Chinese Academy of Sciences, with a scale of 1:100,000, good data accuracy and strong reliability (Liu, 1996). The interpretation and signs in 2000, 2005, and 2015 are the same as those in 2010, including 6 first-class land types and 25 second-class land types, of which, cultivated land includes both dry land and paddy fields. The interpretation results were tested and amended by means of field sample point verification (**Figure 1**). Finally, the cultivated land-use data in 2000, 2005, 2010, and 2015 were extracted for analysis.

Hydrothermal Climate Data

Climatic data were selected from the precipitation and temperature data during the tillage period (May–September) between 2000 and 2015 from “China Surface Precipitation (Temperature) Monthly Value 0.5° × 0.5° Grid Data Set (V2.0).” Due to the lack of temperature data from May to July and September in 2015, the missing data were calculated and supplemented according to the “China Surface Temperature Daily Value 0.5° × 0.5° Grid Data Set.” Additionally, in order to study the response of cultivated land use to regional hydrothermal climate change, the spatial resolution of the hydrothermal climate data was interpolated to 2 km by cubic convolution using the ArcGIS software Resample tool according to the grid scale standard of cultivated land use.

Research Methodology

Climatic Tendency Rate

We calculated the trend direction and degree of climatic factors over time to represent the long-term change trend of climatic factors (Wei, 2007).

x_i represents the climatic factor variation with sample size n, and t_i represents the time corresponding to x_i. A linear regression equation of x_i and t_i is thus established:

$$\hat{x}_i = a + bt_i \quad (i = 1, 2, ..., n) \tag{1}$$

For climatic factor variable x_i and time t_i, the least square estimation of regression coefficient b and constant a is

$$b = \frac{\sum_{i=1}^{n} x_i t_i - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} t_i\right)}{\sum_{i=1}^{n} t_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} t_i\right)^2} \tag{2}$$

$$a = \bar{x} - b\bar{t} \tag{3}$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad \bar{t} = \frac{1}{n}\sum_{i=1}^{n} t_i \tag{4}$$

where b*10 is the climatic factor tendency rate, the unit of temperature tendency rate is °C/10a, and the unit of precipitation tendency rate is mm/10a. The positive or negative value of b indicates the trend direction of climatic factor x, and when $b > 0$, the climatic factor x increases with time t. When $b < 0$, the climatic factor x decreases with time t. The absolute value of b indicates the trend degree of climatic factor x.

Geo-Detector Factor Detection

Through the similarity of the independent variable X and dependent variable Y in the spatial distribution, the extent to which X explains the spatial differentiation of Y can be determined (Wang and Xu, 2017). The greater the similarity, the stronger the influence. Measured by q, the following expression is used:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}$$
$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2, SST = N\sigma^2 \tag{5}$$

where $h = 1, \ldots, L$, h is a delamination of Y or X; N_h and N are the number of units in layer h and the whole region. σ_h^2 and σ^2 are variances of the Y values in layer h and the whole region, respectively. SSW and SST are the total variance in the layer and the total variance in the whole area, respectively. The value range of q is $[0, 1]$. The larger the value of q, the stronger the effect of X on Y, and vice versa. The value of q means that X explains the spatial distribution of $100 \times q$% of Y.

Geo-Detector Interaction Detection

The interaction between different factors of *Xs* was identified, and it was evaluated whether factors $X1$ and $X2$ will increase or weaken the influence of the dependent variable Y when acting together, or whether the effects of these factors on Y are independent of each other (Zhou et al., 2017). We calculated the influence of $X1$, $X2$, $X1 \cap X2$ to Y, respectively, and compared $q(X1)$, $q(X2)$, and $q(X1 \cap X2)$. When $q(X1 \cap X2) < \min(q(X1), q(X2))$, the interaction between $X1$ and $X2$ on Y is nonlinearly weakened. When $\min(q(X1), q(X2)) < q(X1 \cap X2) < \max(q(X1), q(X2))$, the nonlinearity of the single factor weakens. When $q(X1 \cap X2) > \max(q(X1), q(X2))$, it shows a two-factor enhancement. When $q(X1 \cap X2) = q(X1) + q(X2)$, it shows they are independent of each other. When $q(X1 \cap X2) > q(X1) + q(X2)$, it shows a nonlinear enhancement.

RESULTS AND ANALYSIS

Analysis of Cultivated Land-Use Change

From 2000 to 2015, as for the changes of the cultivated land use in the study area, there were basically three types: dry land unchanged, dry land changed to paddy field, and paddy field unchanged (**Figure 2**). The areas where dry land has not changed are mainly located in the central and southern parts of the Sanjiang Plain, accounting for 51.28% of the total area. The areas where dry land has changed to paddy field area are mainly located in the northeast of the Sanjiang Plain,

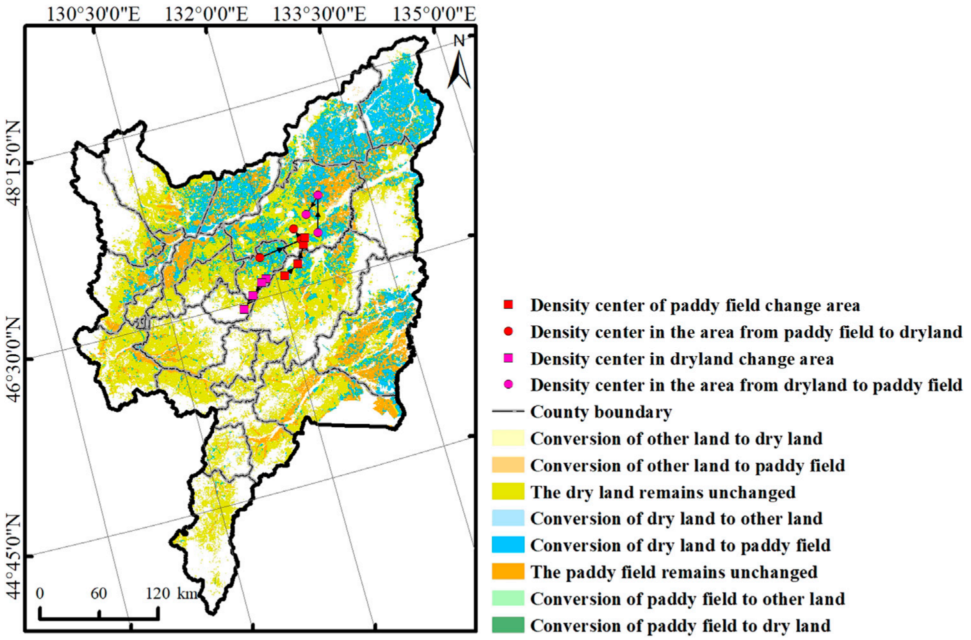

FIGURE 2 | Changes in cultivated land use from 2000 to 2015.

accounting for 24.68% of the total area. The areas where the paddy field has not changed are mainly distributed at the junction of the area where dry land has not changed and the area where dry land has changed to paddy field, accounting for 19.27% of the total area. Using the ArcGIS software mean center tool to calculate the density center of cultivated land-use change, it was found that the density center of dry land change and the density center of paddy field change showed opposite trends. In 2000, 2005, 2010, and 2015, the density center of the area where the dry land changed continued to move to the southwest, while the density center of the area where the paddy field changed kept moving northeast. The density center of the area where paddy field changed to dry land migrated to the northeast first and then to the northwest, with an overall trend of migration to the northeast. The density center from dry land to paddy field showed a trend of migration in the northeast direction first and then in the southwest direction, with an overall trend of migration to the northwest. Generally, the external change in cultivated land use in the Sanjiang Plain between 2000 and 2015 was small. The majority of transformations were internal changes in cultivated land use, and the area ratio of dry land to paddy field in the region gradually decreased from 3.80:1 in the year 2000 to 1.19:1 in 2015.

Analysis of Climate Change of Water and Heat in the Cultivation Period

The average temperature and precipitation during the growing seasons from 2000 to 2015 within the study area were 18.05°C and 428.25 mm, respectively. The monthly variation of air temperature and precipitation during the tillage period is parabolic and reaches its peak in July. The Raster Calculator and Contour tool in ArcGIS software were used to calculate the climate tendency rate and draw isolines (**Figure 3**). The results show that the temperature tendency rate during the tillage period demonstrates a relatively obvious meridional zonality, with a gradual increase from west to east. Apart from the long-term decreasing trend of air temperature in some western regions, most regions show an increasing trend, and the warming range in the northeast of the study area is relatively high. The distribution of precipitation tendency rate within the tillage period does not display obvious zonal characteristics, but the characteristics of high precipitation in the north and low in the south are still obvious. Apart from the continuing decreasing trend in some southern areas, precipitation in most areas has risen, with increases in the northeast of the study area being noticeably high. Simultaneously, the precipitation tendency rate density degree is scattered in the north and dense in the south, and the regional difference of precipitation change in the north of the study area is relatively small, while that in the south of the study area is relatively large.

Response Analysis of Cultivated Land Use to Hydrothermal Climate Conditions

Correlation Analysis

In order to analyze the spatial change of regional cultivated land areas, the ArcGIS software Fishnet tool was used to grid the cultivated land-use data in the study area. In order to avoid patch fragmentation caused by the gridding, based on comprehensively considering spatial heterogeneity, patch size, and other characteristics, the study area was divided into 27,927 2 km × 2 km grids while referring to the landscape ecology requirement of selecting 2–5 times the average patch

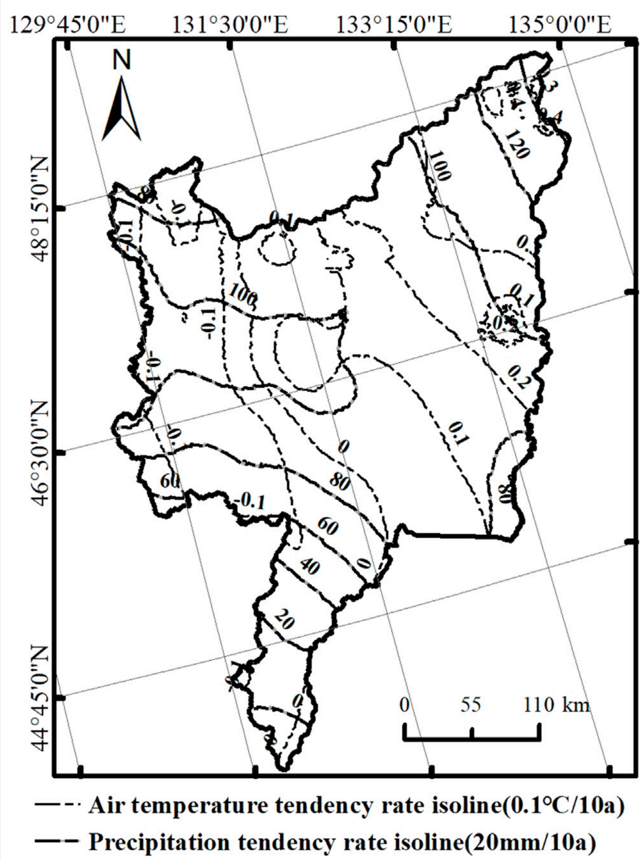

FIGURE 3 | Distribution of isolines of tendency rate of hydrothermal climatic factors from 2000 to 2015.

area as the sampling grid size. We calculated the cultivated land-use change area in the grids between 2000 and 2015, and assigned the corresponding grid according to the calculated area. Since the change of cultivated land use in the study area is mainly an internal change, the response characteristics of dry land and paddy field to hydrothermal climatic factors vary. The changes in dry land and paddy field were calculated separately, and the spatial sequence correlation with hydrothermal climatic factors was attained. The types of cultivated land-use change are counted as dry land unchanged, dry land changed, dry land changed to paddy field, dry land changed to other, other changed to dry land, paddy field unchanged, paddy field changed, paddy field changed to dry land, paddy field changed to other, and other changed to paddy field. We considered the change and distribution of hydrothermal climatic factors during farming periods from 2000 to 2015, selected the temperature tendency rate (Tt), average temperature (Tm), average temperature in May (T5), average temperature in June (T6), average temperature in July (T7), average temperature in August (T8), and average temperature in September (T9). We also analyzed the precipitation tendency rate (Pt), mean precipitation (Pm), mean precipitation in May (P5), mean precipitation in June (P6), mean precipitation in July (P7), mean precipitation in August (P8), and mean precipitation in September (P9). The Pearson correlation coefficient of regional cultivated land-use change and spatial distribution of hydrothermal climatic factors was calculated via the SPSS software Correlation analysis tool.

By analyzing the correlation between dry land changed types and hydrothermal climatic factors (**Table 1**), it was found that the types of dry land changed to paddy field, dry land changed, and dry land unchanged have a relatively strong correlation with hydrothermal climatic factors, while the changes from other types of land to dry land and the changes from dry land to other types of land have a relatively weak correlation with hydrothermal climatic factors. Among all the hydrothermal climatic factors, the positive correlation coefficient between Tt and the conversion of dry land to paddy field is the largest, being 0.424, and the long-term increasing trend in regional temperature promotes the transition from dry land to paddy field. In addition, the negative correlation coefficient between P6 and the conversion of dry land to paddy field is the largest, which is 0.303, and the increase in regional precipitation during June inhibits the transformation from dry land to paddy field. The positive correlation coefficients of P9, Pt, T7, T8 and the conversion of dry land to paddy field are greater than 0.2, and an increase in related hydrothermal climatic factors can promote the transformation from dry land to paddy field. The positive correlation coefficient between P6 and dry land changed has the largest value at 0.264, and the increase of regional precipitation in June promotes the transformation from other land types to dry land. Moreover, the negative correlation coefficient between Tt and dry land changed has the largest value at 0.378, and the long-term increasing regional temperature trend promotes the transformation from dry land to other land types. The negative correlation coefficients of P9, Pt, and dry land changed are larger than 0.2, and the increase of related hydrothermal climatic factors promotes the transfer of dry land. The positive correlation coefficient between T5 and dry land unchanged shows the largest value at 0.283, and the increase in May regional temperature promotes dry land stability. The negative correlation coefficient between Tt and dry land unchanged is the largest at 0.260, and the long-term increasing regional temperature trend inhibits dry land stability and promotes change. The positive correlation coefficients of T6, Tm, T7, and dry land unchanged are greater than 0.2, and the increase in related hydrothermal climatic factors can promote dry land stability. The negative correlation coefficient between P9 and dry land unchanged is greater than 0.2, and the increase in regional precipitation in September has a restraining effect on dry land stability.

Analysis of the correlation between paddy field changed types and hydrothermal climatic factors (**Table 2**) suggests that two types of land, namely paddy field changed and paddy field unchanged, are strongly associated with hydrothermal climatic factors, whereas the conversion of other types to

TABLE 1 | Correlation order between dry land changed types and hydrothermal climatic factors.

Sort	Dry land remains unchanged		Dry land changed		Dry land changed to paddy field		Dry land changed to other land-use types		Other land-use types changed to dry land	
	Correlation coefficient	Factor	Correlation coefficient	Factor	Correlation coefficient	Factor	Correlation coefficient	Factor	Correlation coefficient	Factor
1	0.283**	T5	–0.378**	Tt	0.424**	Tt	0.054**	T7	0.103**	Tt
2	0.273**	T6	–0.268**	P9	–0.303**	P6	0.053**	T6	–0.093**	P6
3	–0.260**	Tt	0.264**	P6	0.296**	P9	0.052**	T5	0.060**	Pt
4	0.228**	Tm	–0.251**	Pt	0.281**	Pt	0.048**	Tm	0.058**	P9
5	0.212**	T7	–0.191**	T8	0.215**	T7	0.042**	T8	0.042**	T7
6	–0.209**	P9	–0.191**	T7	0.214**	T8	0.033**	T9	0.039**	T8
7	0.168**	T9	–0.161**	T9	0.180**	T9	0.026**	P6	0.035**	T9
8	0.166**	T8	–0.158**	Tm	0.179**	Tm	–0.018**	Tt	0.034**	Tm
9	0.142**	P6	–0.132**	T6	0.151**	T6	0.012*	P5	0.031**	T6
10	–0.119**	P7	–0.095**	T5	0.109**	T5	0.012*	Pm	–0.029**	Pm
11	–0.095**	P8	–0.083**	P5	0.088**	P5	0.011	Pt	–0.024**	P8
12	–0.068**	Pm	0.037**	P7	–0.045**	Pm	0.01	P8	0.020**	T5
13	–0.044**	Pt	0.035**	Pm	–0.045**	P7	0.005	P7	–0.019**	P7
14	–0.044**	P5	0.029**	P8	–0.039**	P8	–0.004	P9	–0.009	P5

*Note: ** Denotes a significant correlation at 0.01 (both sides).*
** Denotes a significant correlation at 0.05 (both sides).*

paddy fields, the conversion of paddy fields to dry land, and the conversion of paddy fields to other types have relatively weak correlations with hydrothermal climatic factors. Among all the hydrothermal climatic factors, the positive correlation coefficient between Tt and paddy field changed is the largest at 0.431, and the long-term increasing regional temperature trend promotes the conversion of other land-use types to paddy fields. As for the negative correlation coefficient, the one between P6 and paddy field changed is the largest at 0.307, and the increase of regional precipitation in June promotes the conversion of paddy fields to other land-use types. The positive correlation coefficients of P9, Pt, T8, T7, and paddy field changed are all greater than 0.2, and the increase of related hydrothermal climatic factors can also promote the conversion of other land-use types to paddy fields. As for the positive correlation coefficient, the one between T8 and paddy field unchanged is the largest at 0.236, and the increase of regional temperature in August promotes paddy field stability. The positive correlation coefficients of T9, Tm, T7, and the paddy field unchanged are all greater than 0.2, and the increase of related hydrothermal climatic factors can also promote paddy field stability.

Comprehensive analysis shows that the response of cultivated land-use change and hydrothermal climatic factors is mainly manifested as paddy field changed, dry land changed to paddy field, dry land changed, dry land unchanged, and paddy field unchanged, among which, the conversion from dry land to paddy field is the main constituent of paddy field transfer in and dry land transfer out. Temperature increases in the early stages of tillage favor dry land stability, while average temperature increases in the latter stages favor paddy field stability. The long-term increase in temperature during the farming period, the increase in precipitation in September, and the increase in the long-term trend in precipitation can all promote a reduction of dry land and increase of paddy fields, and promote the switch from dry land to paddy field. The increase of precipitation in June promotes the increase of dry land and decrease of paddy field, while inhibiting the switch from dry land to paddy field.

According to the theory and mechanism of crop growth dynamics, the growth of rice needs certain heat resources and accumulated temperature conditions. Therefore, the trend of long-term increase of air temperature provides a basis for the accumulation of accumulated temperature in the study area, provides necessary conditions for the growth and planting of rice, and is conducive to the expansion of paddy fields. In addition, the same season of water and heat will promote the good growth of rice, and the long-term increasing trend of precipitation is very helpful to rice planting. The dry land in the study area is dominated by maize and soybean, and the water absorption in the early and middle tillage period is the key to affect the quality, while the water demand in the late tillage period is relatively small.

Factor Spatial Effect Analysis

Due to the conversion of dry land to other land, other land to dry land, paddy field to dry land, paddy field to other land, and other land to paddy field, these types of cultivated land-use changes have a low correlation with regional hydrothermal climatic factors (all correlation coefficients <0.2). Consequently, it is ignored in the analysis of factor spatial influences. The types of cultivated land-use change that show a strong correlation with hydrothermal climatic factors were selected, and the spatial influence of hydrothermal climatic factors on cultivated land-use change was further analyzed via the Geographic Detector factor detection tool (**Figure 4**). As the software input requires quantifiable independent variables, it is necessary to reduce the amount of hydrothermal climatic factors, before dividing the independent variables into 15 levels, according to the natural breakpoint method matching the actual study area situation and

TABLE 2 | Correlation between paddy field changed types and hydrothermal climatic factors.

Sort	The paddy field remains unchanged		Paddy field changed		Paddy field changed to dry land		Paddy field changed to other land-use types		Other land-use types changed to paddy field	
	Correlation coefficient	Factor	Correlation coefficient	Factor	Correlation coefficient	Factor	Correlation coefficient	Factor	Correlation coefficient	Factor
1	0.236**	T8	0.431**	Tt	0.096**	T6	0.053**	T8	0.119**	Tt
2	0.218**	T9	−0.307**	P6	0.091**	T7	0.051**	T9	0.112**	P9
3	0.215**	Tm	0.306**	P9	0.091**	T5	0.040**	Tm	0.073**	Pt
4	0.206**	T7	0.281**	Pt	0.084**	Tm	0.034**	T7	−0.073**	P6
5	0.192**	T5	0.208**	T8	0.070**	T8	0.031**	T5	0.058**	T8
6	0.188**	T6	0.204**	T7	0.058**	T9	0.026**	Tt	0.054**	T9
7	0.093**	Tt	0.176**	T9	0.036**	P5	0.026**	T6	0.042**	T7
8	−0.079**	P6	0.169**	Tm	0.033**	Pt	0.025**	P9	0.037**	Tm
9	0.074**	Pt	0.137**	T6	−0.012**	P8	0.024**	P5	0.022**	P8
10	0.058**	P5	0.096**	T5	0.009	P6	0.014*	Pt	0.015*	T6
11	0.053**	P9	0.082**	P5	−0.007	P9	0.012	Pm	0.013*	T5
12	−0.032**	P8	−0.043**	P7	−0.006	Tt	0.011	P8	0.010	P5
13	−0.030**	P7	−0.043**	Pm	−0.005	P7	0.009	P7	0.006	Pm
14	−0.023**	Pm	−0.033**	P8	0.001	Pm	−0.004	P6	−0.002	P7

*Note: **Denotes 0.01 as a significant correlation (both sides).*
** Denotes 0.05 as a significant correlation (both sides).*

relevant literary references. The results show that the influence of regional hydrothermal climatic factors in the spatial distribution on the five types of cultivated land-use change was significant ($p < 0.01$).

Regional hydrothermal climatic factors have the greatest influence on the spatial distribution of paddy field changed, followed by dry land changed to paddy field, dry land unchanged, and dry land changed. Regional hydrothermal climatic factors have the weakest comprehensive explanatory power for the spatial distribution of paddy fields unchanged. Hydrothermal climatic factors with more than 10% influence on the spatial distribution of paddy field changed area are: Tt (23.4%), P6 (20.2%), P9 (15.0%), T9 (14.4%), Pt (14.3%), T8 (11.8%), and P7 (11.5%). The long-term regional temperature changes during the farming period, the precipitation in the middle and late periods of the farming period, the temperature in the late period of the farming period, and the long-term changes of the precipitation in the farming period all have a strong explanatory power for the spatial distribution of paddy field changed. The hydrothermal climatic factors that can induce more than 10% of the spatial distribution of dry land changing to paddy field area are: Tt (22.6%), P6 (20.0%), T9 (14.4%), P9 (14.3%), Pt (13.5%), T8 (11.5%), and P7 (10.6%). The long-term changes of regional temperature during the farming period, the precipitation in the middle and late periods of the farming period, the temperature in the late period of the farming period and the long-term precipitation in the farming period all show a strong explanatory power for the spatial distribution of the dry land changed to paddy field. The hydrothermal climatic factors with more than 10% influence on the spatial distribution of dry land unchanged area are: P9 (14.4%), T5 (13.8%), T6 (13.2%), P7 (11.7%), Tt (11.5%), Tm (10.4%), and T9 (10.3%). Precipitation in the middle and late periods of the regional farming period, the temperature during the farming period, and the long-term changes of temperature during the farming period have a strong explanatory power for the spatial distribution of the dry land areas that do not change. The hydrothermal climatic factors with more than 10% influence on the spatial distribution of dry land changed area are: Tt (18.6%), P6 (16.7%), T9 (11.9%), Pt (11.4%), and P9 (11.4%). The long-term changes of temperature during the farming period, the precipitation in the middle and late periods of the farming period, the temperature in the late period of the farming period, and the long-term precipitation during the farming period have a strong explanatory power for the spatial distribution of the dry land changed area. The explanatory power of hydrothermal climatic factors to the spatial distribution of the area where the paddy field is unchanged is less than 10%. The temperature conditions during the farming period have a strong explanatory power for the spatial distribution of the unchanging areas of paddy field.

Comprehensive analysis shows that the conversion from dry land to paddy field is mainly in the form of paddy field changed and dry land changed, and the influence of hydrothermal climatic factors on the spatial distribution of the above three is relatively consistent. The long-term temperature change trend during the farming period has the strongest explanatory power for the spatial distribution of the above three types. The precipitation in June, the precipitation in September, the temperature in September, and the long-term change trend of the precipitation in the farming period have a large explanatory power, all of which are greater than 10%, and these findings correspond to the results obtained from the correlation analysis of the three elements and the hydrothermal climatic factors. The monthly temperature during the tillage period strongly affects the spatial distribution of unchanging area of paddy field. The temperature is the limiting factor in regional paddy field

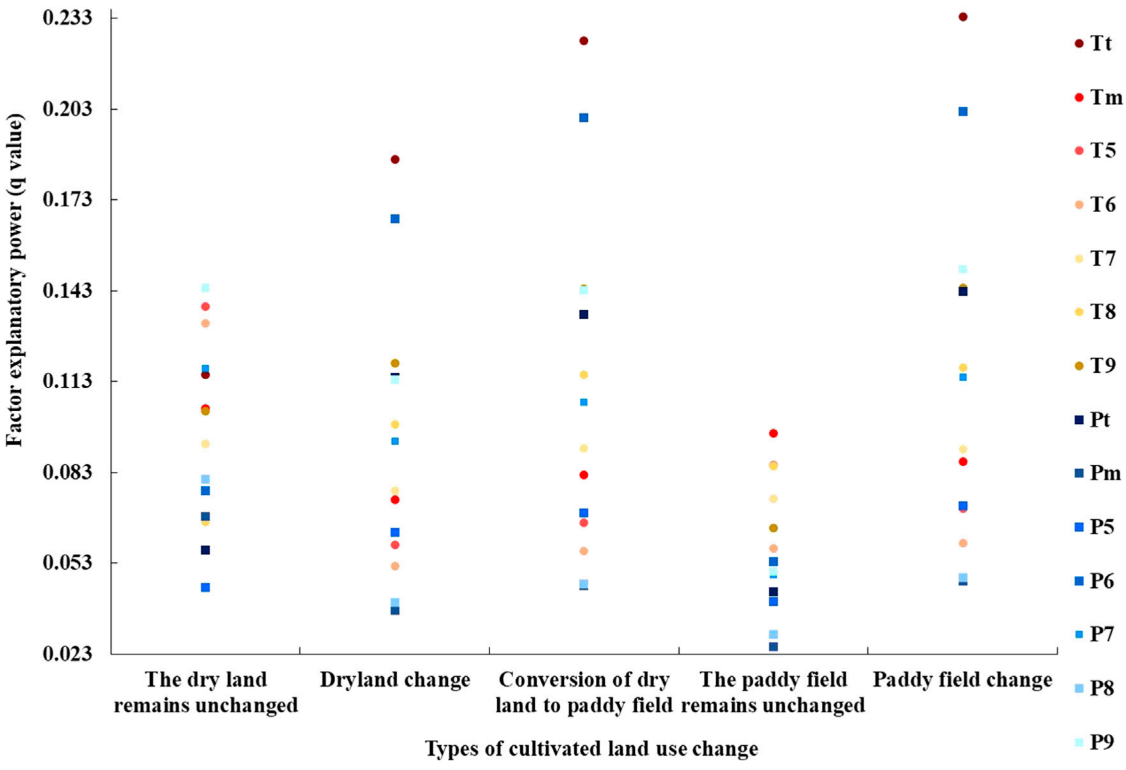

FIGURE 4 | Spatial influence of hydrothermal climatic factors on cultivated land-use change.

planting, and differences in temperature greatly influence paddy field distribution. The precipitation in the later period of the cultivation period, the temperature during the cultivation period, and the long-term temperature change during the cultivation period have a strong explanatory power for the spatial distribution of the dry land areas without change, and related hydrothermal climatic factors affect the distribution of dry land.

Influencing Factors Interaction Analysis

Furthermore, the explanatory power of the spatial distribution of cultivated land-use changes under the interaction of two hydrothermal climatic factors was analyzed. It is found that the two hydrothermal climatic factors have an enhanced interaction effect on the spatial explanatory power of cultivated land-use changes, that is, the interaction effect of any two factors on the spatial distribution of cultivated land-use change is greater than that of one factor alone. Among them, the lowest interactive explanatory power of the hydrothermal climatic factors to the dry land unchanged area is 10.9%, while that to the dry land changed area is 9.7%. The lowest interactive explanatory power of hydrothermal climatic factors for the area from dry land changed to paddy field is 11.5%, while that for the constant paddy field area is 7.9%, and that for the paddy field changed area is 11.7%. Compared with a solitary action, the effect is significantly greater.

The interaction of hydrothermal climatic factors on the top 5 influences on spatial distribution of cultivated land-use change types was analyzed (**Table 3**). The interaction of P6 ∩ P9 on the spatial distribution of dry land changed to paddy field is a two-factor enhancement, and the rest are nonlinear enhancements. The maximum interactive explanatory power of dual hydrothermal climatic factors for the conversion of dry land to paddy field is 40.1%, which is 17.5% higher than the maximum explanatory power of the single factor. The maximum interactive explanatory power of the dual hydrothermal climatic factor to the change of dry land is 35.6%, which is 17.0% higher than the maximum explanatory power of the single factor, while that to the dry land unchanging area is 31.1%, which is 16.8% higher than the maximum explanatory power of the single factor. The maximum interactive explanatory power of the dual hydrothermal climatic factor to the paddy field change area is 39.7%, which is 16.3% higher than the maximum explanatory power of the single factor, while that to the constant paddy field area is 21.6%, which is 12.0% higher than the maximum explanatory power of the single factor. P5 ∩ P6 is the most significant interaction affecting the spatial distribution of the conversion of dry land to paddy field,

TABLE 3 | Spatial interaction and influence of hydrothermal climatic factors on cultivated land-use change.

Types of cultivated land-use change	Main interactions and interactive influence
The dry land remains unchanged	Tt ∩ P7(0.311)Tt ∩ P5(0.306)Tt ∩ T6(0.302)Tt ∩ Pm(0.301)Tt ∩ T9(0.299)
Dry land changed	P5 ∩ P6(0.356)P5 ∩ P9(0.311)Pt ∩ P6(0.301)P6 ∩ P7(0.298)P6 ∩ P9(0.297)
Conversion of dry land changed to paddy field	P5 ∩ P6(0.401)P5 ∩ P9(0.359)Tt ∩ T7(0.349)Tt ∩ T6(0.341)P6 ∩ P9(0.339)
The paddy field remains unchanged	T5 ∩ P(0.216)Tm ∩ P5(0.213)P5 ∩ P6(0.211)Tt ∩ P7(0.209)Tt ∩ P5(0.207)
Paddy field changed	P5 ∩ P6(0.397)P5 ∩ P9(0.372)Tt ∩ T7(0.355)Pt ∩ P6(0.351)Tt ∩ T6(0.348)

paddy field change, and dry land change. Tt ∩ P7 is the most significant interaction that affects the spatial distribution of dry land invariant areas, and T5 ∩ P5 is the most significant interaction that affects the spatial distribution of the constant area of the paddy field.

CONCLUSIONS AND DISCUSSIONS

Conclusions

As an important grain growing area, Sanjiang Plain has experienced significant changes in climate and cultivated land use between 2000 and 2015. The distribution and change characteristics of cultivated land use, the trend in hydrothermal climatic factor changes, and the response of cultivated land use to hydrothermal climate conditions in the study area were analyzed via hydrothermal climate data and cultivated land-use data during the tillage period. Studies have shown that:

1) From 2000 to 2015, the external change of cultivated land use in the study area was small. The internal change of cultivated land use was mainly from dry land to paddy field, and the area ratio of dry land to paddy field gradually decreased from 3.80: 1 in the year 2000 to 1.19:1 in the year 2015. The density center of the dry land change area continued to move to the southwest, and that of the paddy field change area continued to move to the northeast. The density center of the area where paddy field changed to dry land migrated to the northeast as a whole, and the density center of the area where dry land changed to paddy land migrated to the northwest as a whole.
2) The average temperature and precipitation during the farming period from 2000 to 2015 were 18.05°C and 428.25 mm, respectively. The temperature tendency rate during the tillage period showed obvious meridional zonality, and gradually increased from west to east. In addition, the range of warming in the study area was relatively high. The precipitation tendency rate in the tillage period was high in the north and low in the south. The increase of precipitation of the study area was relatively high, and the regional difference was smaller in the north than in the south.
3) The increase of temperature in the early part of tillage promoted dry land stability, while the increase of temperature near the end of tillage promoted paddy field stability. The long-term trend of temperature increased during the cultivation period, the precipitation in September, and the long-term precipitation trend promoted the conversion of dry land to paddy land. The increase of June precipitation inhibited the conversion of dry land to paddy field.
4) Regional hydrothermal climatic factors had significant explanatory power on the spatial distribution of cultivated land-use changes, and the long-term trend of changing air temperature during the tillage period had the strongest explanatory power for the spatial distribution of paddy field changes, which was 23.4%. The conversion of dry land to paddy field was the main form of paddy field change and dry land change. The explanatory power of hydrothermal climatic factors on the spatial distribution of the three types of cultivated land-use changes was relatively consistent, and the long-term temperature trends during the cultivation period had the strongest explanatory power for the spatial distribution of the above three types of cultivated land-use changes. Air temperature is the limiting factor of regional paddy field planting, and changes in air temperature greatly influence paddy field distribution. The precipitation in the later period of the farming period, the temperature during the farming period, and the long-term change trend of the temperature during the farming period have a greater impact on the spatial distribution of dry land areas without change.
5) The explanatory power of the two hydrothermal climatic factors on the spatial distribution of cultivated land-use changes both showed an enhanced interaction, and its effect was significantly higher than through a single factor. P5 ∩ P6 is the most significant interaction that affects the spatial distribution of dry land changed to paddy field area, the spatial distribution of paddy field change area, and the spatial distribution of dry land change area. Tt ∩ P7 is the most significant interaction that affects the spatial distribution of dry land invariant areas, and T5 ∩ P5 is the most significant interaction that affects the spatial distribution of the constant area of the paddy field.

Discussions

Climate is the basic restrictive condition affecting cultivated land-use systems. Water and heat conditions have a direct impact on the distribution and change of cultivated land use by affecting the suitability of crop planting. This paper analyzes the response characteristics of cultivated land-use changes, especially changes in the scale and structure of paddy fields and dry land, and changes in hydrothermal climatic factors during the cultivation period. Northeast China is an area that is sensitive to global environmental change. Global warming increases the accumulated temperature and promotes the northward shift of crop planting boundaries, providing important pre-conditions for an increase in cultivated land (Man et al., 2016). Temperature is the main limiting factor for crop growth in northeast China. Temperature increase has different effects on the production potential of different crops in northeast China. It has the greatest impact on rice, followed by corn and soybeans, which have the least sensitivity to temperature changes (Zhou, 2015). The growth of rice is highly dependent on heat, and the increase of accumulated temperature promotes the northward movement of the suitable paddy field cultivation area (Gao and Liu, 2011). The influence of average annual temperature change on farmland productivity in the Sanjiang Plain is greater than that of average annual precipitation (Guo et al., 2009). Air temperature during tillage significantly influences the NDVI of paddy fields in the Sanjiang Plain (Zhang et al., 2021). The research results of this paper correspond with other relevant research conclusions. Air temperature is the limiting factor in regional paddy field planting, and variation in air temperature greatly influences paddy field distribution. The long-term air temperature change trend during the growing season has the strongest effect on the spatial distribution of conversion from dry land to paddy field, and the trend of increasing temperature will promote the conversion of dry land to paddy field.

Climate change has a certain impact on the use of cultivated land in the study area, especially the composition of dry land and paddy field, and promotes the transformation from dry land to paddy field to a certain extent. However, cultivated land utilization is a complex system, which is influenced by multiple factors such as natural conditions, human activities, and social economy. The influence mechanism is very complex. Regional topography, economic benefits of crops, and policy guidance will have an impact on the change of cultivated land use. This study discusses the impact of climate change on cultivated land use, especially the basic constraints of dryland and paddy field planting, without considering the interaction of climate and other factors, which is the limitation of this study and the direction to be carried out in the future. In addition, in the process of reclaiming wetlands into cultivated land, the change of land cover leads to the change of land surface reflectivity, which has an impact on land surface temperature (Shen et al., 2020). Although during the study period of this study, the regional cultivated land use mainly shows internal changes, that is, the transformation between dry land and paddy land, the influence of cultivated land use on land surface temperature is relatively small. This is still the limitation of this study and the direction to be carried out in the future.

The basic data of cultivated land use used in this study are based on Landsat TM data combined with visual interpretation. Although the interpretation results are modified by sampling data, according to the random sampling method, the calculation accuracy meets the basic research needs. Because of the imaging principle and resolution of remote sensing data, it is different from the real land cover, which cannot truly and completely express the real land cover. The inaccuracy of data sources will make the research results have some uncertainties (Zhang et al., 2017; Shen et al., 2020; Malkoç et al., 2021). At the same time, the accuracy of data sources restricts the research scale, resulting in the analysis accuracy of this study is mesoscale. In the future, we should combine meteorological station data and more detailed land-use data for small-scale analysis and research, and then put forward targeted farming decision-making suggestions.

The change in hydrothermal climatic factors promotes the transformation from dry land to paddy field in the Sanjiang Plain and enhances the development of the regional agricultural economy. However, the expansion of paddy fields has an important impact on the balance and allocation of regional water and soil resources (Lu et al., 2018; Zhou et al., 2018). It is possible that the temperature may decrease due to the "wetland effect" of paddy fields (Du et al., 2019), thus affecting the sustainable use of regional paddy fields. Making full use of the regional conditions and climate change characteristics, monitoring and evaluating the carrying capacity of regional water and soil resources, reasonably controlling the scale of paddy fields, the structure and layout of paddy fields and dry land, and alleviating the contradiction between supply and demand of water and soil resources are urgent problems which need to be solved.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

GD contributed to the conception of the study; LZ performed the experiment; ZW and SE contributed significantly to analysis and manuscript preparation; LZ performed the data analyses and wrote the manuscript; ZC helped perform the analysis with constructive discussions.

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Vulnerability Assessment and Spatio-Temporal Difference Analysis of Inland Fisheries Flood Disaster in China

Honggang Lu, Jiaxi Zheng*, Hanyun Ou, Yinong Liu and Xijian Li

Agricultural Economics, School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China

Vulnerability research is an active option for fisheries to adapt to climate change. Based on the vulnerability analysis framework of the vulnerability scoping diagram, a vulnerability evaluation index system for inland fisheries in China was constructed in three dimensions, including exposure, sensitivity and adaptive capacity. The entropy method was used to evaluate the flood disaster vulnerability of China's inland fisheries from 2010 to 2019 and its decomposition. The temporal and spatial differences between vulnerability and its decomposition were analyzed. Kernel density estimation and factor contribution model were used to analyze the changing trend of vulnerability and main influencing factors. The results show that: during the study period, the vulnerability of inland fisheries in China to flood disasters showed a fluctuating downward trend, and the high vulnerability areas were mainly distributed in South China and the middle and lower reaches of the Yangtze River; the exposure index first decreased and then increased, and the high-exposure regions were mainly concentrated in the middle and lower reaches of the Yangtze River; the sensitivity index first decreased and then increased, and the high-sensitivity areas were concentrated in North-east China, the middle and lower reaches of the Yangtze River, and South China; the adaptive capacity index showed a downward trend, and the areas with lower adaptive capacity were concentrated in the South-west and North-west. From the factor contribution model, the economic losses of fishery floods and the affected area had the greatest impact on the exposure index; fingerling production and freshwater fishery production had the greatest impact on the sensitivity index; the index with a lower contribution to the adaptive capacity index was the total power of fishery machinery and fishery technology promotion. Therefore, building reservoirs, optimizing aquaculture layout and promoting fishery modernization are the keys to reducing the vulnerability of inland fisheries to flood disasters.

Keywords: flood disaster, vulnerability, spatial and temporal differences, China, inland fisheries

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University of Chinese Academy of Sciences, China
Fangting Xie,
Jiangxi Agricultural University, China

****Correspondence:***
Jiaxi Zheng
470507355@qq.com

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INTRODUCTION

Fisheries and aquaculture have made a significant contribution to food security, improved dietary structure and increased income for farmers. Since 1961, global fish consumption has grown at an annual average rate of 3.1%, almost twice higher than the annual growth rate of the world population (1.6%). Over the same period, global fish production has doubled, reaching 179 million tons in 2018 (FAO, 2014). China is the world's largest fish producer and exporter. Since 1991, China's aquaculture production has exceeded that of the rest of the world combined. By 2018, China's aquaculture accounted for 57.9% of the world's aquaculture, with inland and marine fisheries production reaching 31.01 and 31.56 million tons, respectively. However, in recent years, with global warming and rising sea levels, the intensity, frequency and scope of global disasters have been increasing, adversely affecting fishermen, fisheries and economic development. Among them, flood disaster is one of the severe disasters affecting fishery development. In 2005, economic losses caused by floods in China amounted to 2.499 billion yuan, and in 2019, the economic losses reached 6.937 billion yuan, accounting for 51.441% of the total economic losses in fisheries. According to the IPCC report (2019), the global temperature is expected to rise by 1.5°C in the future. This kind of climate change may greatly aggravate the impact of flood disaster on fishery production and restrict the sustainable development of inland fishery.

Therefore, it is necessary to accurately assess the vulnerability of China's inland fisheries to flood disasters, identify the brittle factors of the inland fisheries' vulnerability to flood disasters, and comprehensively and systematically describe its basic characteristics, distribution dynamics, regional differences and spatial distribution from temporal and spatial dimensions. This will help to guide China's inland fisheries to accurately "reduce brittleness" and enhance their disaster resilience.

LITERATURE REVIEW

The concept of vulnerability was first applied in the field of natural disasters. In the early stage of research, some scholars identified and predicted the risk areas of vulnerable groups by calculating the occurrence possibility and impact of disasters (White, 1974). As resource depletion and environmental degradation became increasingly serious in the late 20th century, vulnerability assessment was gradually extended to regional planning, sustainable development, and global environmental status and trend (Timmerman, 1981; Kasperson and Kasperson, 2001). Adger believed that vulnerability refers to a state in which the system exposed to environmental or social changes is sensitive to damage caused by these changes due to the lack of adaptability (Adger, 2006). Turner et al. (2003) believed that vulnerability is the degree of damage that systems, subsystems or system components may experience due to exposure to disasters. The United Nations International Strategy for Disaster Reduction (UNISDR) stated that vulnerability is the inherent property of a system, which is determined by natural, social, economic and environmental factors and processes, and can withstand a variety of stresses (UNISDR, 2004); McCarthy (2001) demonstrated that vulnerability is an effective description of the extent to which a system is susceptible to sustained damages from climate change. In general, vulnerability can be considered as a state in which the system exposed to disturbance evolves in an unsustainable development direction or leads to the possibility of systemic risks due to the sensitivity of internal structures and the lack of adaptive capacity to deal with the disturbance.

Currently, a large amount of literature has focused on disaster vulnerability from both macro and micro perspectives. At the micro-level, Ghosh and Ghosal (2021) analyzed the differences in climate vulnerability between agriculture-dependent villages and forest resource-dependent villages based on flood disasters and analyzed the vulnerability index of farmers to climate change in the study area. Tian and Lemos (2018) examined the impact of farm household assets and labor allocation on climate vulnerability from exposure, sensitivity and adaptive capacity, to illustrate the complex process affecting rural livelihoods and household adaptive capacity. Zhou et al. (2021a) included earthquake disasters in the assessment of farmers' livelihood strength and systematically measured the livelihood resilience of farmers in Sichuan, China, from four aspects: disaster resistance, buffer capacity, self-organizing capacity and learning ability. On the basis of measuring the climate vulnerability of farmers, Peng et al. (2019) further analyzed the coping strategies of farmers. At the macro level, Hoque et al. (2019) constructed an agricultural livelihood vulnerability index based on the research framework of sensitivity, exposure and adaptive capacity, and analyzed the impact of agricultural livelihoods on climate in various regions of Bangladesh. Based on sensitivity, exposure, and adaptive capacity, Wu et al. (2017) included a landscape fragmentation index for correction (a landscape fragmentation index) to assess the vulnerability of agriculture to flood disasters.

The measurement methods of vulnerability mainly include the comprehensive index method and vulnerability function evaluation method. In addition, an increasing number of studies have integrated GIS and RS technology. Zhang et al. (2017) used the comprehensive index method to measure the vulnerability of the Yellow River Delta wetland ecosystem. Nguyen and Bao (2019) assessed the vulnerability to floods of 10 villages in Quang Binh Province, Vietnam, based on the flood vulnerability index. In addition, Abebe et al. (2018) proposed a flood disaster vulnerability evaluation model based on GIS and Bayesian reliability network to analyze the flood vulnerability in different areas of Toronto. Karimzadeh et al. (2014) used the Analytic Hierarchy Process (AHP) to measure the seismic vulnerability of Tabriz City, and used GIS software for regional division. Guo et al. (2019) established 10 indicators, used the Tosis method to measure the drought disaster vulnerability of maize in the central and western regions of Jilin Province and used GIS software to conduct regional research on disaster vulnerability.

In terms of the assessment of fishery vulnerability, most of the existing studies focus on the climate vulnerability of marine fisheries. Allison et al. (2009) established a vulnerability model to analyze the economic vulnerability of 132 countries and the potential impact of climate change on their capture fisheries. Based on the perspective of food security, Ding et al. (2017) analyzed the impact of climate change on the vulnerability of marine fisheries in 109 countries from three aspects: national exposure, sensitivity and adaptive capacity. Qi et al. (2018) used a vulnerability model to assess the vulnerability of marine fisheries in 11 coastal provinces in China from three aspects: exposure, sensitivity and adaptive capacity. Kim et al. (2018) compared the climatic vulnerability of coastal and inshore fisheries and found that the climatic vulnerability of coastal fisheries was higher than that of inshore fisheries. In addition, there is also literature analyzing the vulnerability of wetland fisheries to climate hazards. Naskar et al. (2018) analyzed the vulnerability of wetland fisheries in West Bengal, India, based on climate indicators and stakeholder-perceived vulnerability indicators of wetland fisheries using long-term quantitative data. Puthiyottil et al. (2021), using a stakeholder-driven approach to quantify the impacts of climate change on wetland fisheries, found around seven potential threats to wetland fisheries from climate change.

Based on the above literature, the current research on disaster vulnerability has been extremely rich, involving the construction of indicator systems, analysis of spatiotemporal characteristics, and discussion of related impact mechanisms. This has laid a solid foundation for further in-depth follow-up research. However, there are still some deficiencies in the existing research. Firstly, the existing research does not clarify the climate vulnerability of the inland fishery in the largest aquaculture-producing country (China). Secondly, few studies focus on flood disasters and inland fisheries for vulnerability assessment and analysis. This paper took 31 provinces (cities) in China as the research area, selected 3 dimensions and 12 indicators of exposure, sensitivity and adaptability, established a vulnerability evaluation model for inland fishery flood disasters and conducted regional evaluation based on GIS spatial analysis technology. This will provide decision-making reference for flood mitigation and sustainable development of China's inland fisheries.

Methodology and Data

Study Area and Data Source

China is located in the east of Asia, facing the Pacific Ocean to the east. The terrain is high in the west and low in the east. It has obvious monsoon climate characteristics, and the seasonal changes and regional differences in rainfall are extremely obvious. Seasonal characteristics: flood disasters mainly occurred in May–July in the south, and June and July were the main frequent periods; severe flood disasters in the north were concentrated in June–August, and July and August were the most frequent periods. Regional characteristics: China's seven major river basins (Yangtze River, Yellow River, Huaihe River, Haihe River, Pearl River, Liaohe River, and Songhua River) are closely related to flood disasters. Among them, the Yangtze River, Pearl River and Yellow River basins are the three basins with the highest flood frequency.

China is the world's largest aquaculture country. The inland water area is about 174,710 km^2, accounting for 1.820% of the national land area; the lake area accounts for about 43.066% of the total inland water area, about 75,240 km^2, and the aquaculture area is about 21,510 km^2; reservoirs The total area is about 23,020 km^2, and the cultivable area is about 18,840 km^2; the total area of the pond is about 19,220 km^2. In recent years, China has strictly controlled the intensity of marine fishing, scientifically expanded new space for aquaculture, and the output of aquaculture has increased year by year. As of 2019, China's freshwater aquaculture volume reached 30,137,740 tons, and the total aquaculture area reached 51,160 km^2. At present, China's fishery is in a critical period of modernization. The development model is changing from fishing to aquaculture, from resource development to resource conservation and quality benefits, and from traditional farming to ecological health.

In view of the availability of data, this study took 31 provinces (cities) in China as the research object. The period was 2010–2019. Relevant data on the fishery, rainfall and water area, and the rainfall data were obtained from the China Meteorological daily dataset of China's surface climate data of the National Meteorological Information Center of the Bureau. The fishery-related data was from the "China Fishery Yearbook" and the "China Fishery Statistical Yearbook." The water area-related data was from the "China Water Conservancy Statistical Yearbook."

Model Settings

Polsky et al. (2007) decomposed vulnerability into three elements (i.e., exposure, sensitivity, and adaptive capacity) and proposed a vulnerability scoping diagram (VSD) framework. It provides a clear and comprehensive quantitative assessment of vulnerability through multivariate data organization, clear vulnerability connotation and index system construction method (Polsky et al., 2007). In this paper, flood disasters were taken as the exposure factor of inland fisheries and 12 indicators were selected. Then, based on the definition of vulnerability and combined with the VSD vulnerability assessment framework, an evaluation index system was constructed (**Table 1**). The component, definition and calculation method of indicators of each dimension are presented as follows:

(1) Exposure refers to the extent to which the system is disturbed by the external natural environment and social pressure and reflects the extent to which inland fisheries are affected by flood disasters. The affected area, loss of aquatic products and economic loss of the fishery can directly reflect the impact of flood disaster on fisheries. The amount of rainfall reflects the intensity of flood disasters in a region (Allison et al., 2009; Das et al., 2013). Therefore, the economic loss, aquatic product loss, affected area and the amount of regional rainfall were selected to represent the exposure of inland fisheries to flood disasters.

(2) Sensitivity refers to the degree to which the system is subjected to the positive or negative effects of stress and is used to characterize the sensitivity of the system to disturbance. Total inland fish production, total fish seed production, total fish culture area and fish product processing were selected to represent fishery sensitivity (Handisyde et al., 2006; Allison et al., 2009).

(3) Adaptive capacity refers to the system's ability to cope with flood disasters and reflects the resilience of the fishery system, which is determined by the economy, technology, infrastructure and staffing. Reservoir capacity, the total power of fishery machinery, the total income of fishermen per capita and fishery technology extension institutions were selected to represent adaptive capacity (Das et al., 2016; Mmia et al., 2019).

Data Standardization

In the flood disaster vulnerability assessment of fisheries, in order to eliminate the dimensional differences and the differences in action direction between initial assessment indicators, the original data were normalized using the range to make all indicators have the same action direction (Xu et al., 2019).

Positive indicator: the degree of vulnerability increases with the increase of index values, i.e., the index property is "+," and positive index normalization is obtained by

$$X_{ij}^{'} = \frac{X_{ij} - \min X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{1}$$

Negative index: the degree of vulnerability decreases with the increase of index values, i.e., the index property is "−," and negative index normalization is obtained by

$$X_{ij}^{'} = \frac{\max X_{ij} - X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{2}$$

where $\max(X_{ij})$ and $\min(X_{ij})$ represent the maximum and minimum value of the j index, respectively;X_{ij} and X'_{ij} are the original index value and the normalized value of item j, respectively, i = 1, 2, 3,. . . . . ., m;j = = 1, 2, 3,. . . . . ., n. In this paper, m is the research sample of Chinese provinces, m = 31; n is the number of evaluation indexes, n = 12.

Index Weight Calculation

For a fishery flood disaster vulnerability assessment system, it is necessary to select suitable methods to determine the weight of each index. At present, two methods are mainly used to assign weight: subjective weighting method such as the analytic hierarchy process, expert investigation method and BP neural network technology is highly dependent on experts, subjective and difficult to objectively evaluate the difference of indicators; the entropy weight method, which assigns weight according to the difference between indicators, thus avoiding the subjective will of experts and truly reflecting the influence degree of indicators. In this paper, the entropy weight method was selected to determine weight (Xu et al., 2018; Zhou et al., 2021b), and the specific calculation process is as follows:

(1) Based on the normalized value, determine the index weight y_{ij}:

$$y_{ij} = X'_{ij} / \sum_{i=1}^{m} X'_{ij} \tag{3}$$

(2) Calculate the entropy of the jth index e_j:

$$e_j = -k \sum_{i=1}^{m} (y_{ij} \ln y_{ij}, where k > 0, k = \ln(m) \tag{4}$$

(3) Calculate the difference coefficient of item j as g_j:

$$g_j = 1 - e_j \tag{5}$$

(4) Calculate the weight of each index w_j:

$$w_j = g_j / \sum_{j=1}^{n} g_j. \tag{6}$$

Vulnerability Model Establishment

Flood disaster vulnerability measurements of inland fisheries reflect the internal relationship between exposure, sensitivity and adaptive capacity. Higher exposure and sensitivity indices indicate higher vulnerability of fisheries. On the contrary, a higher adaptive capacity index indicates a higher capability of the fishery to cope with disasters, i.e., the lower vulnerability degree.

According to the method of Polsky et al. (2007) and Morales et al. (2014), a VSD model was constructed to analyze the vulnerability of inland fisheries to flood disasters:

$$V = E + S - AC \tag{7}$$

where V represents vulnerability; E represents exposure; S is sensitivity; AC is adaptive capacity. The weights of E, S and AC were calculated by the entropy method:

$$\begin{aligned} EI &= \textstyle\sum_{j=1}^{4} w_{ej} Y_{eij} \\ SI &= \textstyle\sum_{j=1}^{4} w_{sj} Y_{sij} \\ AC &= \textstyle\sum_{j=1}^{4} w_{aj} Y_{aij} \end{aligned} \tag{8}$$

TABLE 1 | Index system of flood vulnerability assessment of inland fisheries in China.

Component	Indicator	Index properties	Weight		
			2010	2015	2019
Exposure	E1: Flood disaster economic loss of fisheries (Ten thousand yuan)	+	0.0586	0.0693	0.0674
	E2: Loss of aquatic product quantity (in '000 Tons)	+	0.0598	0.0658	0.0675
	E3: Flood disaster-affected area (in hm^2)	+	0.0564	0.0694	0.0702
	E4: Annual rainfall (in mm)	+	0.0779	0.0959	0.0980
Sensitivity	S1: Total inland fish production (in '000 tons)	+	0.0666	0.0841	0.0837
	S2: Freshwater fishery processing (in '000 tons)	+	0.0538	0.0618	0.0589
	S3: Total fish cultured area (in '000 tons)	+	0.0719	0.0883	0.0890
	S4: Total fingerling production (in '000 tons)	+	0.0605	0.0715	0.0720
Adaptive capacity	AC1: Reservoir capacity (m^3)	−	0.0834	0.0915	0.0922
	AC2: Total power of fishery machinery (kW)	−	0.0831	0.1024	0.1031
	AC3: Total income of fishermen per capita (Ten thousand yuan)	−	0.0834	0.0999	0.0995
	AC4: Number of fishery technology extension agencies (in number)	−	0.0827	0.1000	0.0987

Where w_{ej},w_{sj}, and w_{aj} are the weights of the j index of exposure, sensitivity and adaptive capacity, respectively; y_{eij},y_{sij}, and y_{aij} are the normalized values of the first indicator of exposure, sensitivity and adaptive capacity, respectively. Based on the existing studies (Boori et al., 2016; Weis et al., 2016), the exposure, sensitivity, and adaptive capacity indexes were divided into four categories according to the natural breakpoint method and visualized by ArcGis software, in order to intuitively display the flood disaster exposure, sensitivity and adaptability of inland fisheries in China.

Kernel Density Estimation

Kernel density estimation uses a continuous density curve to express the distribution of vulnerability to flood disasters in China's inland fisheries. This method does not use prior knowledge of data distribution or any assumptions. It is only based on the characteristics of the sample data and uses a non-parametric estimation kernel. The density function avoids the defect of subjectively setting the function form in the parameter analysis. Therefore, this method was used in this paper to compare the kernel density curves of different years to reveal the dynamic evolution characteristics of the flood vulnerability of inland fishery and their decomposition at the provincial scale. It is expressed as:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{y_i - \bar{y}}{h}) \tag{9}$$

where n is the number of provinces, y_i is the vulnerability (exposure, sensitivity, and adaptive capacity) of i, $\bar{y}$ is the mean value of all provincial vulnerabilities (exposure, sensitivity, and adaptive capacity) in the current year; K (.) and h represent the core function and bandwidth of stata software.

Factor Contribution Model

A prerequisite for effective vulnerability reduction is to identify and analyze the main influencing factors. In the research on the identification of influencing factors, the factor contribution model has been widely used (Zhou et al., 2018; Yuan et al., 2021). Based on the factor contribution calculation model, the main contributing factors of flood vulnerability of inland fisheries in each province of China were analyzed. The calculation equation is as follows:

$$O_j = \frac{I_j \times w_j}{\sum_{j=1}^{12}(w_j \times I_j)} \times 100\% \tag{10}$$

where O_j is the contribution of item j to vulnerability; I_j is the index deviation degree, which is equal to 1 minus the normalized value X_{ij}; $w_j$is the weight of each indicator.

RESULTS AND ANALYSIS

Vulnerability Assessment of China's Inland Fisheries to Floods

To sum up, this paper calculated the measurement results of the vulnerability of inland fisheries to flood disasters in 31 provinces (cities) in China. In order to visually show the evolution trend of vulnerability to flood disasters of inland fisheries in China, this paper firstly depicted the columnar trend of the mean and median vulnerability of inland fisheries to flood disasters at the country level from 2010 to 2019 (see **Figure 1**). Furthermore, in order to facilitate the investigation of the dynamic trend of the vulnerability of inland fisheries to floods at the regional level, the regions were divided based on the administrative geographical divisions prescribed by China, combining the differences in climate between the north and the south and the distribution of inland fisheries (Zeng et al., 1990; Zhao et al., 2022), i.e., North-east China (Heilongjiang, Jilin, and Liaoning), Huanghuai District of North China (Beijing, Tianjin, Hebei, Shanxi, Neimeng, Shandong, and Henan), the middle and lower reaches of the Yangtze River (Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, and Hunan), South China (Guangdong, Guangxi, Hainan, and Fujian), South-west (Yunnan, Guizhou, Chongqing, Sichuan, and Xizang), North-west (Shanxi, Gansu, Qinghai, Ningxia, and Xinjiang). Thus, a line graph of the average vulnerability to flood disasters of inland fisheries in China as a whole and six regions was drawn (see **Figure 2**).

At the country level, the vulnerability to flood disasters of inland fisheries in China from 2010 to 2019 showed a fluctuating downward trend (see **Figure 1**). The mean and median values in 2010 were 0.352 and 0.314, respectively, and dropped to 0.343 and 0.311 in 2019, indicating that the overall vulnerability of inland fisheries to flood disasters in the country and each province improved. From the perspective of time trend, from 2010 to 2012, the mean value of China's inland fishery flood disaster vulnerability increased from 0.352 to 0.367, and the median increased from 0.314 to 0.331. The reason is that in 2012, seven tropical cyclones made landfall along the coast of China, and the rainfall increased sharply. More than 420 rivers across the country experienced floods that exceeded the warning water level, 70 rivers experienced floods that exceeded the guaranteed water level, and 40 rivers experienced floods that exceeded historical records. Among them, there were 5 flood peaks in the mainstream of the Yangtze River, the largest flood since 1981 in the upper reaches; 4 flood peaks in the mainstream of the Yellow River, the largest flood in the upper and middle reaches since 1989, which caused serious damage to the inland fishery. From 2013 to 2019, the average vulnerability of China's inland fisheries of flood disasters was basically stable, and the vulnerability index first decreased from 0.346 in 2013 to 0.336 in 2016, and then increased to 0.343 in 2019. This is due to the impact of flood disasters and the strategic adjustment of the Chinese government in fishery development in recent years. In 2013, the strategic policy of "giving priority to, combining breeding and fishing, and focusing on breeding" has vigorously promoted the transformation of fishery development mode. As a result, the construction of the fishery modernization system has been accelerated, and the level of fishery mechanization and the income of fishermen have increased significantly. Then, in 2016, China successively issued the "Guiding Opinions of the Ministry of Agriculture on Accelerating the Promotion of Fishery Transformation and Adjustment of Structure" and "The Thirteenth Five-Year Plan

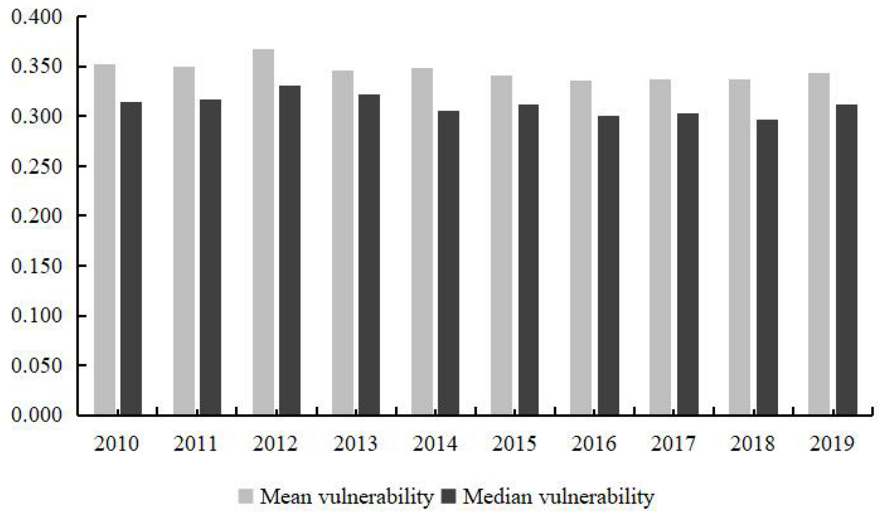

FIGURE 1 | Mean and median vulnerability to flood disasters of provincial inland fisheries from 2010 to 2019.

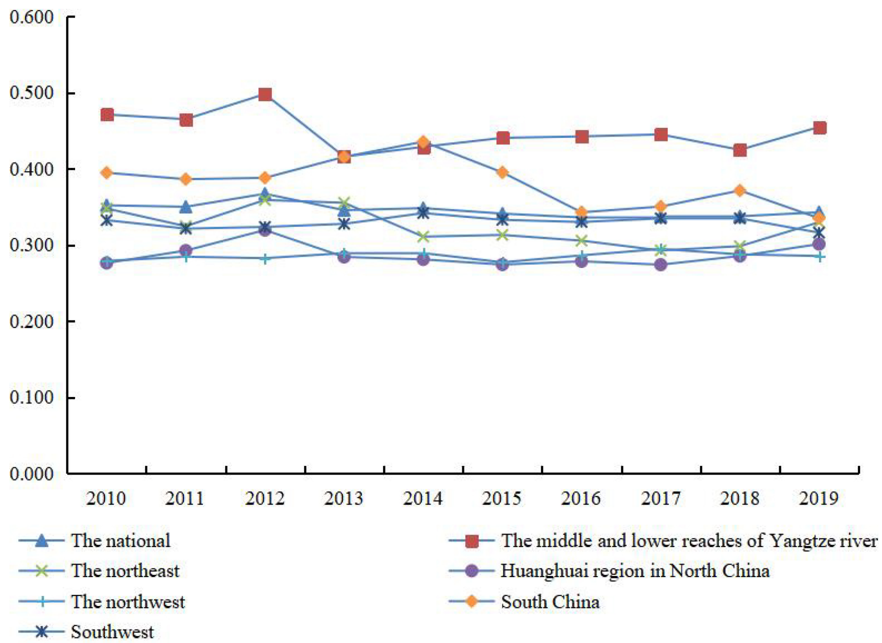

FIGURE 2 | Variation trend of vulnerability to flood disasters in China's inland fisheries from 2010 to 2019.

for the Development of National Fisheries," clarifying that the fishery development goals as "improves quality and efficiency, reduces the quantity and increases income, and promotes green development." Both fishery production and fishery processing have increased significantly, leading to an increase in the vulnerability index.

From a regional perspective (see **Figure 2**), the evolution trend of vulnerability to floods in inland fisheries in the seven regions showed an overall trend of rising first and then falling. The averages in South China and the middle and lower reaches of the Yangtze River were higher than the national average; the averages in North-west China and the Huanghuai region in North China were lower than the national average. The vulnerability index in South China fell significantly during the sample period, with a decline of 15.126%; The vulnerability index of the middle and lower reaches of the Yangtze River, the North-east region and the South-west region decreased slightly during the sample period by 3.484%, 5.180%, and 4.924%, respectively; while the vulnerability index of the Huanghuai region in North China and the North-west region increased. During the sample period, the growth

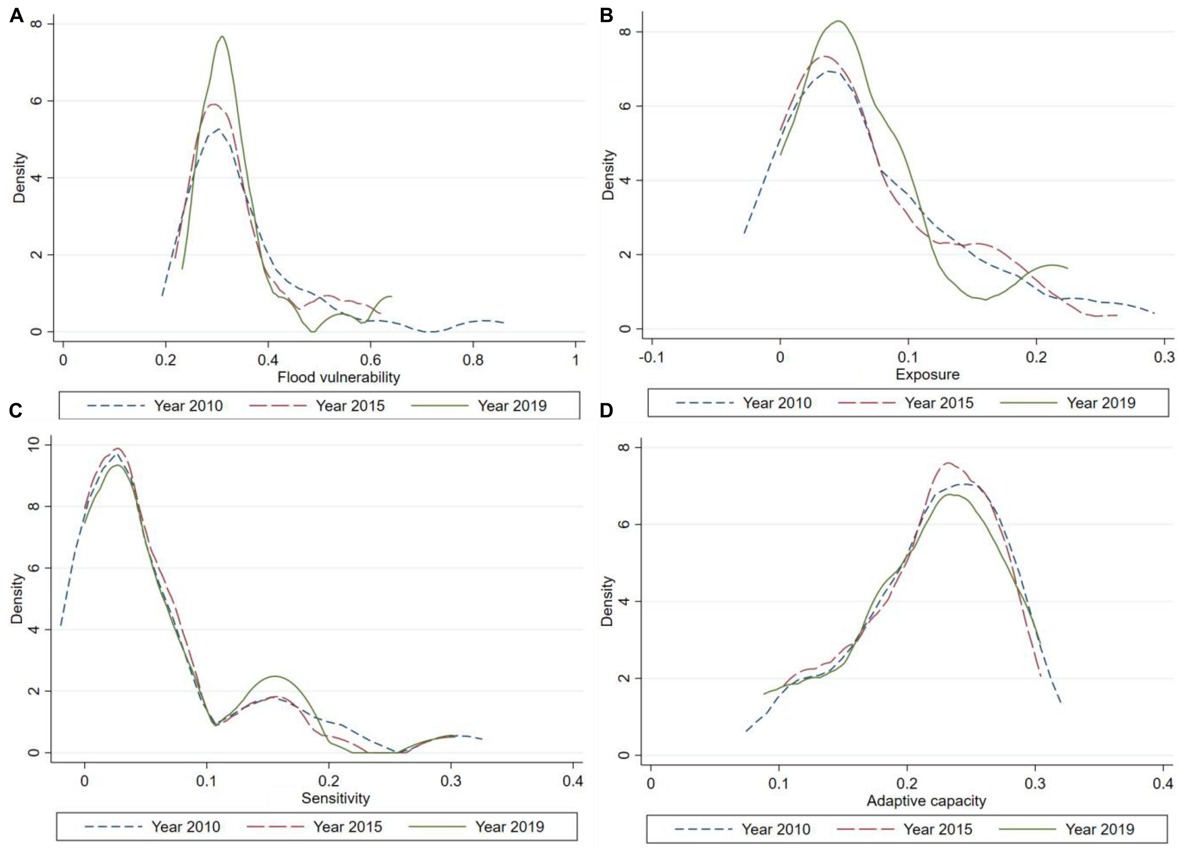

FIGURE 3 | Dynamic evolution distribution of vulnerability to floods and its decomposition terms in China's inland fisheries. **(A)** Flood vulnerability. **(B)** Exposure. **(C)** Sensitivity. **(D)** Adaptive capacity.

rates were 9.004% and 2.291%, respectively. The vulnerability of inland fisheries to flood disasters among the seven regions has tended to be close after 2016, indicating that under the policy support in 2016 and the policy of "four transformations and four optimizations," inland fisheries tend to develop in a coordinated manner.

Non-parametric Kernel Density Estimation

Using the panel data of vulnerability, exposure, sensitivity and adaptive capacity measured above, the non-parametric kernel density estimation method was used to analyze the dynamic evolution law of the vulnerability of inland fishery flood disaster and its decomposition. Due to space limitations, data from 2010, 2015, and 2019 were selected as reference standards, and the results are shown in **Figure 3**.

Figure 3A depicts the dynamic distribution and evolution of vulnerability to flood disasters in inland fisheries in China. Firstly, from the perspective of the central position, the central position of the vulnerability index in 2010, 2015, and 2019 first moved to the left and then to the right, indicating that the vulnerability of China's inland fisheries to flood disasters first decreased and then increased, which is consistent with the previous results. Secondly, in terms of shape, the kernel density curves of the vulnerability index in 2010, 2015, and 2019 all showed a relatively obvious "single peak" state, indicating that the vulnerability of inland fisheries in China to flood disasters showed a convergence trend. Finally, from the point of view of the change in the peak height of the distribution curve, during the observation period, the peak height showed an upward trend. It shows that some provinces were more seriously affected by disasters in recent years, so the absolute difference expanded during the observation period. In addition, the distribution curve had obvious right-tailed characteristics, and the distribution ductility showed a trend of gradually narrowing. It shows that the gap in the vulnerability index of provinces across the country was gradually narrowing.

Figures 3B–D describe the dynamic evolution trends of exposure, sensitivity, and adaptive capacity during the sample observation period, respectively. It can be seen from **Figure 3B** that in general, the nuclear density curve moved to the right, the wave crest becomes steeper, the wave crest height increased, the left tail of the curve converged to the center, and the right tail shrinked. This indicates that the flood exposure index of inland fisheries in China increased as a whole, and the absolute difference increased. Specifically, compared with those in 2010, in 2015, the curve shifted slightly to the left, the main peak became larger, and the right tail shrank, indicating that

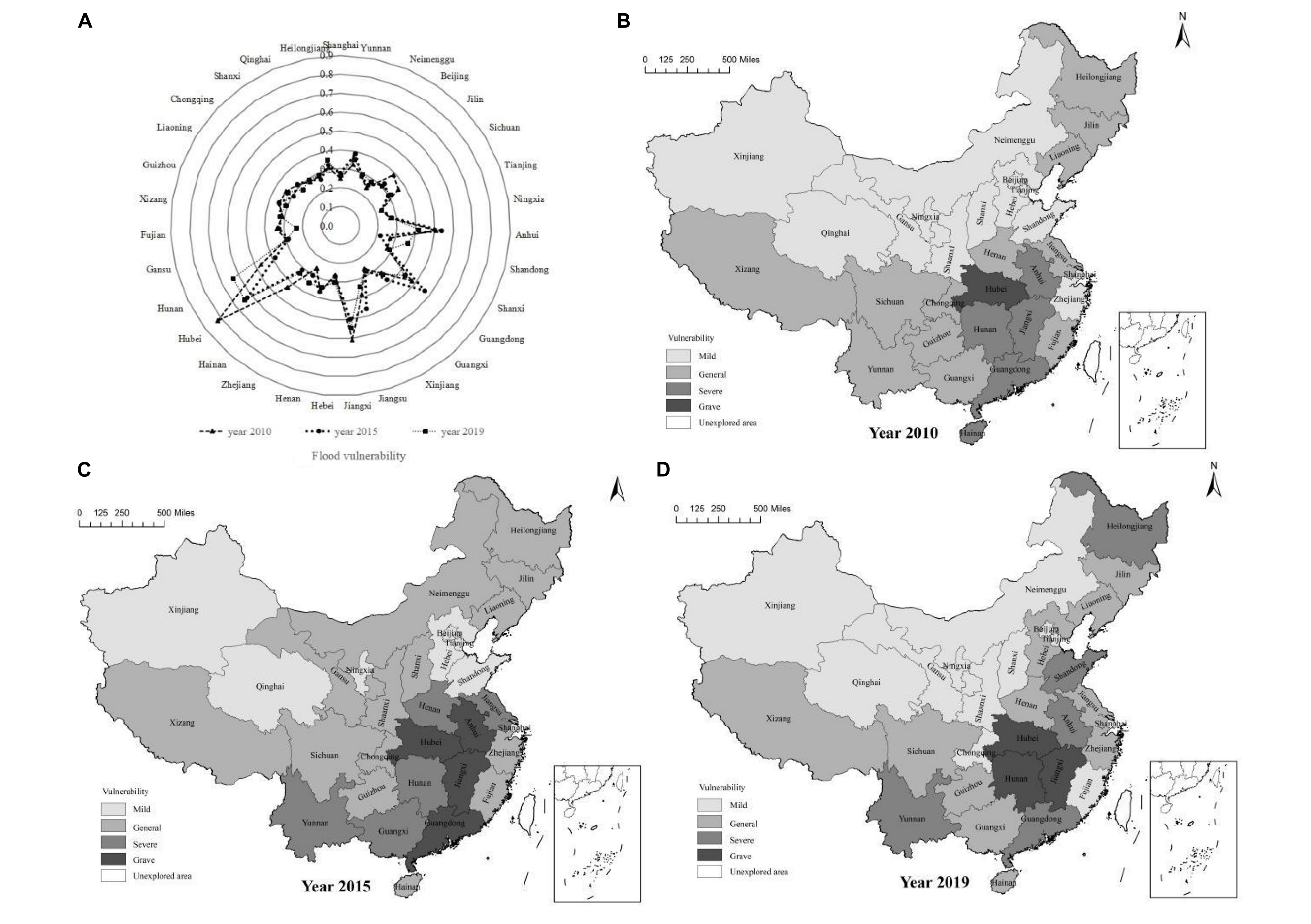

FIGURE 4 | Flood vulnerability assessment results and spatial distribution characteristics of inland fisheries in China from 2010 to 2019. Based on the standard map no. GS(2020)4619 of the standard map service website of the Ministry of Natural Resources, the base map is not modified. **(A)** Represents the radar diagram. **(B)** Represents the year 2010. **(C)** Represents the year 2015. **(D)** Represents the year 2019.

the overall exposure index decreased, the absolute difference expanded, and the gap between provincial exposure indexes narrowed. Compared with that in 2015, in 2019, the curve shifted to the right, the main peak became larger, and the right tail further shrunk, indicating that the exposure index increased as a whole, and the distribution was concentrated, tending to converge. From **Figure 3C**, the variation range of the inner core density curve during the investigation period was small, the peak height decreased in general, and the peak evolved from "single peak" to "double peak," indicating that the sensitivity of China's inland fishery had a certain gradient. The effect was weakly polarized. Although China's provinces (cities) inland fisheries have achieved significant growth in recent years, given the obvious heterogeneity of resource endowments and policy constraints affecting the sensitivity index among different provinces, Some provinces cannot catch up with provinces with high sensitivity index in terms of production and processing in the short term, and the gap between them is likely to continue to widen for a period of time. It can be seen from **Figure 3D** that the inner core density curve was generally shifted to the left, the main peak value decreased, and the left tail shrank, indicating the adaptive capacity[1] of the inland fishery in China to flood disasters improved during the study period, and the absolute difference narrowed.

Analysis of Temporal and Spatial Vulnerability Variation

The flood vulnerability assessment results and the spatial distribution of vulnerability index levels of provincial inland fisheries in China from 2010, 2015, and 2019 are shown in **Figure 4**. From **Figure 4A**, the flood vulnerability of inland fisheries in China showed a declining trend during the study period. The average flood disaster vulnerability index of China's inland fisheries in 2010 was 0.352, with Hubei Province, Jiangxi Province and Anhui Province ranking in the top three (i.e., 0.823, 0.610, and 0.508, respectively). In 2010, severe floods occurred in China, with floods exceeding warning levels in many regions of the Yangtze River basin.

[1]Because the adaptive capacity is a negative indicator, the greater the adaptive capacity index. It means that the adaptive capacity of the region is weaker, and vice versa.

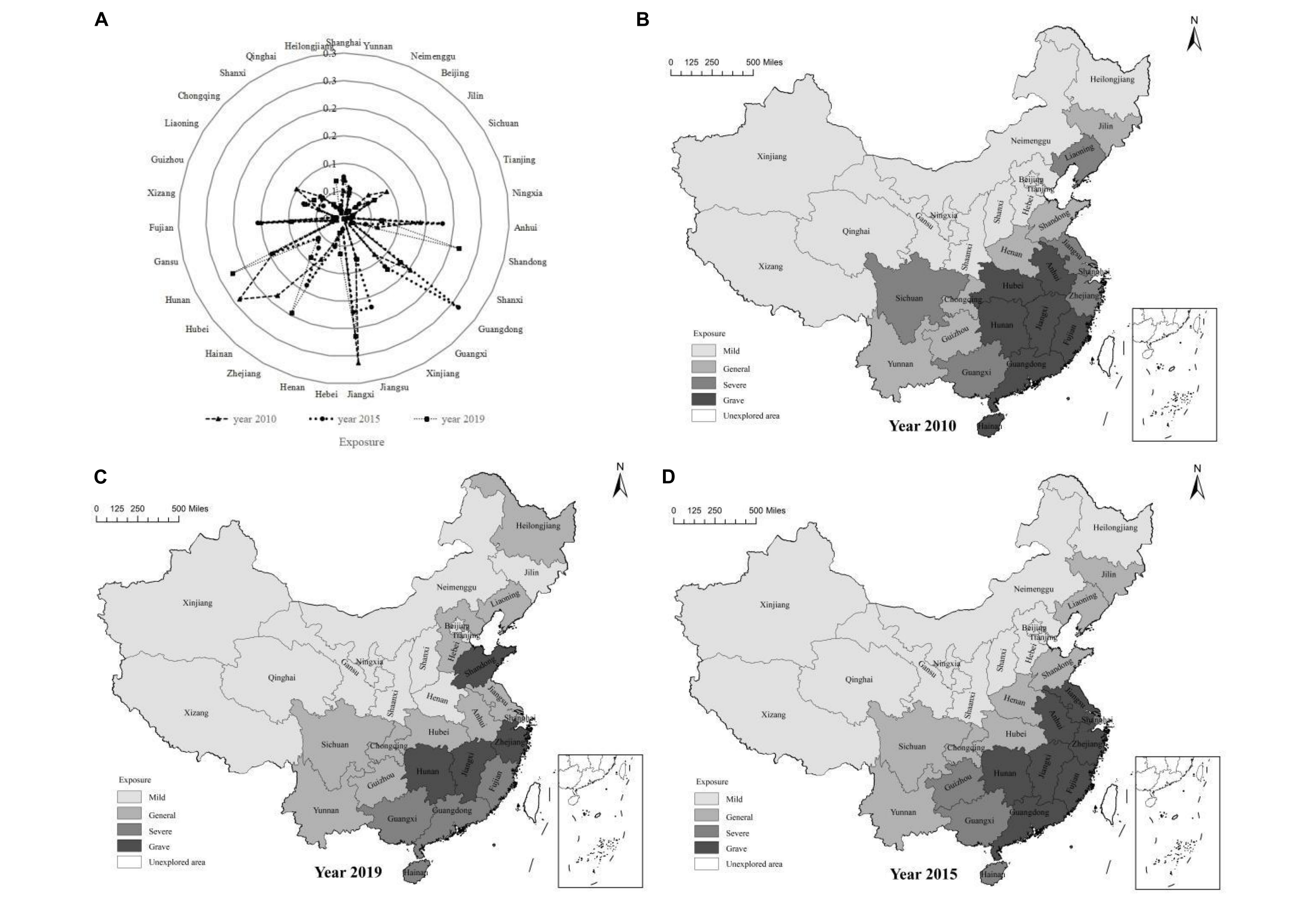

FIGURE 5 | Evaluation results and spatial distribution characteristics of flood disaster exposure of inland fisheries in China from 2010 to 2019. **(A)** Represents the radar diagram. **(B)** Represents the year 2010. **(C)** Represents the year 2015. **(D)** Represents the year 2019.

Inland fishery production was seriously damaged and the area of affected aquaculture reached 674,171 hm^2, of which the total affected aquaculture area (366,371 hm^2) in Hubei, Jiangxi, and Anhui accounted for more than half of the total affected area in China. In 2015, the overall precipitation increased and flooding affected 20 provinces (cities). However, during the 12th Five-Year Plan period[2], China's flood control capacity was significantly improved, the affected area and economic loss of fisheries decreased considerably and the average flood disaster vulnerability index of inland fisheries decreased to 0.341. In 2019, the flood disaster was serious and sustained heavy rainfall occurred in South China and northern South China, which increased the exposure of inland fisheries. Fortunately, with the effective improvement of the adaptability of each region, the vulnerability index of inland fisheries to flood disasters did not increase significantly in 2019, reaching only 0.343.

From **Figures 4B–D**, the areas of high vulnerability to flood disasters in China's inland fisheries are mainly distributed in the middle and lower reaches of the Yangtze River, with an overall spreading trend. In 2010, only Hubei Province was severely vulnerable to disasters. In 2015, the scope of flood disasters expanded, leading to an increase in disaster-prone areas. Hubei, Anhui, Guangxi and Jiangxi were in severe flooding-prone areas. In 2019, the flood disaster vulnerable areas were concentrated in Hubei, Jiangxi, and Henan. In recent years, Hubei province has been a severe disaster-prone area because it has unique advantages in fishery resources, with freshwater fishery production ranking first in China. In addition, most areas of Hubei are located in the middle reaches of the Yangtze River, which is prone to frequent flood disasters, resulting in a high level of flood disaster vulnerability in Hubei Province.

Analysis of Temporal and Spatial Exposure Variation

The evaluation results of inland fishery flood exposure and spatial distribution of Exposure index levels of Chinese provinces from 2010, 2015, and 2019 are shown in **Figure 5**. As can be seen from **Figure 5A**, from 2010, 2015, and 2019, inland fishery flood disaster exposure in Chinese provinces (cities) showed an overall trend of first decreasing and then increasing. In 2010, the average flood disaster exposure index in China was 0.072. The inland

[2]The Twelfth 5-Year Period: 2010 to 2015.

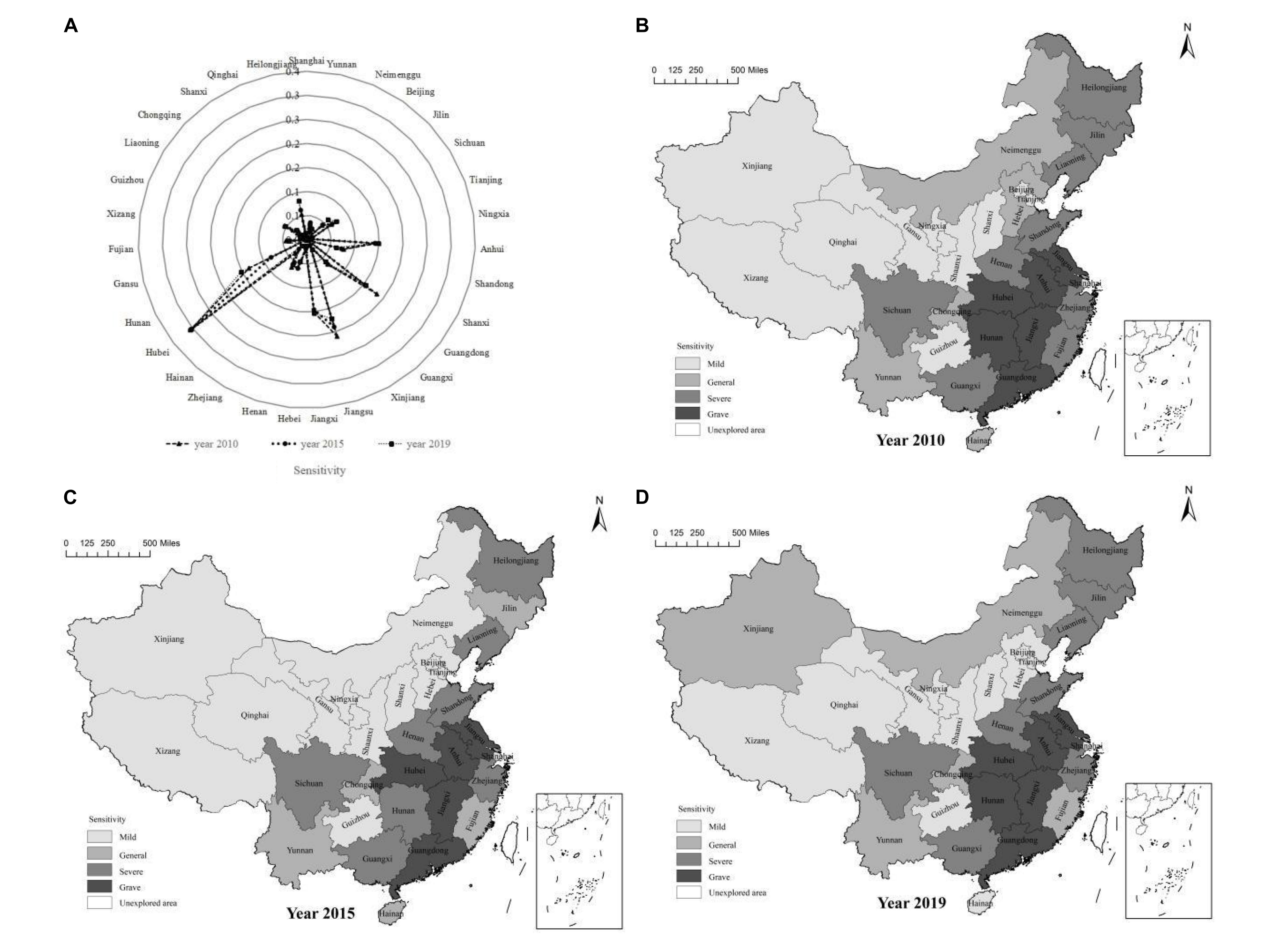

FIGURE 6 | Evaluation results and spatial distribution characteristics of flood disaster sensitivity of inland fisheries in China from 2010 to 2019. **(A)** Represents the radar diagram. **(B)** Represents the year 2010. **(C)** Represents the year 2015. **(D)** Represents the year 2019.

fisheries in Hubei and Jiangxi provinces were seriously affected by flood disasters, with a high level of the flood disaster exposure index (i.e., 0.238 and 0.263, respectively). In 2015, the average flood disaster exposure index in China decreased to 0.069 due to effective flood control, which reduced the affected area and economic loss caused by flood disasters. In 2019, the average flood exposure index in China increased to 0.072. This was due to the continuous rainfall caused by Typhoon "Limaki" in Shandong Province in 2019, which resulted in severe losses of inland fisheries and increased overall exposure.

From **Figures 5B–D**, the areas with high flood exposure are concentrated in South China and the middle and lower reaches of the Yangtze River. In 2010, the areas with severe exposure included Hubei, Anhui, Hunan, Guangdong, Hainan, and Jiangxi provinces, which were affected by heavy rainfall. The economic losses caused by floods in these provinces reached 8.359 million yuan, accounting for 75.23% of the total national economic loss. In 2015, the areas with more severe exposures expanded, with Jiangsu and Zhejiang provinces becoming more severely exposed. In 2019, areas with severe exposure decreased, concentrated in Hunan, Anhui and the coastal provinces such as Zhejiang, Guangdong, Hainan, Fujian, and Guangxi.

Temporal and Spatial Variation Characteristics of Sensitivity

Figure 6 shows the sensitivity evaluation results and spatial distribution of flood disaster vulnerability of Chinese inland fisheries from 2010, 2015, and 2019. From **Figure 6A**, the flood disaster sensitivity of inland fisheries in Chinese provinces from 2010 to 2019 first decreased and then increased. In 2010, 2015, and 2019, average flood disaster sensitivity indexes of inland fisheries were 0.060, 0.056, and 0.059, respectively. Particularly, the flood disaster sensitivity of the fishery in Hubei (0.306, 0.306, and 0.304 in 2010, 2015, and 2019, respectively) was much higher than that in other regions, ranking first in China. Hubei province is one of the important provinces in the development of freshwater fisheries in China and has ranked first in freshwater aquatic products in China for

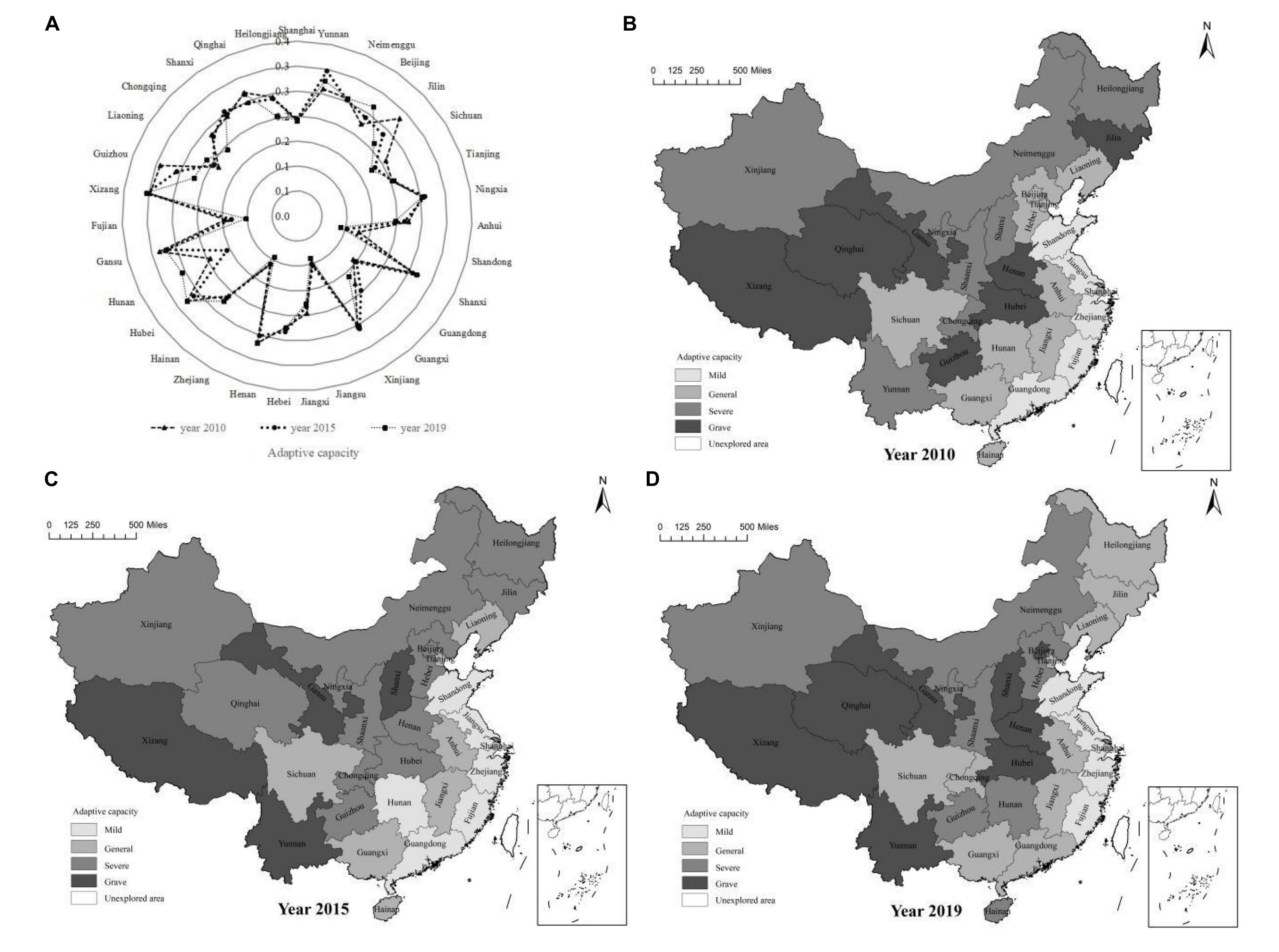

FIGURE 7 | Evaluation results and spatial distribution characteristics of flood disaster adaptive capacity of inland fisheries in China during 2010–2019. **(A)** Represents the radar diagram. **(B)** Represents the year 2010. **(C)** Represents the year 2015. **(D)** Represents the year 2019.

25 consecutive years, which has resulted in a simultaneous increase in sensitivity.

According to **Figures 6B–D**, the areas with high sensitivity to flood disasters are concentrated in North-east China, the middle and lower reaches of the Yangtze River, and South China. In 2010, the most sensitive provinces including Hubei, Hunan, Jiangsu, Jiangxi, Anhui, and Guangdong accounted for 71.54% of the total production of fish species and 62.68% of the total freshwater aquatic products. Hunan province did not become a seriously sensitive area in 2015 because of its weak fishery processing capacity, with only 147,352 tons of freshwater products for processing. In 2019, Hunan province again became a severely sensitive area with the number of freshwater products for processing increasing to 212,098 tons, thus increasing the sensitivity level.

Temporal and Spatial Variation Characteristics of Adaptive Capacity

The evaluation results of adaptive capacity and spatial distribution of flood disaster vulnerability of inland fisheries in Chinese provinces (cities) from 2010, 2015, and 2019 are shown in **Figure 7**. From **Figure 7A**, during the inspection period, the adaptive capacity of inland fisheries in China's provinces (cities) to flood disasters was generally improved, while the adaptive capacity index dropped from 0.220 in 2010 to 0.212 in 2019. Among them, the adaptive capacity of the Xizang was always at the lowest level, with the adaptive capacity index of 0.297, 0.304, and 0.304 in 2010, 2015, and 2019, respectively. Although Xizang has lake resources that account for 35.1% of the country's total area, under the constraints of water resources protection and policy, Xizang's freshwater fishing is limited and the total amount of aquaculture is not large, resulting in the low income of fishermen, the low level of fishing machinery, and less promotion of fishery science and technology. There was no major improvement, and thus the adaptive capacity was at the lowest level. On the contrary, the adaptive capacity of Jiangsu Province was at the highest level in the whole country, and the adaptive capacity index in 2010, 2015, and 2019 were 0.0978, 0.104, and 0.088, respectively. This is due to the fact that Jiangsu Province is located in the

TABLE 2 | Contribution of each index factor of vulnerability to flood disasters of inland fisheries in China in 2019[1].

	Exposure disorder factor		Sensitivity disorder factor		Adaptive capacity disorder factor	
	First contribution	**Second contribution**	**First contribution**	**Second contribution**	**First contribution**	**Second contribution**
Shanghai	E3	E2	S3	S1	AC2	AC4
Yunnan	E3	E1	S3	S1	AC2	AC4
Neimeng	E4	E3	S1	S4	AC2	AC4
Beijing	E4	E3	S3	S1	AC2	AC4
Jilin	E3	E4	S1	S4	AC2	AC3
Sichuan	E3	E1	S4	S2	AC2	AC1
Tianjin	E4	E3	S3	S1	AC2	AC4
Ningxia	E4	E3	S3	S1	AC2	AC4
Anhui	E1	E2	S4	S2	AC2	AC4
Shandong	E4	E2	S4	S1	AC2	AC1
Shanxi	E4	E3	S3	S1	AC2	AC4
Guangdong	E1	E3	S4	S2	AC2	AC1
Guangxi	E3	E2	S3	S4	AC2	AC1
Xinjiang	E4	E3	S1	S4	AC2	AC4
Jiangsu	E3	E1	S4	S2	AC2	AC4
Jiangxi	E1	E2	S4	S2	AC2	AC3
Hebei	E4	E1	S3	S1	AC2	AC4
Henan	E4	E3	S4	S1	AC2	AC4
Zhejiang	E2	E3	S4	S3	AC4	AC1
Hainan	E3	E2	S3	S1	AC4	AC2
Hubei	E1	E2	S1	S1	AC1	AC2
Hunan	E1	E4	S2	S4	AC2	AC4
Gansu	E4	E3	S3	S1	AC2	AC4
Fujian	E3	E2	S3	S4	AC2	AC4
Xizang	E4	E3	S3	S1	AC2	AC2
Guizhou	E2	E1	S1	S3	AC2	AC3
Liaoning	E4	E2	S1	S4	AC4	AC2
Chongqing	E3	E1	S3	S1	AC2	AC4
Shaanxi	E3	E4	S1	S3	AC2	AC4
Qinghai	E4	E3	S3	S1	AC2	AC4
Heilongjiang	E4	E1	S1	S4	AC2	AC4
North-east area	E1	E2	S4	S2	AC3	AC1
Huanghuai District, North China	E4	–[2]	S4	S2	AC1	AC3
Middle and lower reaches of the Yangtze River	E4	E3	S1	S3	AC3	AC2
South China	E3	E2	S4	S3	AC2	–
South-west Region	E4	E3	S1	S3	AC1	AC3
North-west Region	E3	E1	S3	S1	AC1	AC3

[1] *The meaning of the symbols is shown in **Table 1**.*
[2] *—represents a tie for second place across multiple metrics and is therefore not presented.*

middle and lower reaches of the Yangtze River and rich in water resources and fishery resources. The income of fishermen and the promotion of science and technology are at the forefront of the country.

As can be seen from **Figures 4B–D**, the areas with poor adaptability were mainly concentrated in the South-west and North-west regions. In 2010, the regions with poor adaptive capacity were Xizang Autonomous Region, Gansu Province, Qinghai Province, Jilin Province, Henan Province, Hubei Province and Guizhou Province. Among them, Xizang Autonomous Region, Gansu Province, Qinghai Province, Jilin Province, and Guizhou Province were not the main provinces of fishery production, and thus their adaptive capacity was relatively weak. As one of the main provinces of fishery production, Hubei and Henan provinces had weak adaptability due to the low level of fishermen's income. The net income of fishermen per capita in Hubei and Henan provinces was 7,700 and 7,016 yuan, which was lower than the average in China. The level of fishery mechanization was at a low level in the country, resulting in insufficient adaptability. In 2019, the adaptability of Yunnan Province, Shanxi Province and Beijing City decreased. During the observation period, the top four provinces in terms of adaptability were Zhejiang, Jiangsu, Fujian and Shandong. What they had in common was the high level of fishery mechanization and net income of fishermen per capita.

Analysis of Vulnerability Contribution of Inland Fisheries to Flood Disaster

In order to further diagnose the influencing factors of vulnerability to flood disasters in China's inland fisheries, the factor contribution model was used to calculate the contribution of each index factor from exposure, sensitivity and adaptive capacity, and the top two factors were selected. Significant contribution factors were studied (**Table 2**), in order to explore the key factors that lead to the increase of vulnerability to flood disasters in China's inland fisheries, and provide a reference for the decision-making of sustainable development of China's inland fisheries.

Identification of exposure contributing factors: overall, the main contributing factors affecting the exposure to inland fishery flood disasters in China are the economic losses of fishery flood disasters and the affected area. The average contribution of the two factors was 9.064% and 9.028%, respectively. Therefore, strengthening the planning and construction of fishery flood control infrastructure, improving fishery disaster prevention and mitigation emergency plans, and enhancing fishermen's emergency response capabilities should become the key optimizing the future inland fishery system. In terms of sub-regions, the main factors of exposure in the middle and lower reaches of the Yangtze River and South-west China were rainfall and the affected area.

Identification of Sensitivity Contributing Factors: the main contributing factors that affected the sensitivity of China's inland fisheries to flood disasters were fingerling production and freshwater fishery production. From a regional perspective, the main contributing factors to the sensitivity of the middle and lower reaches of the Yangtze River were fishery production and fishery processing. The focus should be on fishery processing and fishery production, strengthening the construction of infrastructure and cold chain transportation equipment, effectively deploying aquatic products from various regions for real-time processing and reducing the impact of disasters; the main contributing factors to the sensitivity of North-east China and the Huanghuai region of North China were the production of fingerlings and the number of fingerlings processed. It is necessary to increase the disaster prevention measures of fingerlings and develop the fishery product processing industry simultaneously; the South-west and North-west regions were sensitive to the stability of aquaculture are aquaculture area and aquaculture output, flood control measures should be implemented focusing on fishery and aquaculture to reduce the risk of flood disasters.

Identification of contribution factors of adaptive capacity: the factors with lower contribution rates affecting the adaptive capacity of inland fisheries in China were the total power of fishery machinery and the promotion of fishery technology. The contribution rates of the two factors were 2.273% and 5.742%, respectively. In terms of sub-regions, the North-east region, the Huanghuai region of North China, the North-west region and the South-west region need to be strengthened in terms of reservoir capacity and fishermen's income. They should also focus on developing modern fishery and improving infrastructure construction, especially in the North-west region under resource and environmental constraints. The South-west region should focus on improving the efficiency of fishery production to ensure the supply of aquatic products as the minimum requirement. The middle and lower reaches of the Yangtze River and South China urgently need to improve the fishermen's income and the level of fishery mechanization. As important areas of China's inland fishery output, the development mode of the fishery should be transformed, the support of scientific and technological equipment should be strengthened, and the comprehensive production capacity of the fishery, market competitiveness should be improved.

CONCLUSION AND DISCUSSION

In this paper, by constructing an evaluation index system of vulnerability to floods and floods of inland fisheries in China, the entropy weight method was used to quantitatively evaluate the vulnerability of inland fisheries to floods and floods in China's provinces. The main conclusion is as below:

(1) From the national level, from 2010 to 2019, the vulnerability of China's inland fishery to floods showed a downward trend. At the regional level, the average value of South China and the middle and lower reaches of the Yangtze River was higher than the national average; the average value of North-west China and the Huanghuai region of North China was lower than the national average; from the perspective of decline, the vulnerability index of South China decreased during the sample period. The vulnerability index of the Huanghuai region in North China and the North-west region increased. (2) From the perspective of the evolution characteristics of dynamic distribution, the distribution characteristics of vulnerability and its decomposition item index showed a certain difference, the vulnerability index showed a trend of first decline and then rise, and the internal difference decreased; the exposure index showed an upward trend, and the absolute difference expanded; the sensitivity index had a certain gradient effect, showing a weak polarization; the adaptability index improved during the investigation period, and the absolute difference narrowed. (3) During the study period, the flood vulnerability index showed a downward trend, and the high vulnerability areas were mainly distributed in the middle and lower reaches of the Yangtze River; the exposure index first decreased and then increased, and the high exposure areas were mainly concentrated in the middle and lower reaches of the Yangtze River and the middle and lower reaches of the Yangtze River and South China; the sensitivity index first decreased and then increased, and the high sensitivity areas were concentrated in North-east China, the middle and lower reaches of the Yangtze River, and South China; the adaptability index showed a downward trend, and the areas with poor adaptability were mainly concentrated in the South-west and North-west area. (4) The dominant factors affecting the

vulnerability of floods and floods in China's provinces had both local consistency and their characteristics. Overall, the economic losses of fishery floods and the affected area had the greatest impact on the exposure index; fish production and freshwater fishery output has the greatest impact on the sensitivity index; the indicators with a lower contribution to the adaptability index were the total power of fishery machinery and the promotion of fishery technology. From a local point of view, each region had main factors that affect its vulnerability. The vulnerability of inland fisheries to flood disasters can be reduced only by reducing various factors according to the regional characteristics and development level can effectively reduce.

Mitigation of the impact of flood disaster on fishery production should be based on the perspective of vulnerability. The first is to strengthen the flood control system for fishery flood disasters and reduce the direct impact of flood disasters on fisheries and fishermen using climate warning, reservoir construction, and fishery insurance. The second is to optimize and adjust the layout of aquaculture productivity, build advantageous production areas for inland fishery production based on high standards, high quality and high efficiency, and simultaneously expand new space for aquaculture. Based on fully guaranteeing disaster prevention and control, other suitable areas should also be expanded scientifically. The third is to speed up the construction of modern fishery, focus on existing high-quality fishery enterprises, vigorously build the entire fishery industry chain, and increase the research and development of key technologies such as improved seed breeding, research and development, cold chain transportation, deep processing, and tail water treatment, so as to realize the integration of the industry chain.

Based on the perspective of vulnerability, this paper constructed an evaluation index system for the vulnerability of inland fisheries to floods from three aspects: Exposure, sensitivity and adaptive capacity, and the vulnerability of inland fisheries to flood disaster in China was comprehensively analyzed from the spatio-temporal scale. This has certain reference significance for China's inland fishery to prevent floods and achieve sustainable development. However, it should be noted that this study also has shortcomings. For example, limited by the availability of data, the period of this paper is small, and it is impossible to analyze the time series development of China's inland fisheries more comprehensively. In addition, due to space limitations, this paper does not conduct in-depth research on the influencing factors. Particularly, if the disaster resistance and mitigation capabilities of China's inland fisheries can be truly alleviated through effective and orderly policy support, this will be a future scientific proposition worthy of in-depth study.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://libvpn.zuel.edu.cn/s/data.cnki.net/yearbook/Single/N2021090041.

AUTHOR CONTRIBUTIONS

JZ and HL: conceptualization, formal analysis, and investigation. HL: methodology and software. HL, HO, YL, and XL: validation. JZ: resources, writing—original draft preparation, writing—review and editing, and project funding acquisition. HO, YL, and XL: data curation. JZ: supervision. All authors have read and agreed to the published version of the manuscript.

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Identification and Measurement of Multidimensional Relative Poverty of Chinese Rural Adults Considering Climate Factors

Xiaoyuan Hou[1]*, *Haitao Wu*[1]* and *Wei Wang*[2]

[1]School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China, [2]College of Management, Sichuan Agricultural University, Chengdu, China

The climate conditions in different regions of China are different, resulting in uneven climate resources owned by residents. It is important to design a comprehensive evaluation method to measure the multidimensional relative poverty (MRP) status and differences in rural areas considering climate factors from the micro-level. With adults as the research object, imitating multidimensional poverty index (MPI) and other indexes, and referring to the relative poverty lines in Britain, Australia, and other countries, this study considers the housing sunshine level and air quality of the living environment, which can reflect the superposition of economy and climate, in the dimension of human settlements environment, and establishes an indicator system of MRP in rural China. Using the Chinese General Social Survey data in 2018 and the A-F method to measure the indicator poverty rate, multidimensional relative poverty index (MRPI), and indicator contribution rate, this study evaluates the MRP in rural China including climate factors. The results show that the poverty rate of sunshine level and air quality indicator in North China is the highest in China, and the MRPI is the lowest. In North China, the sunshine level and air quality indicator poverty rate are 17.47% and 53.01%, respectively. MRPI under K = 1 standard is 0.1182. It shows that the indicator system can identify the typical phenomenon that highly industrialized economic development may negatively affect the environment. MRP alleviation should focus on coordinated governance of the economy, education, health, and the human settlements, we should establish a climate emergency plan for joint prevention and control with the meteorological department, set afforestation protection areas, set climate-related building standards such as sunshine times of rural houses, and improve and upgrade the energy use in rural areas to achieve the harmonious development of the society, economy, and environment and the high-quality life pursued by rural residents.

Keywords: multidimensional relative poverty, sunshine time, rural China, climatic factors, regional differences

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Shaoquan Liu, Institute of Mountain Hazards and Environment (CAS), China

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Guanglin Sun, Nanjing University of Finance and Economics, China
Guo ChangQing, Lanzhou University of Technology, China
Yibin Ao, Chengdu University of Technology, China

***Correspondence:**
Xiaoyuan Hou
houxiaoyuan_hxy@126.com
Haitao Wu
wuhan_haitao@aliyun.com

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1 INTRODUCTION

The Chinese mainland is vast, located in the northern hemisphere, with a wide latitude of coastline. Moreover, the terrain is different in height and topography; the combination of sunshine, air temperature, precipitation, and air circulation is diverse. For China's rural areas, sunshine conditions, as a climatic factor, affect all aspects of farmers' production and life, such as physical health, food crop cultivation, and household income from agricultural production and operation. The sunshine resources of rural residents are differentiated in the whole country. Compared with rural residents living in the South or the plains, those in northern China or mountainous areas can enjoy relatively fewer sunshine resources. Moreover, there are differences in the spatial distribution of traditional leading industries in different regions of the Chinese mainland, and the degree of pollution such as fog and haze in the local environment also varies (Luo and Li, 2018). The air pollution represented by haze has varying degrees of impact on the local living environment, including air quality and sunshine level, and exacerbated the inequality of climate resources owned by residents in different regions. Therefore, poverty research needs to consider climate factors to reveal the multidimensional poverty differences including climate resources.

After the elimination of absolute poverty in China in 2020, the focus of poverty research will shift from relative poverty in a single economic dimension to multidimensional relative poverty (Pan and Yan, 2020; Wang and Feng, 2020; Zhong and Lin, 2020; Wang and Sun, 2021), the abbreviation of multidimensional relative poverty for the latter is MRP. Existing MRP studies focus on the economy, education, health, or living standards, and pay little attention to climatic factors such as sunshine, as well as cannot identify some MRP populations affected by climate. Therefore, it is necessary to change the previous method of measuring poverty with a single income indicator and consider climate factors in the identification, measurement, and governance of MRP.

The poverty status of rural family members is not "homogeneous" (Wu et al., 2013), There are significant differences in the degree, depth, and duration of poverty among the elderly, adults, and minors (Xiong and Song, 2018). The most accurate poverty identification, measurement, and governance should be detailed from the family to the individual level. First of all, according to China's census data, China's rural population at the end of 2018, 2019, and 2020 was 541.08, 525.82 and 509.79 million respectively, And the population aged 15–64 accounted for 68.6% of the total population in 2020. The proportion of the population aged 20–59 in 2018 and 2019 was 60.17% and 59.97%, respectively. The number of rural adults aged 19–59 is not only large but also a high proportion. Rural adults are the core group of primary concern in poverty research. Secondly, most of the existing micro-recognition objects of rural poverty are families (Liu and Wang, 2020; Pan and Yan, 2020; Wang and Feng, 2020), and a few are refined to adult male or female individuals (Chen, 2020; Wang and Liu, 2020; Zhang, 2020), or special groups of adults, such as migrant workers (Yang and Zhuang, 2021). Taking family as the object of identification can only indirectly represent the poverty status of adults. The poverty status of the adult population cannot be fully presented if males or females or specific adults are identified. And lastly, adults' income is the main source of the family economy, and their development reflects the MRP status of the entire family to a certain extent. Therefore, taking adult individuals as the poverty identification object can identify and measure the inequality within rural families, and refine the existing MRP measurement scheme as the main poverty identification object. Referring to the age definition of adults and elderly groups in Chinese laws, adults in this paper are defined as those whose age is greater than or equal to 18 years old and less than or equal to 59 years old.

Imitating the multi-dimensional poverty index (MPI) and other indexes, and referring to the relative poverty measurement schemes of China, the UK, and Australia, this paper attempts to use the latest 2018 survey data of the Chinese General Social Survey (the abbreviation for the latter is CGSS) to build an indicator system for rural adult MRP measurement based on the individual level. Moreover, it aims to compare and analyze the status and characteristics of rural adult MRP, find out the key indicators that lead to the MRP of rural adults, and provide a theoretical basis for improving the policy.

2 LITERATURE REVIEW AND THEORETICAL BASIS

2.1 Literature Review

Most of the existing academic research about climate poverty focuses on the climate's impact on poverty (Leichenko and Silva, 2014; Hallegatte and Rozenberg, 2017; Barbier and Hochard, 2018). Haines and Ebi (2019) found that climate change has an adverse impact on human health and health systems. Climate change will also affect household income. Arouri et al. (2015) used fixed-effect regression to estimate the impact of natural disasters on the welfare and poverty of rural households in Vietnam and found three types of disasters, including storms, floods, and droughts, had negative impacts on household income and expenditure. In addition, some scholars have studied the impact of climate change on migration (Cattaneo and Peri, 2016; Marotzke et al., 2020), food production (Ahmed et al., 2011; Tigchelaar et al., 2018), and labor productivity (Burke et al., 2015).

Sen's (1999) feasible capability theory states that poverty needs to be measured from the aspects of individual feasible capability as well as freedom, including health, education, public service, spirit, and other dimensions, which instill a theoretical foundation for integrating climate factors into multidimensional poverty research. After this, the international research on multidimensional poverty paid more attention to individual development and subjective feelings and emphasized the importance of the living environment. Currently, the multidimensional poverty of families or individuals at the micro-level is mostly studied by combining non-monetary indicators such as education, health, and living environment with monetary indicators such as the economy (Alkire and Apablaza, 2016; Chen et al., 2017; He et al., 2017; Pérez-Cirera et al., 2017; Li S. et al., 2020; OPHI, 2020). The multidimensional poverty indicator system in some studies considered climate factors. Kahlan et al. (2021) set up a climate-related indicator system including "disaster preparedness" and "people affected by drought" to measure the multi-dimensional poverty of Iranian families. Zhang et al. (2019) considered China's photovoltaic poverty alleviation areas as the object and included sunshine time and other indicators in the identification scope of multidimensional poverty. Yin et al. (2017) took into account the climate-related index of natural disasters in the multidimensional poverty indicator system of remote poverty alleviation and relocated families in China. Zhou et al. (2021) considered 124,000 poverty-stricken villages identified by China's targeted poverty alleviation at the end of 2013 as the research object, and selected climate-related indicators such as temperature change, precipitation change, and natural disasters to measure multi-dimensional poverty in villages.

After China eliminated absolute poverty in 2020, multidimensional poverty was transformed into MRP. Xu et al. (2021) selected climate-related indicators such as precipitation and used counties of 31 provinces (municipalities) in China as the research object to measure the MRP at the macro level. Wei and Zhang (2021) set a disaster area indicator reflecting climate factors to measure MRP in Rural Areas of China.

Generally, the existing research began to include some climate factors in the identification and measurement of multidimensional poverty but it was mainly aimed at special scenarios such as disasters and photovoltaics, and there is a lack of poverty research in normalized scenarios. Few articles directly consider normal climate indicators such as sunshine and air quality when constructing a multidimensional relative poverty index, the abbreviation of multidimensional relative poverty index for the latter is MRPI. The research objects include counties or villages at the macro level and families at the micro level, which are not detailed at the individual level. Therefore, based on the existing academic achievements, this paper considers rural adults as the research object, integrates climate factors into the MRP indicator system, and considers the normalized living environment after the superposition of the economy and climate as the scenario to measure and reveal the MRP status and regional differences of Chinese rural adults under the joint action of economy and climate.

2.2 Theoretical Basis

As the literature review shows, the theoretical analysis of the formation mechanism of MRP in Rural China is fragmented at present. However, the mechanism of MRP among rural adults in China can be sorted out from existing literature. The existing literature on MRP involves four dimensions: economic, education, human settlements, and health. Among them, capital scarcity and low investment efficiency are important causes of economic poverty in China's rural areas (Huang et al., 2016). An income gap in the process of economic growth also leads to economic poverty in China's rural families (He, 2018). The formation of educational poverty is caused by the low level of human capital (Cheng et al., 2016), the uncertainty of the return on education investment (Gustafsson and Li, 2004), and the unequal distribution of education resources (He, 2018). Sunshine level, air pollution (Duan and Wang, 2020), geographical location of housing, and other factors together lead to poverty in China's rural human settlements (Zhang and Jin, 2006). The reason why climate factors should be considered in the dimension of human settlements is that a livable environment cannot be separated from clean air, sufficient sunshine, appropriate temperature and humidity, and other factors closely related to climate. The temperature and humidity of the living environment largely depend on the sunshine level. China's "Urban Residential District Planning and Design Standard" clearly stipulates that the sunshine time of houses shall not be less than 1 hour. In addition, a high-quality living environment also needs clean air. In terms of health poverty, the unequal distribution of medical resources in rural China and the lack of health knowledge among rural residents lead to health poverty (He, 2018; Wang and Liu, 2019).

The MRP of rural adults in China is dynamic, which is mainly manifested in three aspects: time, region, and population. In terms of time, the MRP of rural adults in China changes over time. In terms of regions, China can be divided into seven regions: Northeast, North, Northwest, East, Central, South, and Southwest. The MRP of these seven regions not only varies but also changes. In terms of population, the poverty degree of the MRP population will change. If the MRP degree of rural adults increases, the non-poverty population may change into an MRP population. If the MRP of rural adults in China is alleviated, the MRP population will be transformed into a non-poverty population.

3 MRP IDENTIFICATION STANDARD OF CHINESE RURAL ADULTS CONSIDERING CLIMATE FACTORS

Sen (1999) believes that poverty not only needs to be considered from economic dimensions such as income but also needs to find out whether people's capability is deprived. Therefore, the cognition of poverty needs to be increased from a single "income" dimension to a multidimensional dimension such as education opportunities and health level, which also requires that poverty measurement methods adapt to the needs of multi-dimensional measurement. The World Development Report released by the World Bank in 2000 defines poverty as the deprivation of welfare. Poverty not only refers to material deprivation but also includes low levels of education and health. People gradually realize that poverty is a complex and comprehensive social phenomenon, in addition to income, poverty also involves the lack of multiple dimensions such as education, health, housing, and public goods (Ding, 2014). China's poverty alleviation standard for the poor is "Two Assurances and Three Guarantees, that is, assured food and clothing, and guaranteed education, medical treatment, and housing. By 2020, China eliminated the population in absolute poverty, and the basic needs such as food, clothing, education, medical treatment, and housing of rural residents have been guaranteed. The expectations of rural residents for a better life are diversified, multi-level, and multifaceted: rural residents are looking forward to better education, more satisfactory income, higher level of medical and health services, more comfortable living conditions, more beautiful environment, and higher quality living environment. Therefore, along with the dimensions of economy, health, and education, this paper also adds human settlements including climate factors to more comprehensively evaluate the MRP status of rural adults in China.

3.1 Economic Dimension

Based on the simple and easy to operate income proportion method first proposed by Townsend (1979), the EU, OECD, and other regional, international organizations and countries generally set the identification standard of relative poverty as a proportion of average income or median income in practice (Li et al., 2021). Taking high-income countries such as the UK and Australia as examples, the relative poverty standard adopted by the UK is 60% of the median income (JRF, 2020), and that by Australia is 50% and 60% of the median household disposable income (Davidson et al., 2018). Most Chinese scholars believe that the relative poverty line of income should be set to be 40%, 50%, or 60% of the median per capita income (Shen and Li, 2020; Zhang and Duan, 2020). The proportion of median income adopted as the identification standard of relative poverty depends on a country's income level and the government's willingness to alleviate relative poverty; for China, the problem of unbalanced and insufficient development is serious, and the per capita income level lags behind that of high-income countries. Therefore, we cannot directly learn from the identification criteria in high-income countries; after the absolute poverty standard is changed to the relative poverty standard, to alleviate its impact on the poverty alleviation policy, it is reasonable to use the median income of 40% as the relative poverty standard (Li X. H. et al., 2020). Considering China's actual and international experience, this paper selects the median per capita income of 40% of households as the income poverty line of the economic dimension. If the per capita income of households is less than the poverty line, it is assigned as 1, which is in the state of poverty, otherwise, it is 0, which indicates non-poverty.

3.2 Health Dimension

Health itself, as a kind of capital, is both a kind of wealth and an investment product (Wang and Liu, 2006). Having a healthy body can bring more social opportunities, and the level of health has a direct impact on individual labor productivity and social labor productivity. Disease itself not only affects income but also reduces the quality of life of patients, leading to poverty, the afflicted having less capital, and fewer development opportunities. In this paper, the self-rated physical health and the number of hospitalizations for illness with better data availability are selected to comprehensively reflect adults' health. The self-rated health indicator reflects the perceptual evaluation of rural adults, and the number of hospitalizations reflects their health status. If the self-rated body is significantly unhealthy or relatively unhealthy, the value is 1. If it is relatively healthy or significantly healthy, the value is 0. The value for respondents who have been hospitalized due to illness in the past 12 months is 1, otherwise, it is 0.

3.3 Education Dimension

Education plays an obvious role in expanding individual social opportunities and is also an important way to accumulate cultural capital. The higher the level of education, the more likely individuals are to move to the upper strata of society; On the contrary, the lower the level of education, the more likely individuals are to move to the bottom of society or even fall into relative poverty (Thomas, 2021). As an important labor force in the family, the education status of rural adults plays an important role in the choice and development of livelihood strategies for themselves and their families (He et al., 2019). Therefore, it is also a key dimension to identify MRP. The education level reflects the self-development ability of adults. The indicator level below junior middle school is assigned as 1, otherwise, it is 0. The frequency of reading books, newspapers, or magazines in free time can reflect the acquired habit of continuing education. Hence, if the frequency of reading in free time is daily, or several times a week, a month, or a year or less, it is assigned as 0, and for people who never read, they are assigned 1.

3.4 Human Settlements

From 2014 to 2022, the first document annually issued by the Chinese central government mentioned the improvement of the rural residential environment. The climate-related living environment includes sunshine, rainfall, temperature, and air quality. The climatic factors such as rainfall and temperature are exogenous variables, and most are determined by regional climatic conditions. However, the sunshine level of the respondents' residential houses and the air quality of the self-rated residential environment are determined by climatic factors, local economic development level, and affected by personal decision-making factors such as the owner's building site, orientation, and floor. It can better reflect personal feelings about the sunshine time of residential houses and the air quality of the living environment. According to the division of China's climate zones and the number of urban permanent residents, the sunshine time of residential buildings should be more than two or 3 hours on a cold day and more than 1 hour on the winter solstice. Considering that the residential population density in rural areas is much lower than that in cities, and the sunshine time of houses is more abundant, the average in winter is less than 2 hours, which is assigned as one and greater than or equal to 2 hours, which is assigned as 0. Regarding the air quality of the indicator living environment, if the respondents agree or significantly agree that the air quality is good, the value is 0; otherwise, the air quality is poor, and the value is 1. See **Table 1** for specific dimensions and indicator selection, critical values, and weights.

TABLE 1 | MRP indicator system of Chinese rural adults considering climate factors.

Dimension	Indicator	Criticality and assignment	Weights
Economic dimension	Per capita household income	If less than the median of 40% of the per capita income of households, then it is assigned as 1, otherwise it is 0	1/4
Health dimension	Self-rated health	Self-evaluation as significantly unhealthy and relatively unhealthy is assigned as 1, otherwise, it is 0	1/8
	Number of sick hospitalizations	In the past 12 months, the number of hospitalizations due to illness is assigned as 1, otherwise, it is 0	1/8
Education dimension	Education level	Below junior middle school is assigned as 1, otherwise, it is 0	1/8
	Frequency of reading in free time	If never read a book, newspaper, or magazine in the past year, the value is assigned as 1, otherwise, it is 0	1/8
Human settlements	Housing sunshine level	If the average sunshine time of residential houses in winter is less than 2 h then the assigned value is 1, otherwise, it is 0	1/8
	Air quality of living environment	If agree or strongly agree that the air quality of the living environment is good then it is assigned as 0, otherwise, it is 1	1/8

4 MRP MEASUREMENT RESULTS OF CHINESE RURAL ADULTS CONSIDERING CLIMATE FACTORS

4.1 Data Sources and Research Methods

This paper adopts CGSS, which covers the survey data from 2003 to 2018, as the main data source for the study of Chinese society. It is widely used in scientific research, teaching, and government decision-making. The sunshine time data was added in 2018. In this paper, the latest data from 2018 were used to obtain a sample of 1,311 adults in rural China after data cleansing. This article will further refine the data into seven areas in rural China, respectively, the Northeast (Heilongjiang Province, Jilin Province, and Liaoning province), East China (Shanghai Municipality, Jiangsu Province, Zhejiang Province, Anhui Province, Fujian Province, Jiangxi Province, Shandong Province, Taiwan province), North China (Beijing, Tianjin Municipality, Shanxi Province, Hebei Province, Inner Mongolia autonomous region), Central China (Henan Province, Hubei Province, Hunan Province), South China (Guangdong Province, Guangxi Zhuang Autonomous Region, Hainan Province, Hong Kong Special Administrative Region, Macao Special Administrative Region), Southwest China (Sichuan Province, Guizhou Province, Yunnan Province, Chongqing Municipality, Tibet Autonomous Region), and Northwest China (Shaanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region). Among them, the database does not have data for Taiwan Province, Hainan Province, Tibet autonomous Region, Xinjiang Uygur Autonomous Region, or the Hong Kong and Macao special administrative regions.

This paper uses the A-F method, which is widely used by the United Nations and other organizations and many scholars to calculate multidimensional poverty, to measure the MRP of rural adults. A-F method includes two Cutoffs, also known as the dual Cutoff Identification Approach. The first step is to set multidimensional poverty indicators and corresponding indicator deprivation critical values. The second step is to calculate the aggregate deprivation score of an individual and set the aggregate deprivation critical value. If the aggregate deprivation score of an individual exceeds this critical value, it is identified as multidimensional poverty (Alkire and Foster, 2011).

Assuming that the rural individuals are composed of n individuals, each rural individual investigated is set as y_{ij} at different indicators. y_{ij} represents the value of individual i on indicator j, where and j together form the $n \times d$ matrix. The matrix consists of the row vector $y_i = (y_{i1}, y_{i2}, \ldots y_{id})$ and column vector $y_j = (y_{1j}, y_{2j}, \ldots y_{nj})$, where, the row vector is the poverty status of rural individual i in d indicators, and the column vector is the investigated status of rural individuals n in j indicators.

Defines a vector z_j $(z_j > 0)$, this vector is the deprivation threshold for the y matrix, that is, the poverty line on the j indicator, and z is the poverty line vector of any indicator. After the first cut off, the y matrix will evolve into a deprivation matrix composed of 0 and 1:

$$g_{ij} = \begin{cases} 1, x_{ij} < z_j \\ 0, x_{ij} \geq z_j \end{cases} \tag{1}$$

$g_{ij} = 1$ means that when rural individual i is deprived of indicator j, if $g_{ij} = 0$ means that rural individual i is not deprived of indicator j. Represents the poverty of individual i in indicator j. Meanwhile, define a column vector $c_i = \sum_{j=1}^{d} g_{ij}$ to represent the sum of the total number of deprivation indicators undertaken by the i indicator.

This paper uses the equal-weighted method, to sum up the deprivation values of various indicators of MRP. Let the weight vector be w. One element w_j is the weight for indicator j. Let $\sum_{j=1}^{d} w_j = d$, that is, the sum of weights of all rural individuals in the j indicator is equal to d.

K represents the threshold of the indicator, c_i represents the sum of the weight of the indicator of deprivation of the individual i, and compared with the value of K, the identification function ρ_k of poverty-deprived individuals after the second cutoff is obtained.

$$\rho_k = \begin{cases} 1, c_i \geq K \\ 0, c_{ij} < K \end{cases} \tag{2}$$

If $\rho_k = 1$, individuals are identified as MRP population, and if $\rho_k = 0$, individuals are identified as non-MRP population. In order to obtain the final M_0 (MRPI), let $M_0 = \mu(g(k)) = HA$, where $g(k)$ is a new matrix of non-MRP populations with a value of 0 in each indicator, and H is the (multidimensional) headcount

TABLE 2 | Overall indicator poverty rate of Chinese rural adults including climate factors (units: %).

Indicator	Per capita household income	Self-rated health	Number of sick hospitalizations	Education level	Frequency of reading in free time	Housing sunshine level	Air quality of living environment
China	39.21	64.45	22.12	16.86	14.42	7.7	28.07
Northeast	43.86	69.59	27.49	23.98	13.45	4.68	30.41
North	23.49	51.81	7.23	12.05	7.83	17.47	53.01
Northwest	41.32	69.42	24.79	31.4	19.01	11.57	11.57
East	35.94	60.58	12.46	12.46	12.46	5.51	29.57
Central	36.71	68.6	28.02	14.98	17.39	4.35	29.47
South	38.46	56.41	26.92	6.41	15.38	1.28	24.36
Southwest	53.81	72.2	35.43	18.83	18.83	9.42	14.35

ratio. If an individual is deprived in more than K indicator, it belongs to the MRP population. A is the average deprivation share among the poor.

4.2 Indicators of Poverty Include the Results of Climate Factors

Table 2 shows the indicator poverty rate of rural adults in different regions of China calculated according to the MRP indicator system of rural adults including climate factors. As seen in the overall indicator poverty rate of China in **Table 2**, the education level in the education dimension indicators and the frequency of reading, newspapers, or magazines in free time show higher poverty rates, both exceeding 39%. The poverty rate of air quality in the dimension of human settlements is 28.07%, ranking third among all seven indicators, but the poverty rate of the housing sunshine level indicator is low, which is 7.70%. Generally, the poverty of air quality indicator is prominent in China, while that of the housing sunshine level indicator is not.

North and Northwest regions of housing sunshine level indicator poverty rate are over 11%, while other areas of the housing sunshine level indicator poverty rates are below 9.5%. Northwest and Southwest air quality of living environment indicator poverty rates are less than 14.4%, while in the Central, South, Northeast, and East regions the air quality of living environment indicator poverty rates is between 24% and 30.5%, The poverty rate of air quality of the living environment in the North is 53.01%. Comparing the indicator poverty rates for the Northeast, East, Central, South, Southwest, and Northwest with North China shows that the indicators of air quality and housing sunshine level in North China are the poorest. The housing sunshine level in South China and the air quality in Northwest China are the best. The economy and industry of North China are relatively developed, with severe haze in winter, and its geographical location is in the north of China. Therefore, the poverty rate of housing sunshine level, and air quality indicators in this region are the highest, but that of economic and educational indicators is the lowest. The results show that the MRP including sunshine level and air quality indicators can reveal the regional poverty difference of human settlements under the double superposition of climate and economic factors.

4.3 MRP Index Including Climate Factors

K = 1, 2, or 3 respectively indicate that rural adults have MRP with more than one dimension, two dimensions, or three dimensions. The MRP indicator system has four dimensions, and K can be assigned as 1, 2, or 3. Among them, the K = 1 standard can identify the MRP population with more than one dimension, two dimensions, and three dimensions, and the incidence of MRP under the K = 1 standard is the highest. The K = 2 standard can identify the MRP population with more than two dimensions and more than three dimensions, whose incidence of MRP is less than the MRP rate under the K = 1 standard. The K = 3 standard can identify the MRP population in more than three dimensions, and the incidence of MRP under this criterion is the lowest. **Table 3** describes the incidence of poverty, average deprivation degree, and MRPI of rural adults in various regions of China when K = 1, 2, and 3. When K = 1, the MRPI for the 7 regions are ranked from high to low as Southwest, Northeast, Northwest, Central, South, East, and North China. When K = 2, the MRPI indices for the 7 regions from high to low are Northeast, Northwest, Southwest, Central, East, South, and North China. When K = 3, only the Northwest, East, and Southwest regions of MRPI have more than three dimensions of MRP population, while the incidence of MRP in other regions is 0.

Comparing the MRP measurement results of China's overall, Northeast, East, North, Central, South, Southwest, and Northwest China in **Table 3**, we find that there are regional differences in China's MRP situation. North China is the richest in the country, with the lowest MRPI, and the MRP situation in this area is the least serious, while Southwest China and Northeast China have higher MRPI under the standard of K = 1, 2, or 3, and show a relatively serious MRP condition.

4.4 Contribution Rate of MRP Dimension and Indicator Including Climate Factors

Tables 4, **5** further break down the MRP considering climate factors to obtain the contribution rates of different dimensions and indicators of rural adults in China and Northeast, East, North, Central, South, Southwest, and Northwest China regarding MRP. By comparing the measurement results of the contribution rates of different dimensions to MRP in **Table 4**, it can be seen that the contribution rates of different dimensions in China are education, economic, health, and human settlements in

TABLE 3 | MRP measurement results of Chines rural adults including climate factors.

K	K = 1			K = 2			K = 3		
Measured value	Incidence of poverty	Average deprivation degree	MRPI	Incidence of poverty	Average deprivation degree	MRPI	Incidence of poverty	Average deprivation degree	MRPI
China	0.3509	0.4864	0.1707	0.0847	0.3367	0.0285	0.0038	0.3000	0.0011
Northeast	0.3801	0.5385	0.2047	0.1579	0.3356	0.0530	0.0000	0.0000	0.0000
North	0.2711	0.4361	0.1182	0.0241	0.3281	0.0079	0.0000	0.0000	0.0000
Northwest	0.4050	0.5026	0.2035	0.1322	0.3359	0.0444	0.0083	0.2917	0.0024
East	0.2638	0.4629	0.1221	0.0522	0.3333	0.0174	0.0058	0.2917	0.0017
Central	0.3865	0.4828	0.1866	0.0821	0.3382	0.0278	0.0000	0.0000	0.0000
South	0.3333	0.4567	0.1522	0.0385	0.3125	0.0120	0.0000	0.0000	0.0000
Southwest	0.4664	0.4988	0.2326	0.1166	0.3438	0.0401	0.0090	0.3125	0.0028

TABLE 4 | Contribution rate of dimensions considering climate factors.

Dimension	K-value	Economic dimension	Health dimension	Education dimension	Human settlements
China	K = 1	0.3017	0.1822	0.404	0.1123
	K = 2	0.3378	0.2191	0.3378	0.1054
	K = 3	0.2778	0.2500	0.2778	0.1944
Northeast	K = 1	0.3214	0.1857	0.3821	0.1107
	K = 2	0.3448	0.2138	0.3310	0.1104
	K = 3	0.0000	0.0000	0.0000	0.0000
North	K = 1	0.1401	0.1528	0.4459	0.2611
	K = 2	0.2857	0.0952	0.3334	0.2857
	K = 3	0.0000	0.0000	0.0000	0.0000
Northwest	K = 1	0.2944	0.2386	0.3756	0.0914
	K = 2	0.3488	0.2442	0.3372	0.0698
	K = 3	0.2857	0.1429	0.2858	0.2858
East	K = 1	0.2315	0.2077	0.4303	0.1305
	K = 2	0.2917	0.2604	0.3333	0.1146
	K = 3	0.2857	0.2858	0.2858	0.1429
Central	K = 1	0.3495	0.1682	0.3883	0.0939
	K = 2	0.3696	0.1848	0.3370	0.1087
	K = 3	0.0000	0.0000	0.0000	0.0000
South	K = 1	0.4211	0.1368	0.3579	0.0842
	K = 2	0.4000	0.1333	0.4000	0.0667
	K = 3	0.0000	0.0000	0.0000	0.0000
Southwest	K = 1	0.3470	0.1638	0.4169	0.0722
	K = 2	0.3357	0.2308	0.3426	0.0909
	K = 3	0.2667	0.2666	0.2666	0.2000

descending order. By region, under K = 1 and K = 2 standards, the contribution rate of human settlements dimension in the North is higher than that of the health dimension, while that of other regions is lower than that of the health dimension. Under the K = 3 standard, the contribution rate of human settlements' environment and economic dimensions in the North is 0.

Regarding China as a whole in **Table 5**, when K = 1, 2, or 3, the contribution rate of income indicator is the highest, and that of the housing sunshine level of residential houses and self-rated air quality indicator are low. In terms of regions, when K = 1, for Northeast, Northwest, and Southwest regions, frequency of reading in free time and per capita household income are the indicators with higher contribution rates, while number of sick hospitalizations, housing sunshine level, and air quality of living environment are the indicators with lower contribution rates. For North China, the indicator contribution rate of education level, frequency of reading in free time, and air quality of living environment is higher, while the contribution rate of the number of sick hospitalizations is lower. For East China, the contribution rate of education level, frequency of reading in free time, and per capita household income is higher, while the contribution rate of housing sunshine level is lower. For central China, the contribution rate of frequency of reading in free time and household per capita household income is higher, while the contribution rate of housing sunshine level is lower. For South China, the contribution rates of frequency of reading in free time and per capita household income are higher, while the contribution rates of self-rated health and housing sunshine level are lower.

Regarding regions, different from the other six Chinese regions, the economically developed North China has higher indicator contribution rates of sunshine level and air quality in

TABLE 5 | Contribution rate of indicators considering climate factors.

Indicator	K value	Per capita household income	Self-rated health	Number of sick hospitalizations	Education level	Frequency of reading in free time	Housing sunshine level	Air quality of living environment
China	K = 1	0.3017	0.1034	0.0788	0.1777	0.2263	0.0324	0.0799
	K = 2	0.3378	0.1321	0.0870	0.1605	0.1773	0.0368	0.0686
	K = 3	0.2778	0.1389	0.1111	0.1389	0.1389	0.0833	0.1111
Northeast	K = 1	0.3214	0.1214	0.0643	0.1750	0.2071	0.0286	0.0821
	K = 2	0.3448	0.1379	0.0759	0.1517	0.1793	0.0414	0.0690
	K = 3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
North	K = 1	0.1401	0.0955	0.0573	0.1720	0.2739	0.0955	0.1656
	K = 2	0.2857	0.0476	0.0476	0.1429	0.1905	0.0952	0.1905
	K = 3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Northwest	K = 1	0.2944	0.1675	0.0711	0.1624	0.2132	0.0457	0.0457
	K = 2	0.3488	0.1744	0.0698	0.1744	0.1628	0.0349	0.0349
	K = 3	0.2857	0.1429	0.0000	0.1429	0.1429	0.1429	0.1429
East	K = 1	0.2315	0.1098	0.0979	0.1929	0.2374	0.0237	0.1068
	K = 2	0.2917	0.1458	0.1146	0.1458	0.1875	0.0208	0.0938
	K = 3	0.2857	0.1429	0.1429	0.1429	0.1429	0.0000	0.1429
Central	K = 1	0.3495	0.0841	0.0841	0.1553	0.2330	0.0065	0.0874
	K = 2	0.3696	0.1196	0.0652	0.1522	0.1848	0.0000	0.1087
	K = 3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
South	K = 1	0.4211	0.0526	0.0842	0.1579	0.2000	0.0105	0.0737
	K = 2	0.4000	0.0000	0.1333	0.2000	0.2000	0.0000	0.0667
	K = 3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Southwest	K = 1	0.3470	0.0843	0.0795	0.1976	0.2193	0.0361	0.0361
	K = 2	0.3357	0.1259	0.1049	0.1748	0.1678	0.0629	0.0280
	K = 3	0.2667	0.1333	0.1333	0.1333	0.1333	0.1333	0.0667

the dimension of human settlements than the self-rated health and the number of sick hospitalizations in the dimension of health. Similar to the results in **Table 2**, the characteristics of indicator contribution rate in North China also show that for economically developed regions in Northern China, MRP including sunshine level and air quality indicator can measure the difference in indicator contribution rate between regions under the superposition of climate and economy. This further shows that the sunshine level and self-rated air quality are the indicators to be selected, and their necessity exceeds the self-rated health and the number of sick hospitalizations in the health dimension.

5 RESEARCH CONCLUSION

Relative poverty, which takes climate into account, needs to be measured in multiple dimensions. The multidimensional poverty measurement method has achieved good results in China, and the multidimensional poverty identification and withdrawal criteria of "Two Assurances and Three Guarantees" in Rural China have laid a solid foundation for the MRP identification, measurement, and governance. However, poverty also exists in the dimensions of health, education, and human settlements. In **Table 2**, the poverty rate of the self-rated health indicator in the health dimension is higher than that of the Per capita Household income indicator in the economic dimension. For the North region, the indicator poverty rate of Air quality of living environment in the dimension of human settlements exceeds that of Per capita household income. Wang and Feng (2020) also conclude that China's relative poverty needs multidimensional measurement, and suggested that the MRP indicator system should include human settlements factors.

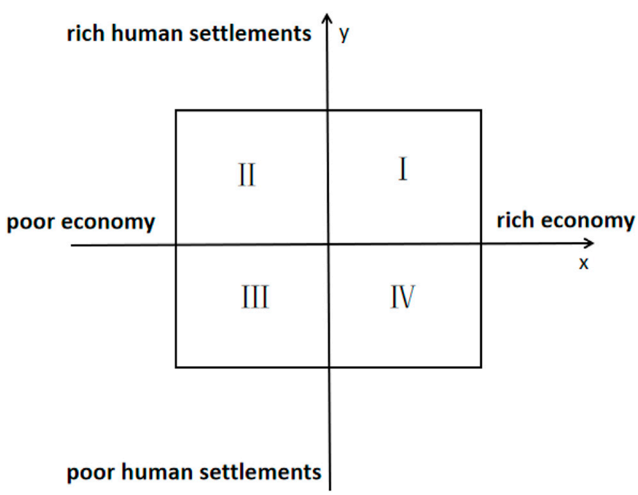

FIGURE 1 | Regional classification of economic climate superposition.

The housing sunshine level and the air quality indicator of living environment are the comprehensive embodiment of people's micro-climate, economic development, and pollution degree. As shown in **Table 2**, the indicator poverty rate of housing sunshine level in North China is the highest, 17.47%, and that in

South China is the lowest, 1.28%. The poverty rate of air quality of living environment indicator in North China is the highest, 53.01%, and the lowest in Northwest China at 11.57%. Selecting the indicators of the sunshine level and air quality can measure the regional differences of MRP in China under the superposition of economic climate.

According to the results of the MRP measure, the Chinese mainland can be divided into four types. As shown in **Figure 1**, the horizontal axis represents the regional economic development level and the vertical axis represents the quality of regional human settlements. Region I is an area with a rich economy and human settlements, region II has a poor economy but rich human settlements, region III has a poor economy and poor human settlements, and region IV has a rich economy but poor human settlements. The poverty and contribution rates of economic indicators in North China are low; however, the indicator poverty rate and the contribution rate of the dimension of human settlements are high. Hence, this area is a typical representative of region IV, being economically rich but its human settlements poor. Southwest China is a typical representative of region II with rich human settlements but a poor economy. The indicator poverty rate and the contribution rate of the economic dimension are at a high level, but the indicator poverty rate and the contribution rate of the human settlements dimension are low. The classification of regions will change with the changes in regional economic development level and human settlement. Region Ⅱ (economic development level in poverty but human settlements rich) will change into region Ⅰ (level of economic development and human settlements rich) by developing the local economy, but if the economic development has brought the serious pollution, the region Ⅰ will change into region Ⅳ (economic development level rich but human settlements poor).

The measurement results in North China show that the relevant indicators of climate factors such as housing sunshine level and air quality can identify the poor people with lack of sunshine and poor air quality, and measure the regional MRP difference caused by the superposition of economic climate. The industrialization and economic level of North China are higher than the Chinese mainland, but it also brings haze pollution (Li, 2018). This reveals a typical phenomenon of regional social and economic development: the highly industrialized economic development may be at the expense of the environment, which is a “blind spot” of MRP measure and does not consider sunshine and air factors. This study has made up for this shortcoming. Therefore, identifying and measuring the poverty in the dimension of human settlements will help in studying and formulating targeted governance measures. Some such measures are as follows: Strengthen departmental cooperation and establish climate emergency plans for joint prevention and controlling the meteorological department. Set afforestation protection areas to prevent over-exploitation of forest and other green areas. Drawing lessons from the building standards of urban houses, setting construction standards for rural houses in terms of climate such as sunshine hours and rectifying a number of rural houses that lack sunshine. Improve and upgrade the energy use structure in rural areas and promote the use of clean and efficient energy. Improve the environmental protection awareness of rural people, and include them in the knowledge system of compulsory education. The typicality of North China has certain enlightenment for China and other economies in the world to realize the harmonious development of the economy and environment. Only by considering the poverty governance of regional economic development and human settlements, we can comprehensively realize the high-quality life pursued by rural residents.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

XH conceived the idea for this study. XH conducted the statistical analysis. HW and WW contributed to the final write-up.

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Predicting a Suitable Distribution Pattern of Dominant Tree Species in the Northwestern Sichuan Plateau Under Climate Change and Multi-Scenario Evaluation of Carbon Sink Potentials

Guangjie Wang[1,2], Xuemei Han[2]*, Chen Yang[2] and Jiangcheng Qian[2]

[1]The Institute of Geography and Resources Science, Sichuan Normal University, Chengdu, China, [2]Key Lab of Land Resources Evaluation and Monitoring in Southwest, Ministry of Education, Chengdu, China

Climate change threatens the global living environment, and afforestation-based carbon sequestration is an effective measure to relieve and adapt to climate changes. In this study, the ideal distribution patterns of *Abies*, *Picea*, *Quercus*, and *Betula* species in forests in Mao County, China, were simulated and predicted, respectively, using the maximum entropy niche model, MaxEnt. Afterward, suitable distribution patterns of the four dominant tree species under different scenarios were simulated by overlaying suitable distribution areas for each species. Subsequently, the total carbon sinks of the suitable distribution patterns were estimated by combining the biomass expansion factors (BEFs). The optimal scenario for carbon sequestration was found by comparing the total carbon sinks under different scenarios. By comparing the results with existing forest resources in Mao County, the maximum increase of the carbon sink potential was estimated. The results demonstrated the following: 1) the MaxEnt model has a good simulation effect and the average AUC of the four tree species is higher than 0.8, indicating that the potential distribution areas of the dominant tree species have relatively high accuracy in model simulation. 2) The suitable area size order of the four dominant tree species is *Picea* > *Abies* > *Betula* > *Quercus*. The total suitable area is 295,593.28ha. The order of biomass of the four tree species per unit area is *Abies* > *Betula* > *Picea* > *Quercus*. 3) When it is suitable to plant multiple tree species simultaneously, the planting combination mode of the trees was chosen according to biomass to obtain maximum carbon reserves. The carbon reserve of this combination mode was 15.81 Tg C. 4) Compared with existing forest resources, the maximum carbon reserve potential of the four dominant tree species can increase to 2.13 Tg C in the future. In this study, suitable distribution patterns and carbon sink potentials of the four dominant tree species in the northwestern Sichuan Plateau were analyzed and predicted. The results provided a reference for afforestation plans, tree species selection, and regional distribution layouts for future carbon sequestration projects in the plateaus. The study is beneficial for increasing economic benefits and the ecological value of forest carbon sinks in plateaus.

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Dingde Xu, Sichuan Agricultural University, China

Reviewed by:
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Fei Liu, Institute of Mountain Hazards and Environment (CAS), China

***Correspondence:**
Xuemei Han
xm_han0513@126.com

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1 INTRODUCTION

Global climate warming has many adverse effects on food security, health, the environment, and social-economic development. It has become a global challenge that threatens human survival and sustainable development. Greenhouse gas emissions caused by human activities are major causes of global climate warming at present. There are two major pathways to lowering the concentration of greenhouse gases in the atmosphere: decreasing "carbon sources" and increasing "carbon sinks". Forests are the largest carbon pool in terrestrial ecosystems. They have an irreplaceable role in lowering concentrations of greenhouse gases and are an important pathway to relieving global climate change effectively (Canadell and Raupach, 2008). Recently, the carbon sink problem of forests has become a research hotspot in relevant fields. Forest ecosystems have rich species diversity and a complicated hierarchical structure (Kurz and Apps, 1993). The carbon sequestration capacity of forest ecosystems on a regional scale is measured according to estimations of carbon reserves of forest resources. Different forest distribution patterns and forest population structures may have different carbon reserves (Kaul et al., 2010). Moreover, increasing the forest stock volume unscientifically may break the balance of terrestrial ecosystem elements. Therefore, studying the suitable distribution pattern of dominant tree species in the region and evaluating their carbon sink potential based on this distribution pattern will have important theoretical and practical significance to increase the carbon sequestration capacity and ecological benefit in these regions.

In previous studies on forest carbon sinks, scholars analyzed the characteristics of forest carbon sinks from the perspectives of the estimated carbon sink volume of the global forest system (FRA, 2015; Pan et al., 2011); biomass, carbon reserves, and the carbon sequestration potential of specific tree species (Kaul et al., 2010; Hariyadi et al., 2019); carbon sequestration, the emission-reduction potentials of forests, and the cost of carbon sequestration projects in different regions and at different climate temperature belts (Raihan et al., 2019); and total carbon reserves and the economic value of carbon sinks in forest landscape ecosystems (Nereoh et al., 2022). Estimating the carbon sink potential of forests based on suitable tree species in plateau mountain areas is yet to be studied.

To predict the dominant tree species in a region, it is important to estimate the carbon sink potential of forests in a region. At present, studies on tree species mainly involve the influence of climate change on tree species distribution (Dyderski et al., 2018), the prediction of temporal-spatial distribution variations of dominant tree species in a region (Chakraborty et al., 2016), and changes in tree species distribution under the climate model using the DISTRIB model (Iverson et al., 2019). All of these studies have focused on forest protection and management, and few were concerned with the ecological value of tree species distribution. In other words, few studies analyzed the ecological benefits of species distribution from the perspective of afforestation-based carbon sequestration.

For studies on the prediction of species distribution, species distribution models based on maximum entropy (MaxEnt) and machine learning theory, that is, niche models, have been widely applied to study the potential distribution scope and laws of species in the study area. Based on the maximum entropy theory, MaxEnt evaluates niches of species with a specific algorithm by combining the distribution time-point data of species and corresponding environmental variables. Then, it reflects the adaptation of species to their habitat according to the entropy value (or probability) through machine learning simulation and establishes a prediction model of the most suitable growth of different species (Elith et al., 2011). Geographical environmental factors have important influences on the distribution features of different species. This model is of significance to the study of the spatial distribution of species under environmental and climate change by establishing laws between environmental factors and species distributions.

Afforestation is one of the most effective methods to improve the climate and environment and relieve climatic changes. Choosing the appropriate tree species and creating the optimal carbon sink is the most important problem in carbon sequestration based on afforestation. In this study, Mao County in the northwestern Sichuan Plateau was chosen as the study area. Using the ecological niche model MaxEnt, suitable distribution patterns of four dominant tree species (*Abies*, *Picea*, *Quercus*, and *Betula*) were discussed. The carbon sink capacities of four dominant tree species under different scenarios and the future carbon sink potential were calculated using the biomass expansion factor method. Moreover, the suitable distribution scope and increasing carbon sink potential of the four dominant species in Mao County were predicted. These results will aid in the selection and layout of appropriate tree species in future afforestation plans. The results provided a reference for the increase in the forest stock volume and forest carbon sequestration in Mao County in the future.

2 DATA AND METHODOLOGY

2.1 Study Area

Mao County is in the northwest of the Sichuan Province, China, on the southeast edge of the Qinghai-Tibet Plateau. It has unique climatic conditions, landforms, and hydrological characteristics. It has a plateau-type monsoon climate, with an average annual temperature of 12.2°C, average annual precipitation of 486.3 mm, and annual evaporation of 1,500 mm. The landform is mainly high mountains and valleys. The terrain inclines from the northwest to the southeast. The average elevation of the peaks is about 4000m, with a maximum of 5,230 m and a minimum of 906 m (**Figure 1**). Mao County possesses rich forest resources;

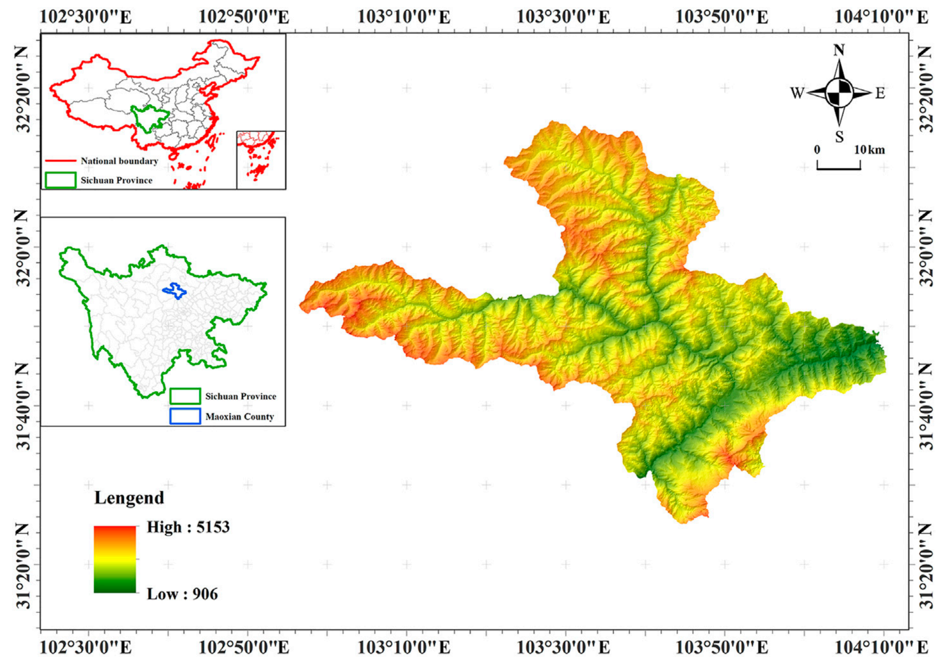

FIGURE 1 | Location of the study area.

arbor species are mainly *Abies*, *Picea*, *Betula*, *Quercus semicarpifolia*, *Cyclobalanopsis glauca*, etc. Among them, the proportion of *Picea* is the highest (17.51%), followed by *Abies* (17.43%), *Quercus* (9.09%), and *Betula* (7.22%). There are developed water resources and water systems in the region mainly belonging to the Minjiang River. There is sufficient water volume, a steep river bed, and a great natural drop to give rich water power resources. Mao County is an accumulation area of cultures including those of Qiang and Zang nationalities in China; it retains a long history of characteristics of Tibetan areas and the culture of the Qiang nationality.

2.2 Data Source

2.2.1 Data of Sampling Points

The MaxEnt model is built according to the relationship between sampling points and environmental variables. Under general conditions, the simulation accuracy of the model becomes more stable, and the effect is better with an increasing sample size (Hirzel and Guisan, 2002; Mcpherson and Rogers, 2004). Through a survey of existing tree species in the forest, it was found that *Abies*, *Picea*, *Betula*, and *Quercus* grow the best and account for the highest proportion; hence, they were chosen as the four dominant tree species in this study. Data from sampling points of these four dominant tree species were collected from the latest forest survey database of Mao County. According to the distribution of tree species, a bottom class was used as the unit. To prevent excessive aggregation of distribution points, a 5-km buffer zone was built up for each point, and overlaying sample plots in the buffer zone were eliminated, thus obtaining data on the distribution sampling points of the four tree species. Combined with a field survey, sampling points were eliminated, and finally, 4,307 sampling points were collected, including 836 sampling points for *Abies*, 1,241 sampling points for *Picea*, 1,320 sampling points for *Quercus,* and 910 sampling points for *Betula* (**Figure 2**).

2.2.2 Environmental Variables

In this study, 15 environmental variables within the topography, climate, soil, and evaporation were chosen as major factors that influence the distribution of *Abies*, *Picea*, *Quercus*, and *Betula* (**Table 1**). Topographic data came from the DEM elevation data website[1]. Elevation data in Mao County were collected using the ArcGIS extraction tools. Slope and aspect data were collected by the grid surface analysis of the 3D analysis tool. Evaporation capacity data and climate data were obtained from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences[2]. Soil data sampling points were gained from the forest survey database of Mao County, and relevant vector data of soil factors were collected through the interpolation analysis.

2.3 Methodology

2.3.1 Application of the MaxEnt Model

The MaxEnt model was used to predict a suitable planting layout for the four dominant tree species in Mao County. The MaxEnt model is an ecological niche model based on maximum entropy and machine learning theory developed by Professor Steven Phillips and Miro Dudik et al. from the AT&T Laboratory of

[1]http://www.gscloud.cn/.
[2]http://www.resdc.cn/DOI.

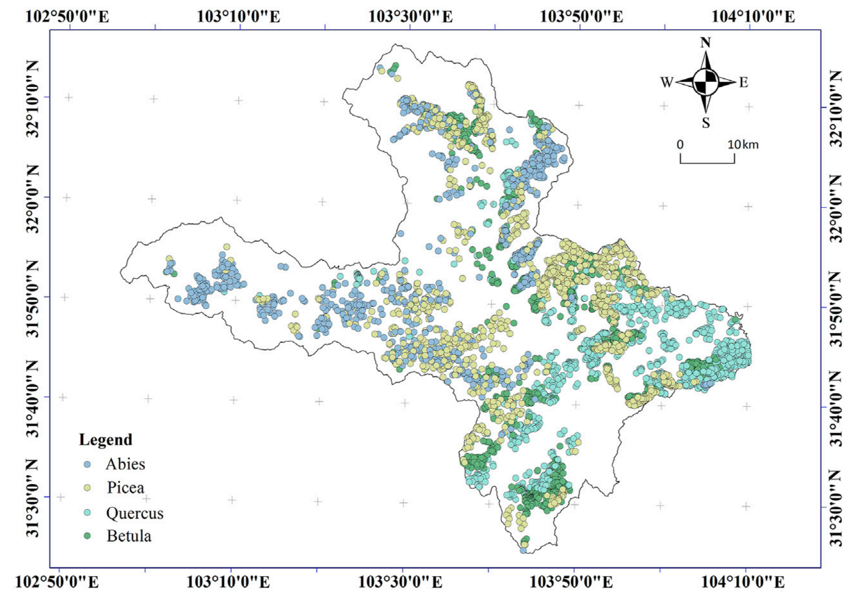

FIGURE 2 | Locations of sampling points of the four dominant tree species.

TABLE 1 | Environmental variable factors used in the model.

Number	Environmental variable	Environmental variable factor
1	Topographic factors	Altitude (DEM)
2		Aspect
3		Slope
4	Meteorological factors	0 °accumulated temperature (At0)
5		Average annual precipitation (Pa)
6		Humidity index (NDMI)
7		Drying index (aridity)
8		Annual average temperature (Ta)
9		Evaporation capacity
10	Soil factors	pH value
11		Water conservation
12		Soil texture
13		Soil type
14		Soil depth
15		Soil moisture

Princeton University to study the geographic spatial distribution of species (Phillips, 2005; Phillips et al., 2006; Phillips and Dudík, 2008). Now, the MaxEnt model has been extensively used to predict animal migration, plant distribution, plant diseases, and insect pests, and in other fields ((Shao et al., 2011; Cao et al., 2021; Zeng et al., 2021). The MaxEnt model has the advantages of low requirements of sample size, flexible variable processing (only needs occurrence data), good de-noising effect, and high prediction accuracy.

The MaxEnt model forms the spatial distribution pattern of species by establishing the relationship between samples and environmental layers. For the model setting, the test set was determined as 25%, and the training set was 75%. Response curves were run, and pictures of predictions were produced with a jackknife to measure variable importance. The output form was logistic curves (Babasaheb et al., 2014). To improve the precision and accuracy of the model, the number of operations was set at 10 and the mean values were chosen as the final results. The accuracy of the MaxEnt model was determined by the receiver operating characteristics (ROC) which were gained from the operation of the model; its characteristics were defined by the area under the curve (AUC), ranging between 0 and 1. Generally, if the AUC is 0.5–0.7, the model has a poor simulation effect. If the AUC is 0.7–0.8, the model has a moderate simulation effect. If the AUC is 0.8–0.9, the model has a good simulation effect. If the AUC is 0.9–1, the model has an extremely good simulation effect (Hanley and Mcneil, 1982).

With respect to the division of suitable distribution areas based on the model, the suitable areas of tree species under different scenarios were divided into four grades with reference to previous studies and practical situations encountered in Mao County: grade 1: <0.1, unsuitable area; grade 2: 0.1–0.3, moderately suitable area; grade 3: 0.3–0.5, highly suitable area; and grade 4: >0.5, optimally suitable area.

2.3.2 Carbon Sink Estimation Method

Carbon sinks of four dominant arbor species were estimated using the biomass expansion factor (BEF) method. The BEF method is a popular method to estimate carbon sinks of forests, especially arbors. This method converts the stock volume of tree species into biomass using the BEF calculation and then multiplies the biomass by the carbon stock (CF) of the species, thus obtaining the carbon sink of the species (Wu et al., 2018). The specific formula is as follows:

$$B = \mathrm{V} * \mathrm{SVD} * \mathrm{BEF}, \tag{1}$$

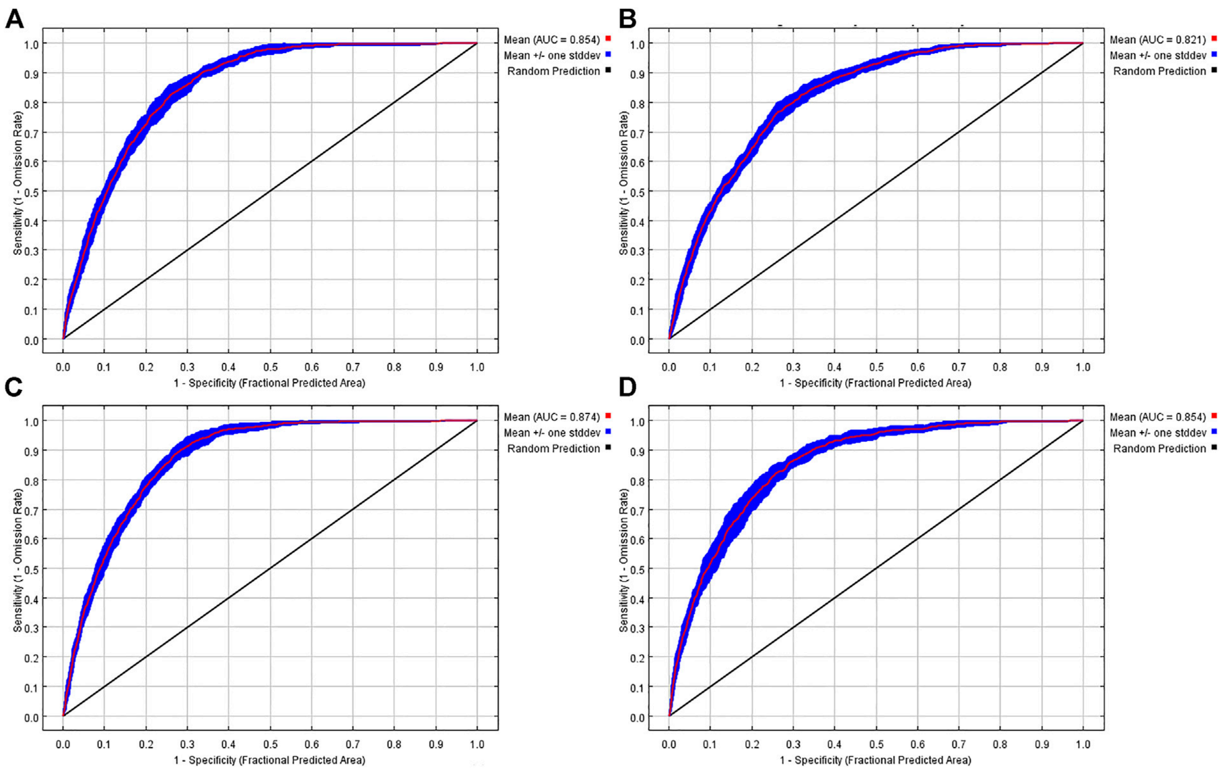

FIGURE 3 | AUC values of ROC curves of *Abies* **(A)**, *Picea* **(B)**, *Quercus* **(C)**, and *Betula* **(D)**.

$$C = B*CF*S, \tag{2}$$

where:

B——biomass of arbor species per unit area (dry substance) (t/ha); V——carbon stock of arbor species per unit area (m^3/ha); SVD——density of basic timber (dry substances) of arbor species (t/ha); BEF——biomass expansion factor of arbor species; B——biomass of arbor species per unit area (dry substance) (t/ha); C——biomass carbon sink of arbor species (t); CF——carbon stock per tons of dry substances of tree species (t/tons); S——area of arbor species (ha).

Among the aforementioned parameters, V was obtained from the forest survey data of Mao County. SVD and BEF used the reference values of national and IPCC carbon accounting parameters. CF used the carbon stock of dominant tree species in China from the *Guideline for Carbon Sink Accounting of Forest Ecosystem*.

3 RESULT ANALYSIS

3.1 Model Accuracy

The accuracy of the MaxEnt model was determined by the AUC of the receiver operating characteristic (ROC) curve. In this study, the average AUC values of *Abies, Picea, Quercus,* and *Betula* were 0.854, 0.821, 0.874, and 0.854, respectively (**Figure 3**). This result shows the MaxEnt model has good accuracy, and its predictions of the suitable distribution of tree species are relatively reliable (Elith J et al., 2011).

3.2 Suitable Distribution of Four Dominant Tree Species Under Different Scenarios

In this study, the distribution zones of *Abies, Picea, Quercus,* and *Betula* were predicted using the MaxEnt model, thus simulating their suitable distribution patterns (**Figure 4**). It can be seen from **Figure 4** that the suitable area for *Picea* is the largest, covering almost the whole study area. According to the calculations, the suitable planting area reaches 143,716.18 ha. The suitable area for *Abies* is mainly located in the northwest regions and is calculated to be 132,924.40 ha. The suitable area for *Quercus* is concentrated in the southeast regions and is calculated to be 68,509.62 ha. The suitable area for *Betula* is concentrated in the central and southeast regions, calculated as 95,871.17 ha.

Since the suitable areas for the four dominant tree species overlap to some extent, weighted overlapping of different suitable areas for *Abies*, *Picea*, *Quercus*, and *Betula* was performed. Considering the development plan of Mao County, existing development areas and non-forest agricultural development zones were excluded, and spatial distributions of suitable areas for the four dominant tree species under four scenarios were concluded (**Table 2**). Scenario 1: when the suitable area of the same grade has an overlap of two or more species and one of the species is *Abies*, *Abies* is chosen as the dominant species. Scenario

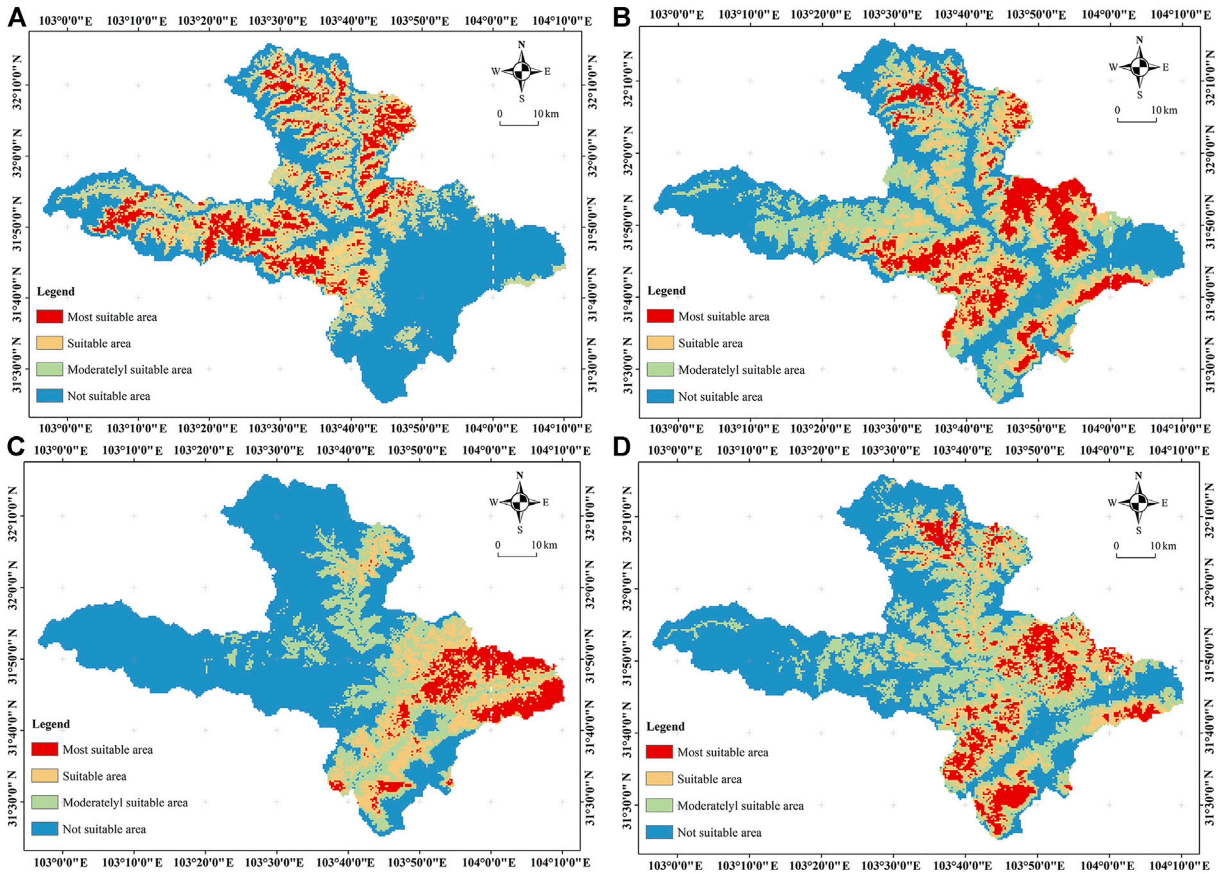

FIGURE 4 | Distribution patterns of suitable areas of four tree species: **(A)** *Abies*; **(B)** *Picea*; **(C)** *Quercus*; and **(D)** *Betula*.

TABLE 2 | Distributions of different suitable areas for four dominant tree species under four scenarios (area/ha.).

Scenario	Tree species	Highly suitable area	Optimally suitable area	Moderately suitable area	Total suitable area	Percentage
Scenario 1	*Abies*	44819.56	43045.37	45059.5	132924.42	44.97%
	Picea	24119.66	14992.23	6867.71	45979.61	15.56%
	Quercus	20260.22	17539.67	7270.69	45070.58	15.25%
	Betula	35729.39	20430.39	15458.89	71618.67	24.23%
Scenario 2	*Abies*	41002.02	36022.15	31677.60	108701.77	36.77%
	Picea	24119.66	14992.23	6867.71	45979.61	15.56%
	Quercus	20230.38	17539.67	7270.69	45040.74	15.24%
	Betula	39576.77	27453.61	28840.79	95871.17	32.43%
Scenario 3	*Abies*	44682.91	41584.20	39364.05	125631.16	42.50%
	Picea	24119.66	14992.23	6867.71	45979.61	15.56%
	Quercus	26016.62	20400.85	22092.14	68509.62	23.18%
	Betula	30109.63	19030.38	6332.89	55472.90	18.77%
Scenario 4	*Abies*	29625.92	25813.89	17648.48	73088.29	24.73%
	Picea	58510.42	42802.56	42403.21	143716.18	48.62%
	Quercus	16871.57	14578.99	6444.25	37894.82	12.82%
	Betula	19920.92	12812.22	8160.85	40894.00	13.83%
Total		124928.83	96007.66	74656.79	295593.28	--
Percentage		42.26%	32.48%	25.26%	100%	--

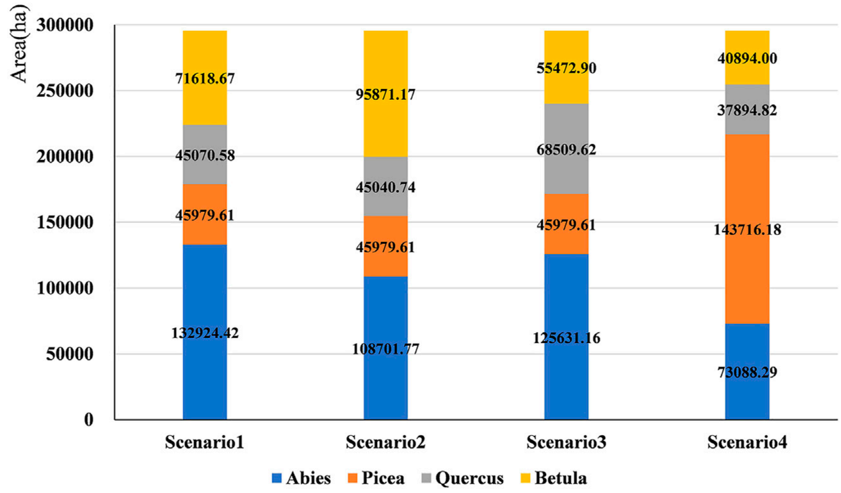

FIGURE 5 | Comparison of suitable areas of four dominant tree species under four scenarios.

2: when the suitable area of the same grade has an overlap of two or more species and one of the species is *Betula*, *Betula* is chosen as the dominant species. Scenario 3: when the suitable area of the same grade has an overlap of two or more species and one of the species is *Quercus*, *Quercus* is chosen as the dominant species. Scenario 4: when the suitable area of the same grade has an overlap of two or more species and one of the species is *Picea*, *Picea* is chosen as the dominant species.

The total suitable areas of *Abies, Picea, Quercus,* and *Betula* amounted to 295,593.28 ha. Under all four scenarios, the highly suitable area was the largest (124,928.83 ha.), accounting for 42.26% of the total suitable area. Its suitable area is the second largest (96,007.66 ha.), accounting for 32.48% of the total suitable area. The moderately suitable area is 74,656.79 ha, and it accounts for 25.26% of the total suitable area (**Table 2**).

Scenario 1: the suitable area for *Abies* is the largest, at 132,924.40 ha., and accounts for 44.97%. The suitable area for *Betula* is the second largest, at 24.23%. The suitable areas for *Picea* and *Quercus* are relatively small, at 15.56 and 15.25%, respectively (**Table 2**).

Scenario 2: the suitable area for *Abies* decreases by 24,222.65 ha., but its suitable area is still the highest, at 108,701.77 ha., and accounts for 36.77%. The suitable area for *Betula* increases by 24,252.5 ha. (**Figure 5**) to 95,871.17 ha, which accounts for 32.43% (**Table 2**). The suitable areas for *Picea* and *Quercus* change slightly. This indicates that suitable areas of *Abies* and *Betula* overlap greatly and are relatively large.

Scenario 3: the suitable areas for *Abies* and *Betula* decrease compared with those in scenario 1 and scenario 2. The suitable area for *Abies* decreases by 7,293.26 ha. to 125,631.16 ha, but its suitable area is still the highest, which accounts for 42.50% of total suitable areas. The suitable area for *Betula* decreases significantly by 16,145.77 ha compared to that in scenario 1 and 40,398.27 ha. (**Figure 5**) compared to that in Scenario 2. The suitable area for *Betula* is 554,729 ha, which accounts for 18.77%. The suitable areas for *Quercus* increased by 23,439.04 ha to 68,509.62 ha, which accounts for 23.28% of the total suitable area (**Table 2**). The suitable area for *Picea* remains the same. This reflects that the suitable areas for both *Picea* and *Quercus* are relatively small. Compared with other species, the overlapping areas of *Picea* and *Quercus* are relatively large, indicating extensive areas suitable for both *Picea* and *Quercus*.

TABLE 3 | Biomasses of *Abies*, *Picea*, *Quercus*, and *Betula* per unit area.

Tree species	V (m3/hm2)	SVD (m3/hm2)	BEF	B (t/hm2)
Abies	198.70	0.366	1.72	125.09
Picea	155.08	0.342	1.72	91.22
Betula	124.41	0.541	1.37	92.21
Quercus	83.53	0.676	1.56	88.09

Scenario 4: suitable areas for *Abies, Quercus,* and *Betula* decrease compared with those in the previous three scenarios. Among them, the suitable area for *Abies* decreases the most, by 59,836.13 ha (**Figure 5**), compared to that in scenario 1, and the proportion declines from 44.97 to 24.73%. The suitable area for *Picea* is doubled. It increased by 97,736.57 ha. compared to that in scenario 1 to 143,716.18 ha, which accounts for 48.62%. The suitable areas for *Picea* and *Abies* are the most similar and the largest. Moreover, the suitable area for *Betula* decreases by 30,724.67 ha compared to that in scenario 1 (**Table 2**). This indicates that the overlapping areas of *Betula* and *Picea* are the largest. The suitable area for *Quercus* decreases to the lowest value, which also indicates the small overlapping areas of *Quercus* and *Picea*.

3.3 Carbon Sink Calculation

3.3.1 Biomass of Four Dominant Tree Species per Unit Area

Biomass is the total cumulative organic matter of forest ecosystems and is an important index used to measure the forest ecological environment (Andersson et al., 2000). The

TABLE 4 | Carbon stock of suitable distribution patterns under four scenarios.

Scenario	Tree species	Forestry area (ha)	Biomass (t/ha)	Carbon content (t/t)	Carbon stock (Tg C)	Total carbon stock (Tg C)
Scenario 1	*Abies*	132924.4	125.09	0.51	8.48	15.81
	Picea	45979.61	91.22	0.5	2.10	
	Quercus	45070.59	88.09	0.5	1.99	
	Betula	71618.67	92.21	0.49	3.24	
Scenario 2	*Abies*	108701.8	125.09	0.51	6.93	15.34
	Picea	45979.61	91.22	0.5	2.10	
	Quercus	45040.74	88.09	0.5	1.98	
	Betula	95871.17	92.21	0.49	4.33	
Scenario 3	*Abies*	125631.2	125.09	0.51	8.01	15.64
	Picea	45979.61	91.22	0.5	2.10	
	Quercus	68509.62	88.09	0.5	3.02	
	Betula	55472.9	92.21	0.49	2.51	
Scenario 4	*Abies*	73088.29	125.09	0.51	4.66	14.74
	Picea	143716.2	91.22	0.5	6.56	
	Quercus	37894.82	88.09	0.5	1.67	
	Betula	40894	92.21	0.49	1.85	

biomasses of *Abies, Picea, Quercus,* and *Betula* per unit area were calculated using **Formula 1**. The biomass of *Abies* is the highest (125.09 t/ha), followed by *Betula* (92.21 t/ha), *Picea* (91.22 t/ha), and *Quercus* (88.09 t/ha), successively (**Table 3**).

3.3.2 Carbon Sink Analysis Under Different Scenarios

The suitable distribution patterns of four dominant tree species under different scenarios were simulated.

On this basis, the carbon stock of suitable distribution patterns, as well as the total carbon sinks under four scenarios, was calculated through **Formula 1** and **Formula 2** (**Table 4**).

Among the four scenarios, the carbon stock of scenario 1 was the highest. In other words, *Abies* is chosen as the dominant species and the total carbon stock is 15.80 Tg C. Specifically, the carbon stock of *Abies* is significantly higher than those of other species (**Table 4**). The carbon stock of scenario 3 ranks second, with *Quercus* chosen as the dominant species and a total carbon stock of 15.64 Tg C. Among them, *Abies* still shows the highest carbon stock, followed by *Quercus* (**Table 4**). The carbon stock of scenario 2 ranks third, with *Betula* chosen as the dominant species and a total carbon stock of 15.34 Tg C. Among them, *Abies* still shows the highest carbon stock, followed by *Betula* (**Table 4**). The carbon stock of scenario 4 is the lowest. When *Picea* is chosen as the dominant species, the total carbon stock is 14.74 Tg C. *Picea* shows the highest carbon stock, followed by *Abies* (**Table 4**).

3.3.3 Analysis of Scenarios for Optimal Carbon Stock

The carbon stock of forests is related to biomass, carbon stock, and carbon content, to different extents. To maximize carbon stock, scenario 5 was simulated; here, when there are several tree species overlapping in the suitable areas, the species with the maximum biomass is chosen as the optimal selection. In other words, *Abies* is chosen as the first choice, followed by *Betula, Picea,* and *Quercus*, successively. The carbon stock of scenario 5 is calculated as 15.81 Tg C (**Table 5**), which is higher than those of the previous four scenarios (0.01 Tg C up to 1.07 Tg C). This result reflects that tree species should be chosen according to biomass. Higher biomass and area lead to a higher carbon content and higher carbon stock.

3.3.4 Analysis of Optimal Carbon Sink Potentials

Since the carbon sink capacity of scenario 5 is the best and its carbon stock is the highest, scenario 5 is chosen to estimate carbon sink potentials that can be increased. Scenario 5 is superposed with existing land types. Existing development zones and non-forest agricultural development zones are excluded. According to the principle of maximum forest carbon sinks excluding the existing forest area, the distribution of suitable areas of the four dominant tree species is gained (**Figure 6**). In this way, the maximum carbon sink capacity that can be increased in suitable areas of four dominant tree species can be calculated, thus estimating potential carbon stock for the future (**Table 6**).

Now, the forest area in Mao County is large. Due to unreasonable forest resource development and utilization in the early stages, a lot of suitable forests, cutover lands, and wastelands for afforestation and artificial repair remain unused. It can be seen from **Figure 5** that suitable areas for the four dominant tree species are mainly distributed in suitable unused regions on two banks of the Min River as well as wasteland, cutover land, and suitable wasteland in the northwest and east regions. Carbon sink potential mainly comes from the increasable carbon sink of suitable forests. It can be seen from **Table 6** that the suitable forest area that can be increased in the future in Mao County measures 39,884.28 ha, and the maximum carbon sink potential can be increased to 2.13 Tg C. Specifically, the suitable area of *Abies* can be increased the most, amounting to 17.875.88 ha, and its carbon sink potential is the highest. Carbon storage can be increased by 1.14 Tg C. The suitable area of *Betula* ranks second in terms of expansion potential and can be increased by 10,216 ha, which can

TABLE 5 | Carbon stock of the optimal scenario.

Scenario	Tree species	Forestry area (hm^2)	Biomass (t/hm^2)	Carbon content (t/t)	Carbon stock (Tg C)	Total carbon stock (Tg C)
Scenario 5	*Abies*	132924.4	125.09	0.51	8.48	15.81
	Picea	53155.37	91.22	0.5	2.42	
	Quercus	37864.97	88.09	0.5	1.67	
	Betula	71648.51	92.21	0.49	3.24	

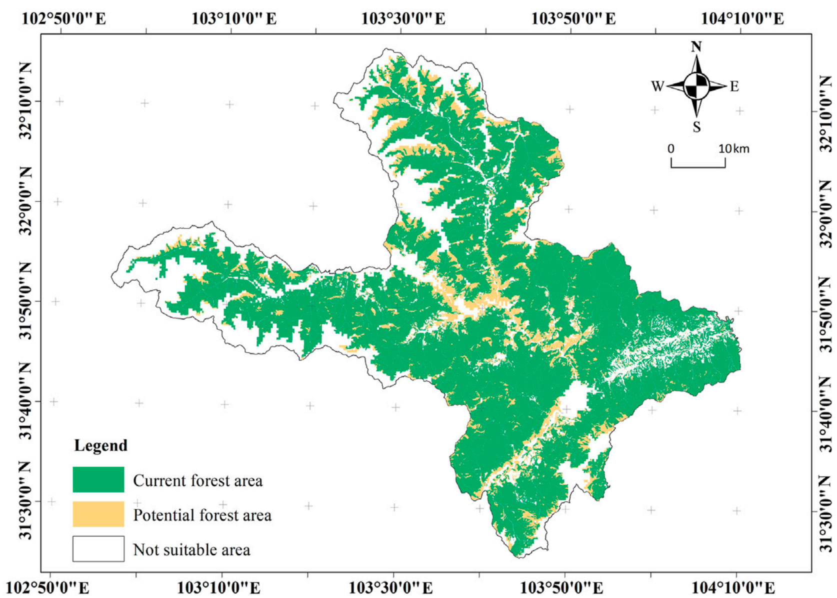

FIGURE 6 | Carbon sink potential distributions of the optimal scenario.

TABLE 6 | Carbon stock potential of the optimal scenario.

Tree species	Area (hm2)	Biomass (t/hm2)	Carbon content (t/t)	Carbon stock (Tg C)	Total carbon stock (Tg C)
Abies	17875.88	125.09	0.51	1.14	2.13
Picea	6120.41	91.22	0.5	0.28	
Quercus	5671.46	88.09	0.5	0.25	
Betula	10216.52	92.21	0.49	0.46	

increase the carbon stock by 0.46 Tg C. The suitable area of *Quercus* is increased the least, by 5,671.46 ha, thereby increasing carbon stock by 0.25 Tg C.

4 DISCUSSION

Suitable areas of *Abies*, *Picea*, *Quercus*, and *Betula* were simulated in this study through the MaxEnt model. Simulation results showed that average AUC values of four dominant tree species are higher than 0.8, indicating that the accuracy of the simulation results is relatively high. The MaxEnt model can simulate suitable areas for four dominant tree species well. The results also verified the accuracy of the MaxEnt model in studying species distribution.

The results demonstrated there are suitable areas for *Abies, Picea, Quercus,* and *Betula* in Mao County. The total suitable area for the four dominant tree species is 295,593.28 ha (**Figure 7**). Among these areas, the optimally suitable area is the largest (42.26%), followed by the suitable area (32.48%) and moderately suitable area (25.26%) (**Table 2**). Among the four dominant tree species, the area suitable for *Picea* is the

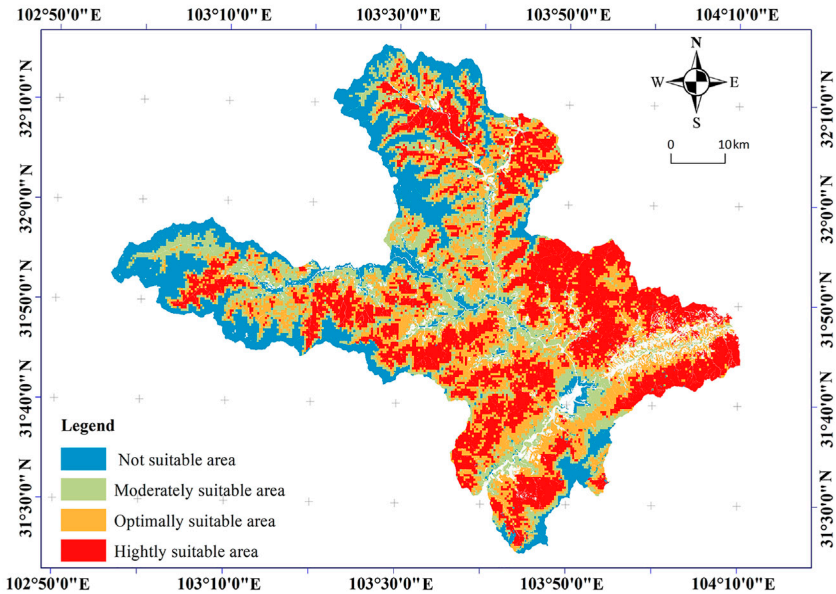

FIGURE 7 | Overlapping distribution of suitable areas of four tree species.

largest (143,716.18 ha). The suitable area of *Picea* covers a wide range and is concentrated in high-altitude areas in the northwest, central, and southeast regions of Mao County except for the plateaus, ice fields, and snow belts (**Figure 4B**). The area suitable for *Abies* is the second largest (132,924.40 ha); it is mainly concentrated in the northwest of Mao County (**Figure 4A**). The area suitable for *Betula* is the third largest (95,871.17 ha); it is mainly concentrated in the central and southeast regions of Mao County (**Figure 4D**). The area suitable for *Quercus* is the smallest (68,509.62 ha), it is concentrated in the southeast and valley areas in Mao County (**Figure 4C**). *Betula* and *Quercus* belong to broad-leaved forests, and they prefer the southeast valleys with a relatively low altitude and appropriate climate. According to the influencing factor curves, the model can recognize differences in suitable altitudes among the four dominant tree species (**Figure 7**).

The chosen four dominant trees have climate and geographic conditions appropriate for growth in Mao County. *Picea* and *Abies* belong to coniferous forests and are cold-resistant species that are distributed in low-temperature alpine regions. Mao County is located in the southeast region of the Qinghai-Tibet Plateau where there are many mountains, high altitudes, and low temperatures. It is more suitable for the growth of *Picea* and *Abies* (Liu et al., 2002); therefore, these two species have large overlapping areas. According to the response curves of altitude data and topographic factors of the model results, the altitude appropriate for the growth of *Abies* is about 2,800–3,700 m (**Figure 8A**), and the altitude appropriate for the growth of *Picea* is about 2,600–3,500 m (**Figure 8B**). The growth areas for *Picea* and *Abies* are similar. It is important to note that although *Picea* and *Abies* have relatively strong cold resistance and shade tolerance, *Picea* belongs to shallow-root species and is appropriate to grow in regions with low temperatures, high altitudes, and deep soil layer thickness. Hence, it is mainly distributed in mountainous regions with high altitudes and deep soil thickness in the central and southeast regions. In regions close to the northwest regions of Mao County, there are high altitudes, low temperatures, large-scale exposed rocks, and low soil thickness. These regions are inappropriate for *Picea* but appropriate for *Abies, Betula,* and *Quercus* which belong to broad-leaved forests. The suitable altitude for *Betula* is 2,300–3,200 m (**Figure 8D**) and the suitable altitude for *Quercus* is 1200–2,800 m (**Figure 8D**). These two species mainly grow in the southeast valley regions where they have relatively low altitudes and appropriate climates. Combining the results with the terrain characteristics, high in the northwest and low in the southeast of Mao County, suitable areas for *Abies*, *Picea*, *Betula,* and *Quercus* gradually range from northwest to southeast.

The carbon stock under different scenarios was analyzed using the BEF method. The test found that the carbon sink capacity of scenario 5 is the best: tree species are chosen according to biomass per unit area, and tree species with high biomass are chosen as much as possible, thus enabling maximum carbon stock. The total carbon sink capacity of tree species is closely related to the biomass, area, and carbon content of a single tree. Although the carbon content of species in different regions is different, the carbon content of coniferous forests is higher than broad-leaved forests (Birdsey, 1992; Lehtonen et al., 2004). In scenario 5, *Abies* has the largest planting area, followed by *Betula, Picea,* and *Quercus,* successively. In view of the biomass and carbon

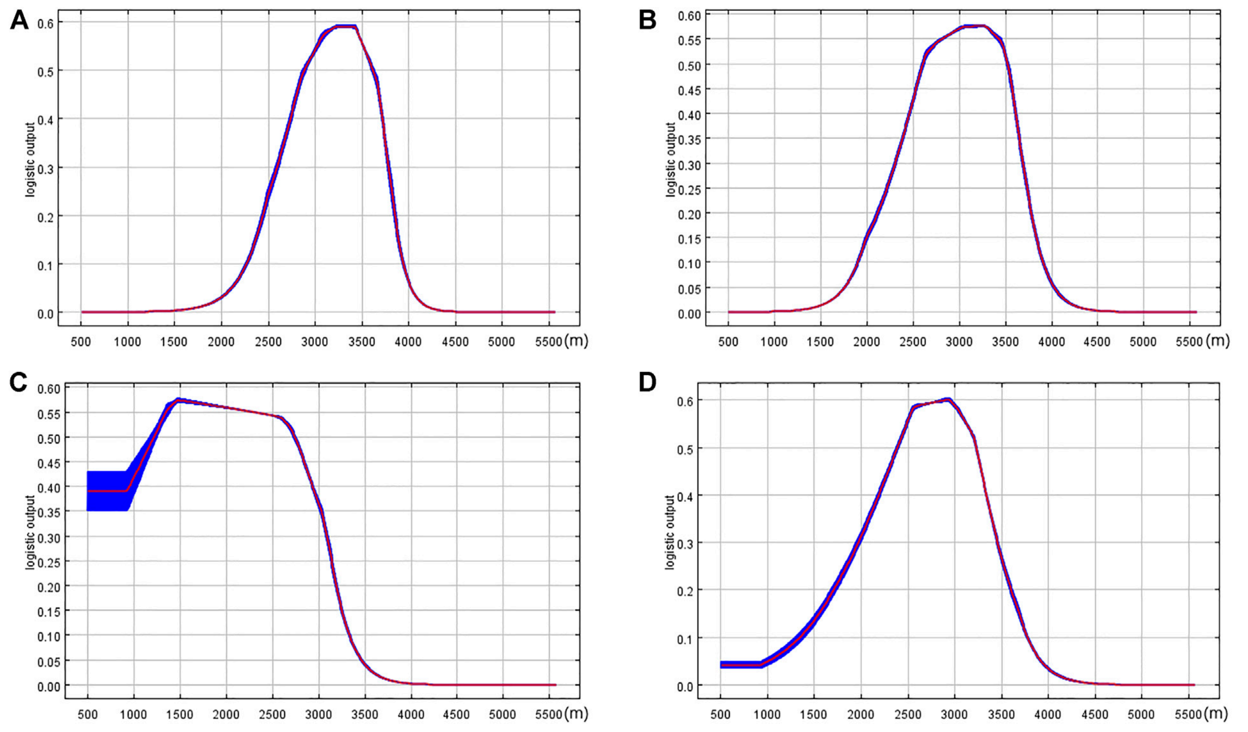

FIGURE 8 | Effects of altitude on the suitable area distributions of four dominant tree species: **(A)** *Abies*; **(B)** *Picea*; **(C)** *Quercus*; and **(D)** *Betula*.

content of the four dominant tree species, although the suitable area of *Picea* is the largest, the suitable areas of *Picea* and *Abies* overlap greatly. Given the same carbon content, since the biomass and carbon sequestration of *Abies* are higher than those of *Picea*, *Abies* is the first choice. *Picea* and *Betula* have similar biomass and carbon content; therefore, the carbon stock is relatively high when the area of *Betula* is larger than *Picea*. However, this does not mean the carbon sequestration ability of *Betula* is better than that of *Picea*. Looking at the carbon stock per unit area, since the carbon content of *Picea* is higher than that of *Betula*, the carbon stock per unit area is 45.61 t/hm^2 for *Picea* and 45.18 t/hm^2 for *Betula*. Therefore, the carbon stock per unit area of *Picea* is higher than that of *Betula*. This is consistent with previous research conclusions (Cheng et al., 2008). In this study, dominant tree species are chosen according to biomass in scenario 5. Since the overlapping areas of *Abies* and *Picea* are large and the biomasses of *Abies* and *Betula* are higher than those of *Picea*, *Picea* is replaced by *Abies*, thus making the area of *Betula* larger than that of *Picea*. Consequently, the total carbon stock of *Betula* is higher than that of *Picea*. Moreover, the total carbon stock of the study area in scenario 5 is higher than in other scenarios, indicating that scenario 5 is the optimal one.

In the present study, suitable distribution patterns of four dominant tree species in Mao County were discussed, and suitable areas of different species under different scenarios were discussed. Moreover, the carbon stock was acquired for different scenarios using the BEF method. The optimal scenario was chosen, and the optimal carbon sink potentials were calculated. The results provide a reference for afforestation-based carbon sequestration in Mao County in the future. However, there remain some aspects worthy of further discussion. When discussing suitable distribution patterns of the four dominant tree species, the influence of changes in the climatic environment with time on an area suitable for the tree species was ignored. In fact, areas suitable for afforestation may vary with climatic changes, which must be considered in practical planning. Meanwhile, the carbon sink potential was calculated, and the BEF and SVD of the four tree species all used universal values for different regions, but the influence of differences in tree ages was ignored. Carbon sink potentials at different tree ages were further analyzed in subsequent studies.

5 CONCLUSION

There are many suitable areas for *Abies*, *Picea*, *Quercus*, and *Betula* in Mao County. The suitable areas of *Abies* and *Picea* are the largest, followed by *Betula*. The suitable area of *Quercus* is the smallest. With consideration of the carbon sink potential of the ecological environment, tree species were chosen first according to biomass and maximum carbon stock. In the optimal scenario, the order of suitable areas of the four species was *Abies* > *Betula* > *Picea* > *Quercus*, and the order of carbon stock was the same: *Abies* > *Betula* > *Picea* > *Quercus*. In the future, Mao County should plant suitable tree species in unused regions at two banks of the Min River, wastelands in the northwest and east mountain areas, cutover lands, and wastelands appropriate for afforestation to increase carbon sinks. Therefore, the future afforestation plan in Mao County should first choose large-scale planting of *Abies*, followed by *Betula* and *Picea*. *Quercus* is the last choice. Such an afforestation plan would achieve the maximum carbon stock. This can not only increase the economic benefits of carbon sinks but can also offer the ability to significantly improve and adapt to climate changes.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

Designing experiments: GW and XH; performing experiments: CY and XH; analyzing experimental results: GW and XH; writing manuscript: GW, XH, and JQ; review and Editing: GW, XH, CY, and JQ.

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Can Environmental Risk Management Improve the Adaptability of Farmer Households' Livelihood Strategies? ——Evidence From Hubei Province, China

Chongmei Zhang[1], Xin Luo[1], Jiahao Song[2]*, Zhuoying Fu[1], Zeng Huang[1] and Wei Wang[1]*

[1]Department of Agriculture and Forestry Economics and Management, College of Management, Sichuan Agricultural University, Chengdu, China, [2]Department of Rural and Regional Development, College of Management, Sichuan Agricultural University, Chengdu, China

With the rising temperature, uneven precipitation and frequent occurrence of extreme weather caused by global climate change, agricultural production is facing more severe challenges. Based on the sustainable livelihoods framework, this paper measures the index of farmer households' livelihood strategy adaptability and analyzes the benefits of farmer households' environmental risk management on livelihood strategy adaptability by using microscopic research data of 970 farmer households' livelihoods in Hubei Province, China, in 2020. This paper found that the farmer households' environmental risk management variables have a significant impact on the adaptability of farmer households' livelihood strategies, with the stronger the farmer households' environmental risk management capacity, the more adaptable its livelihood strategy. The impact of farmer households' environmental risk management variables on livelihood strategies varies for farmer households with different income levels. Therefore, this paper proposes that we should improve farmers' perception of climate change, promote the diffusion of adaptive technologies, improve agricultural insurance policies, give full play to the collective role of village collectives, companies and cooperatives, and promote the transformation and upgrading of livelihood approaches to further improve the adaptability of livelihood strategies.

Keywords: climate change, environmental risk management, farmer households, livelihood strategy adaptation, sustainable livelihoods

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****Correspondence:***
Jiahao Song
sjh799286572@qq.com
Wei Wang
wangwei@sicau.edu.cn

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1 INTRODUCATION

Climate change is the main environmental risk faced by farm households in their agricultural production activities and has serious and far-reaching impacts on agricultural production. The adoption of adaptive livelihood strategies has become an important means for farmers to cope with environmental risks such as climate change, which helps stabilize farmers' livelihoods and secure agricultural income (Barham et al., 2014; Jin et al., 2015; Feng et al., 2017; Dougherty et al., 2020). With the increasing problems of rising temperatures, uneven precipitation and frequent extreme disaster weather brought about by global climate change, agricultural production is facing more severe challenges and food security is further affected. Adaptive behaviors such as adjusting agricultural production practices, spreading production risks, and changing livelihood strategies have become the main ways of coping with climate change and managing environmental risks. China is one of the leading countries affected by climate change and is exposed to a variety of environmental risks. Farming households located in rural areas of China are often poorly capitalized, have a single livelihood strategy, and are less resilient to environmental risks (Liu et al., 2018a). Therefore, exploring how to adopt long-term mechanisms for climate-resilient technologies, enhance the environmental risk management capacity of farmers, improve the adaptability of farmers' livelihood strategies and promote their sustainable development has become a focus of attention for researchers and policy makers.

Studies have shown that strengthening risk management and improving the adaptability of farmers' livelihood strategies are effective ways to achieve sustainable development, and have an important impact on the quality of household income (Gao and Lu, 2021). Farming households need to optimize the allocation of asset elements, choose multiple livelihood activities suitable for household development, increase income sources and quality, and reduce livelihood vulnerability as a means to sustain and improve household living standards (Khatun and Rov, 2016; Sun, 2018). However, in the process of choosing livelihood strategies, the risk management measures adopted by farmers gradually show diverse and different characteristics due to the diversity of risks faced by households (Heltberg et al., 2015), farmers' risk management capacity is further affected, which ultimately acts on household livelihood strategy adaptation. For rational farmers, the process of adaptation of their livelihood strategies is a behavioral strategy based on a combination of resource allocation that ensures that the environmental risks faced by farmers are within tolerable limits. Can environmental risk management play an effective and positive role in the selection and adaptation of farmers' livelihood strategies? What are the mechanisms underlying this role? In view of this, this paper establishes a theoretical analysis framework to empirically analyze the benefits of farm households' environmental risk management on the adaptation of livelihood strategies using microscopic research data on farm households' livelihoods in Hubei Province, China in 2020. We also classify farm households according to the level of household income and explore the mechanism of the role of farm household income in the impact of environmental risk management on the adaptation of livelihood strategies. On this basis, putting forward policy suggestions is of great significance for farmers to better cope with environmental risks and establish a long-term mechanism for adaptability of livelihood strategies.

Compared with previous studies, this paper has three main marginal contributions: first, it analyzes the livelihood strategy adaptability of farm households from the perspective of environmental risk management, which helps to enrich the research in the fields related to farm household risk management and livelihood strategy adaptability. Second, we adopt an econometric approach to measure the livelihood strategy adaptability of farm households in Hubei Province, China, to explore the mechanism of the effect of farm household income on environmental risk management on livelihood strategy adaptability, and to provide an empirical basis for the study of the measurement and influencing factors of livelihood strategy adaptability. Thirdly, we develop effective risk management strategies for farmers with different income categories, and provide decision ideas for farmers to improve their livelihood strategy adaptability.

2 LITERATURE REVIEW AND THEORETICAL ANALYSIS

2.1 Review of Relevant Literature

Adaptation is an important topic of research for the International Human Dimensions Programme on Global Environmental Change (IHDP). With the enrichment and expansion of the connotation and extension of ecological adaptability, the study of adaptability (force) has become a Frontier issue in comprehensive disciplinary research (Jiang et al., 2020). Among them, studies on climate change adaptive behavior are more extensive. For example, Feng et al. (2018a) examined the effect of asset specificity on climate change adaptive production behavior of professional farmers using micro-survey data from apple farmers in eight counties in Shaanxi Province. Among them, studies on climate change adaptive behavior are more extensive. Li et al. (2021) constructed a framework for analyzing farmers' "climate change perception-adaptive behavior" decisions to explore the influence of farmers' climate change perception on their adaptive farming behavior. Mao Hui et al. (2022) used an experimental economics approach to measure farmers' risk aversion and systematically examined the effect of risk aversion on farmers' climate-adaptive technology adoption behavior and the mechanism of action. There have been many studies on the factors influencing adaptive behavior of farm households. Livelihood capital is the main consideration for the adoption of adaptive behavior by farm households (Zhao et al., 2020). Farmers with better financial capital endowment are more inclined to adopt climate-adaptive technologies (Xu et al., 2018). Social capital and income provide sufficient material basis for farmers to adopt climate-adaptive technologies (Li et al., 2018). In addition, stable social networks, educational level of household heads, and policy support such as technology training and technology demonstration all have positive effects on farmers' climate-adaptive technology adoption behavior (Barrett et al., 2003; Goyal and Netessine, 2007; Yang, 2018; Zhang et al., 2019).

Farmers' livelihood strategy adaptability refers to the ability and process of resisting risks in a vulnerable ecological environment by adopting measures such as changing production methods, ecological migration or diversifying livelihood strategies (Xu and Hu, 2018a). Adaptation of livelihood strategies is an important issue for sustainable development in ecologically fragile areas (Shi, 2015). Existing studies on the livelihood adaptability of farm households mainly focus on relocated farm households and farm households in rural tourism areas. For example, Lai (2016) constructed an analytical framework for livelihood adaptation of migrant relocated farm households from social-ecological system adaptation theory, and analyzed the livelihood adaptation strategies, perceived resilience and their influencing factors of migrant relocated farm households in Ankang, Shanxi. Liu et al. (2018b) explored the livelihood adaptive capacity of relocated farm households in the concentrated contiguous special hardship areas of the Qinba Mountains and its influence on livelihood adaptation strategies. Li et al. (2020) used the Socio-Ecological Systems (SES) analysis framework to analyze the livelihood adaptation strategies and livelihood adaptability of farm households in rural tourism areas. Wen et al. (2020) used three typical rural tourism sites in Yan'an city as examples, combined the sustainable livelihood analysis framework and adaptation theory, analyzed the adaptation strategies and adaptation patterns of farm households under rural tourism disturbance, and quantitatively measured the adaptation results of farmers with different adaptation patterns.

Risk refers to the uncertainty or loss of the outcome of the choice of future livelihood strategies (Crane, 1984; Yang et al., 2018), and environmental risk refers to the rise in temperature, uneven precipitation, and frequent occurrence of extreme disaster weather brought about by global climate change. Risk management is a series of measures taken to identify, select and prevent the occurrence of future risks to them (Chen and Ding, 2003). Academic research on risk management includes the following three main areas: first, research on the factors influencing the choice of farmers' risk management strategies. Many scholars have shown that farmers' livelihood capital and individual endowments, farmers' subjective risk perceptions and risk attitudes, and risk categories and degrees all have an impact on the choice of risk management strategies (Tai et al., 2009; Menapace et al., 2012; Kira, 2017; Chen and Wei, 2019). The second is the research on countermeasures and policies for risk management. For example, Cheng and Du (2017) based on the risk management theoretical framework, explored agricultural drought risk management from the perspective of environmental changes and food security, and proposed countermeasures for agricultural drought risk management in three dimensions: technical innovation, institutional construction, and mechanism innovation. Zhao et al. (2019) sorted out the construction, effectiveness, and problems encountered in the U.S. agricultural risk management policy system, and observed and analyzed the direction of the new U.S. Farm Bill in 2018. For example, Hu and Wen (2021) explored the mediating role of livelihood risk management based on the impact of livelihood capital on the sustainable livelihoods of poor farmers. Wei and Yang (2021) showed that agricultural insurance plays a "mediating effect" in the "farm-biased" impact of labor resource allocation.

To sum up, there are abundant related researches on risk management and farmers' livelihood adaptation, which provides a good theoretical basis for this study, but there are still the following shortcomings: First, the studies on livelihood adaptation mainly focus on relocated farmers and farmers in rural tourism areas, and few studies have been conducted on the livelihood adaptation of other farmers. Second, the existing literature on risk management mainly includes studies on the influencing factors of risk management strategy selection, countermeasures and policies of risk management, and the mediating and regulating roles of risk management, but lacks studies that use risk management as an explanatory variable to explore the benefits of risk management on the adaptation of farmers' livelihood strategies.

2.2 Theoretical Analysis

The Sustainable Livelihoods Analysis Framework (**Figure 1**) developed by the UK Department for International Development (DFID) states that people make their living in a vulnerable environment and livelihood risks are present throughout the whole process of achieving a sustainable livelihood, directly affect the livelihood capital they have and their choice of livelihood strategies, further affect livelihood consequences. Therefore, farmer households need to optimize the allocation of livelihood capital, choose multiple livelihood strategies suitable for household development, improve their risk management capacity and the adaptability of their livelihood strategies, and strive to output better livelihood outcomes.

Farmers diversify their choice of livelihood strategies as a means to adapt to climate change. Risk management is a series of adaptive strategies adopted by farmers to identify, select and prevent the occurrence of future risks. The adaptive strategies of farmers to adapt to environmental risks mainly include internal risk avoidance and external risk avoidance strategies (Gu and Lu, 2015). Internal risk aversion strategies are the ways in which farmers rely on their own strengths to manage risk. Based on their own risk perceptions and risk preferences, farmers adopt appropriate soil testing and fertilizer application techniques and appropriate application behaviors to achieve livelihood objectives such as risk reduction and profit increase, which influence agricultural production decisions and livelihood strategy adaptation (Feng et al., 2018b; Qi et al., 2020). External risk aversion strategies are the ways of relying on external forces for risk management. Farmers can diversify agricultural risks, cover losses and reduce income uncertainty by purchasing agricultural insurance (Liu et al., 2021). The government plays an indispensable role in mitigating risks and pressure on farmers' livelihoods. The government has implemented a series of support measures such as arable land protection policies and ecological subsidies to mitigate the risks of farmers' adoption of green production techniques, improve farmers' income and stabilize farmers' livelihoods to a certain extent (Huang et al., 2020). Farmers join collective actions in the form of cooperatives, village collectives and companies to share external risks, adapt and adjust their livelihood strategies (Kassie et al., 2013; Jia and Lu, 2018). The important role that farmers play in risk diversification and transfer by relying on informal mechanisms such as social ties and collective organizations to form risk management mechanisms is an important factor influencing the adaptability of their livelihood strategies. Relying on a single risk management strategy alone can hardly produce positive results, and only by adopting diversified and differentiated risk management and livelihood strategies based on one's capital endowment and external forces, improving farmers' risk management capacity and gradually adapting to livelihood

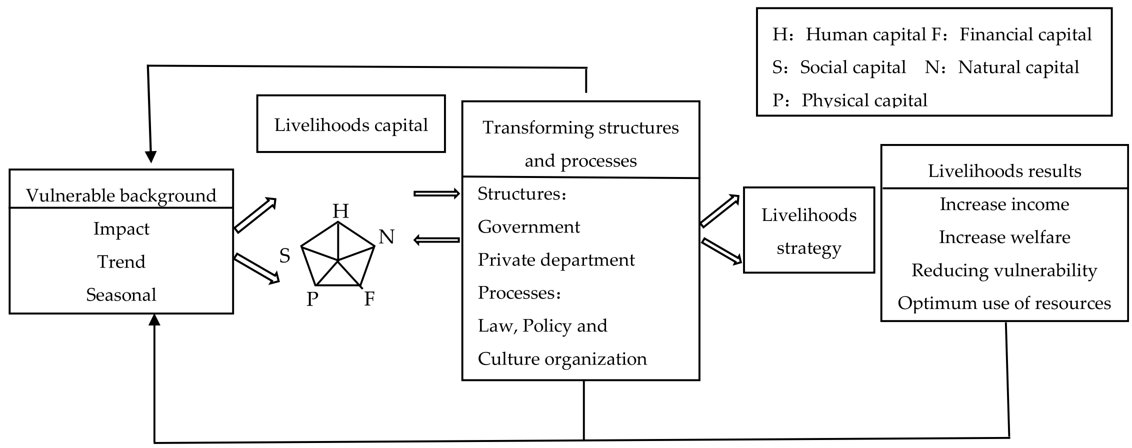

FIGURE 1 | Sustainable livelihoods framework.

risks, can more positive results be achieved. Therefore, in a given context, the choice and adaptation of adaptive livelihood strategies by farmers is determined by the status of their risk management capacity. The stronger the risk management capacity of farmers, the more options they have and the better they are able to use different types of livelihood strategies to improve the adaptability of livelihood strategies to stabilize household livelihoods.

Based on the above analysis, the following research hypothesis is proposed for this paper: the stronger the environmental risk management capacity of farmers, the more adaptable their livelihood strategies.

3 MATERIALS AND METHODS

3.1 Sample and Data Sources

The data used in this paper comes from a field survey conducted by the research team on the livelihoods of farming households in Hubei Province in 2020. The survey obtained basic information about farming households; household natural, social, financial and physical capital; production operations and farming households' rural perceptions. The survey was conducted in Honghu city and Qichun county in Hubei Province, China, which cover basically all the terrain in Hubei Province, including plains, hills and mountains, and are to some extent representative of the livelihoods situation in Hubei Province. The survey was conducted using a random sampling method, and the population surveyed involved 39 administrative villages in 12 townships, with 30–40 households selected from each village for the survey. A total of 1,100 questionnaires were distributed and 1,050 questionnaires were eventually returned. After excluding the missing samples, 970 valid samples were obtained. This paper also classifies farm households equal to income, drawing on existing literature on income grouping criteria to classify farm households into three categories: low income, middle income and high income (Cai et al., 2020; He and Zhou, 2020). Farmers with per capita household income less than RMB 8,000 were classified as low income, those with per capita household income between RMB 8,000 and RMB 30,000 were classified as middle income, and those with per capita household income greater than or equal to RMB 30,000 were classified as high income. The distribution of the sample is detailed in **Table 1**.

3.2 Definition of Variables

3.2.1 Farmers' Livelihood Strategy Adaptation Variables

In this paper, livelihood strategy adaptability is reflected by the fact that farmers engage in multiple types of livelihood activities. The diversity of livelihood strategies is an important component of farmers' livelihood strategies to improve the quality of life and increase farmers' income, and its index level directly affects the strength of farmers' livelihood adaptability (Xu and Hu, 2018b). This paper draws on the research method of scholars Gao and Lu (2021) and adopts the Simpson index to measure the adaptability of farmer households' livelihood strategies. Simpson's index is one of the composite indicators reflecting diversity and balance, and the value of this index is taken to increase gradually with the richness and balance of farmer households' livelihood strategies (Dong et al., 2019). The specific public indices are as follows.

$$\text{S.I.} = 1 - \sum_{i=1}^{N} P_i^2 \quad (1)$$

In **Eq 1**, N denotes the type of livelihood strategy, and this paper uses the income of each type of livelihood strategy for calculation, including agricultural business income, wage income, property income and transfer income; P_i denotes the proportion of the i livelihood type. the value of S.I. ranges from 0 to 1, and the larger the value, the higher the index, indicating the stronger the adaptive capacity of farmer households' livelihood strategies. When the value of S.I. is 0, farmers have a single livelihood type and the least adaptive capacity; when the value of S.I. is 1, it indicates that farmers adopt multiple livelihood strategies and have the highest adaptive capacity.

TABLE 1 | Sample distribution.

City (County)	Town	Administrative Villages	Effective Sample	Low Income	Middle Income	High Income
Honghu	4	20	547	108	299	140
Qichun	8	19	423	103	247	73
Total	12	39	970	211	546	213

TABLE 2 | Variable definition table.

Category		Variable Name	Variable Definitions
Explained variable		Livelihood Strategy Adaptability	Calculated Using Simpson's index
Explanatory variables	Risk management capability	Risk management capability	Calculated using the entropy weighting method
	Internal risk management	Soil testing and fertilizer application techniques	Adopted = 1, not adopted = 0
		Organic pesticide technology	Adopted = 1, not adopted = 0
	External risk management	Agricultural insurance	Whether to purchase agricultural insurance (Adopted = 1, not adopted = 0)
		Cooperatives	Participation in a cooperative or not (Adopted = 1, not adopted = 0)
		Enterprise's help	Whether agricultural production is assisted by village-run enterprises (yes = 1, no = 0)
		Agricultural subsidies	Income from agricultural subsidies (CNY, logarithm)
Control variables	Human capital	Average education level of household members	1 = illiterate, 2 = not graduated from primary school, 3 = primary school, 4 = junior high school, 5 = senior high school, 6 = tertiary and above
		Labor proportion	The proportion of household labor force in the total household population
		Proportion of the trained workforce	The proportion of the workforce trained in professional skills of the total workforce
	Natural capital	Land area	Family per capita land area (mu)
	Physical capital	Housing area	Per capita living area of a family (square meters)
	Social capital	Relationships with friends and relatives	Are there any relatives in the family who are village cadres or above (township cadres or above = 2, village cadres = 1, no = 0)
		Relationships with neighbors	The numbers of neighbours who visit each other
	Financial capital	Money lending	Whether to lend to others (yes = 1, no = 0)
		Financial products	Whether investing in financial products (Yes = 1, No = 0)

3.2.2 Farmers' Environmental Risk Management Variables

Environmental risk management is the core explanatory variable in this paper, and there is a large body of relevant literature on the selection and measurement of environmental risk management indicators. This paper draws on the research of scholars Gu and Lu (2015) and adopts a multi-indicator approach to classify farmer households' environmental risk management indicators into internal risk management and external risk management. Internal risk management mainly includes soil testing and fertilizer technology adoption behavior and organic pesticide technology adoption behavior. External risk management consisted of the following four variables: 1) Agricultural insurance. That is, whether farmers purchase agricultural insurance to obtain insurance payouts to diversify risks. 2) Cooperatives. That is, whether farmers participate in co-operatives to increase their organization and resilience to risk. 3) Enterprise's help. That is, whether farmers receive help from village-run enterprises for their production. 4) Whether farmers receive government help, which is measured in this paper by taking the agricultural subsidies received by farmers (see **Table 2** for details).

Drawing on the research of scholars such as Wang et al. (2021), the entropy weighting method is used to determine the weights of farmers' risk management capacity indicators system to measure the composite score. The higher the calculated composite score, the stronger the risk management capability of the farmer. The specific measurement steps are as follows:

First, dimensionless processing of the indexes is carried out:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \tag{2}$$

In **Formula (2)**, X'_{ij} represents the normalized value of index j of sample i. X_{ij} represents the variable value of index j of sample i. $\max(X_j)$ represents the maximum value of index j, and $\min(X_j)$ represents the minimum value of index j.

Second, the information entropy of each index is calculated:

$$E_j = -\frac{1}{\ln n}\sum_{i=1}^{N} P_{ij}\ln P_{ij} \tag{3}$$

Among them, $P_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{N} X'_{ij}}$.

To determine the weight of each index, the entropy value of each index is calculated using **Formula (3)** (E1, E2, . . . , Em). To

TABLE 3 | Descriptive statistics of variables.

	Sample Size	Mean	Standard Deviation	Minimum value	Maximum value
Livelihood strategy adaptability	970	0.2054	0.1891	0	0.6650
Risk management capability	970	0.0069	0.0041	0	0.0223
Soil testing and fertilizer application techniques	970	0.0876	0.2829	0	1
Organic pesticide technology	970	0.2351	0.4242	0	1
Agricultural insurance	970	0.1701	0.3759	0	1
Cooperatives	970	0.0567	0.2314	0	1
Enterprise's help	970	0.0526	0.2233	0	1
Agricultural subsidies	970	4.4322	2.7669	0	12.6115
Average education level of household members	970	4.9746	2.5868	0	25
Labor proportion	970	0.6488	0.2632	0	2
Proportion of the trained workforce	970	0.6416	0.7842	0	5
Land area	970	1.8059	7.2566	0	200
Housing area	970	52.8377	35.3319	0	266.6667
Relationships with friends and relatives	970	0.2505	0.5280	0	6
Relationships with neighbors	970	7.3495	7.5197	0	80
Money lending	970	0.0402	0.1965	0	1
Financial products	970	0.0072	0.0847	0	1

calculate the weight of each index using the entropy value method, the following equation is used:

$$W_j = \frac{1 - E_j}{\sum E_j} \left(0 \le j \le m\right) \tag{4}$$

Finally, the risk management capability is calculated according to the weight of the index:

$$Z_i = \sum\nolimits_{i=1}^{14} X_{ij} * W_j \tag{5}$$

3.2.3 Control Variables

The control variables introduced in this paper are mainly the livelihood capital owned by farmer households, which consists of the following five components: 1) Human capital, including three measures of the average education level of the labor force, the proportion of labor force and the proportion of trained labor force. 2) Natural capital, which is measured by the average land area per capita owned by farmers. 3) Physical capital, which includes the average area of housing per farmer as an indicator. 4) Social capital, including two indicators of family and friend relations and neighborhood relations. 5) Financial capital, including two indicators of whether farmers borrow money from others and whether farmers buy financial products (see **Table 2** for details).

3.3 Model Construction

In order to test the research hypothesis of this paper, the Tobit regression model was constructed using the Livelihood Strategy Adaptation Index measured by the method described in the previous section as the explanatory variable, the soil testing and fertilizer application technology, organic pesticide technology, agricultural insurance, cooperatives, village enterprise assistance and agricultural subsidies selected in this paper as explanatory variables, and five livelihood capital as control variables as follows.

$$Y = a + bX_i + cControl_i + \varepsilon_i \tag{6}$$

In the above equation, Y denotes the adaptability index of farmers' livelihood strategies, X denotes farmers' risk management, i is the type of risk management, including soil testing and fertilizer technology, organic pesticide technology, agricultural insurance, cooperatives, village enterprise help and agricultural subsidies, control is a set of control variables, and a and ε_i denote the constant and random disturbance terms.

4 ANALYSIS OF EMPIRICAL RESULTS

4.1 Descriptive Statistical Analysis

Table 3 shows the descriptive statistical characteristics of the variables. The maximum value of the Livelihood Strategy Adaptation Index is 0.6650, the minimum value is 0, and the mean value is 0.2554, indicating that there is a large gap in the adaptability of farmers' livelihood strategies, and most farmers' livelihood strategy adaptability is at a low level. The core explanatory variable risk management capability has a maximum value of 0.0223, a minimum value of 0 and a mean value of 0.0069. the mean values of the core explanatory variables soil testing and fertilizer application technology, organic pesticide technology, agricultural insurance, cooperatives and village enterprise assistance are 0.0876, 0.2351, 0.1701, 0.0567 and 0.0526 respectively, which shows that most of the farmers have not adopted soil formula fertilizer technology and organic pesticide technology, and very few of them have joined cooperatives and received assistance from village enterprises. The mean value of the average education level of the labor force was 4.9746, indicating that the average education level of farming households was above junior high school in both Honghu city and Qichun county, Hubei Province. The mean value of the labor force share was 0.6488, indicating that more than half of the members of the household were capable of working. The mean value of the proportion of trained labor

TABLE 4 | Full sample regression results.

	Livelihood Strategy Adaptability (Full Sample)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Risk management capability	7.5614*** (5.11)	—	—	—	—	—	—
Soil testing and fertilizer application techniques	—	–0.0210 (-0.98)	—	—	—	—	—
Organic pesticide technology	—	—	0.0285** (2.00)	—	—	—	—
Agricultural insurance	—	—	—	0.0490*** (3.04)	—	—	—
Cooperatives	—	—	—	—	0.0605** (2.27)	—	—
Enterprise's help	—	—	—	—	—	0.0571** (2.11)	—
Agricultural subsidies	—	—	—	—	—	—	0.0099*** (4.52)
Average education level of household members	0.0070*** (2.75)	0.0077*** (3.02)	0.0079*** (3.07)	0.0075*** (2.92)	0.0076*** (2.95)	0.0078*** (3.06)	0.0070*** (2.75)
Labor proportion	0.0395** (1.68)	0.0535** (2.26)	0.0527** (2.23)	0.0491** (2.08)	0.0511** (2.16)	0.0523** (2.21)	0.0417* (1.77)
Proportion of the trained workforce	–0.0115 (-1.48)	–0.0097 (-1.23)	–0.0119 (-1.51)	–0.0108 (-1.38)	–0.0105 (-1.34)	–0.0114 (-1.46)	–0.0105 (-1.35)
Land area	0.0015** (1.76)	0.0024*** (2.80)	0.00217** (2.56)	0.0019** (2.23)	0.0021** (2.40)	0.0023*** (2.74)	0.0017** (2.03)
Housing area	0.0004** (2.52)	0.0004** (2.28)	0.0004** (2.45)	0.0004** (2.43)	0.0004** (2.33)	0.0004** (2.37)	0.0004** (2.43)
Relationships with friends and relatives	–0.0003 (-0.03)	0.0011 (0.09)	0.0007 (0.06)	0.0006 (0.05)	0.0007 (0.06)	0.0004 (0.04)	0.0001 (0.01)
Relationships with neighbors	–0.0013 (-1.59)	–0.0012 (-1.42)	–0.0013 (-1.56)	–0.0011 (-1.33)	–0.0012 (-1.45)	–0.0012 (-1.41)	–0.0013 (-1.54)
Money lending	0.0016 (0.05)	0.01215 (0.40)	0.0098 (0.32)	0.0069 (0.23)	0.0074 (0.24)	0.0100 (0.32)	0 0.0047 (0.15)
Financial products	0.0429 (0.61)	0.0594 (0.83)	0.0631 (0.89)	0.0472 (0.66)	0.0285 (0.39)	0.0382 (0.53)	0.0514 (0.73)
Sample size	970	970	970	970	970	970	970

*Note: ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively. The values in parentheses are the t values.*

force is 0.6416, indicating that more than the average household labor force has received skills training.

4.2 Analysis of Model Regression Results

Table 4 shows the results of the full-sample regression of the effect of environmental risk management on the adaptation of farmers' livelihood strategies. The core explanatory variable farm household risk management capacity has a significant positive effect on farm household livelihood strategy adaptability at the 1% level, indicating that the higher the risk management capacity of farm households, the more adaptable their livelihood strategies are. The core explanatory variable, soil testing and fertilizer application technology, had a negative impact on the adaptation of farmers' livelihood strategies, but was not found to be significant. The reason for this may be that soil testing and fertilizer application technology has not yet been widely used in the study area, traditional fertilizer application patterns and blind fertilizer application still exist, and farmers' acceptance of soil testing and fertilizer application technology is low due to fertilizer application perceptions. The core explanatory variable, organic pesticide technology, was significantly positive at the 5% level, indicating that farmers' adoption of organic pesticide technology can significantly improve their livelihood strategy adaptability. The core explanatory variable agricultural insurance was significantly positively associated with the variable livelihood strategy adaptability at the 1% level, and the purchase of agricultural insurance by farmers can effectively diversify environmental risks and improve their ability to adapt their livelihood strategies. The core explanatory variables co-operatives and enterprise help are both significantly positive at the 5% level, indicating that farmers joining co-operatives and receiving help from village-level enterprises can improve their livelihood strategy adaptive capacity. The core explanatory variable, agricultural subsidies, was significantly positive at the 1% level, indicating that government-granted agricultural subsidies had a significant positive impact on the livelihood strategy adaptability of farm households.

The paper also divides the sample into three categories of low, middle and high income according to the income of the farming households, and regresses the sample in groups. **Table 5** shows the regression results for the low-income farming sample. The core explanatory variables soil testing and fertilizer application technology, organic pesticide technology, agricultural insurance and enterprise assistance all had a positive effect on the adaptation of farmers' livelihood strategies, but none of them passed the significance test. The reasons for this are as follows: for low-income farmers, the adoption of soil-formulation fertilizer technology and organic pesticide technology is more costly and relatively more technically difficult, and most farmers prefer traditional fertilizer and pesticide application techniques to reduce production costs. Low-income farmers have relatively low demand for agricultural insurance purchases and less chance of seeking help from enterprises due to the small scale of agricultural production. The core explanatory variable co-

TABLE 5 | Regression results for the low-income sample.

	Livelihood Strategy Adaptation (Low-Income Sample)				
Soil testing and fertilizer application techniques	0.0164 (0.32)	—	—	—	—
Organic pesticide technology	0.0030 (0.08)	—	—	—	—
Agricultural insurance	—	0.0583 (1.43)	—	—	—
Cooperatives	—	—	0.1113* (1.86)	—	—
Enterprise's help	—	—	—	0.0837 (1.45)	—
Agricultural subsidies	—	—	—	—	0.0121** (2.16)
Average education level of household members	0.0122** (2.42)	0.0113** (2.25)	0.0112** (2.23)	0.0118** (2.36)	0.0104** (2.06)
Labor proportion	0.1353*** (2.83)	0.1382*** (2.91)	0.1362*** (2.87)	0.1333*** (2.80)	0.1254*** (2.64)
Proportion of the trained workforce	−0.0203 (-1.13)	−0.0193 (-1.08)	−0.0213 (-1.20)	−0.0202 (-1.13)	−0.0201 (-1.14)
Land area	0.0329*** (3.47)	0.0310*** (3.27)	0.0345*** (3.70)	0.0336*** (3.57)	0.0254** (2.55)
Housing area	−0.0004 (-0.94)	−0.0003 (-0.78)	-0.0004 (−1.04)	−0.0003 (-0.82)	−0.0003 (−0.70)
Relationships with friends and relatives	0.0158 (0.65)	0 0.0118 (0.49)	0.0157 (0.65)	0.0140 (0.58)	0.0189 (0.79)
Relationships with neighbors	−0.0031 (-1.26)	−0.0029 (-1.21)	-0.0026 (−1.06)	−0.0029 (−1.20)	-0.0034 (−1.40)
Money lending	0.0712 (0.46)	0.0838 (0.55)	0.0696 (0.46)	0.0707 (0.46)	0.0696 (0.46)
Financial products	0.1267 (0.60)	0.1230 (0.59)	0.1337 (0.64)	0.1261 (0.60)	0.0863 (0.41)
Sample size	211	211	211	211	211

*Note: ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively. The values in parentheses are the t values.*

TABLE 6 | Regression results for the middle-income sample.

	Livelihood Strategy Adaptation (Middle-Income Sample)				
Soil testing and fertilizer application techniques	0.0045 (0.17)	—	—	—	—
Organic pesticide technology	0.0146 (0.89)	—	—	—	—
Agricultural insurance	—	0.0184 (0.97)	—	—	—
Cooperatives	—	—	0.0458 (1.41)	—	—
Enterprise's help	—	—	—	0.0669** (2.11)	—
Agricultural subsidies	—	—	—	—	0.0011 (0.43)
Average education level of household members	0.0037 (1.14)	0.0037 (1.12)	0.0036 (1.10)	0.0042 (1.28)	0.0036 (1.10)
Labor proportion	0.0040 (0.14)	0.0031 (0.10)	0.0006 (0.02)	0.0030 (0.10)	0.0037 (0.12)
Proportion of the trained workforce	−0.0076 (−0.81)	−0.0066 (−0.71)	−0.0057 (−0.62)	-0.0075 (−0.81)	−0.0064 (−0.69)
Land area	0.0366*** (7.69)	0.0366*** (7.72)	0.0371*** (7.88)	0.0373*** (7.95)	0.0365*** (7.36)
Housing area	0.0001 (0.50)	0.0001 (0.44)	0.0001 (0.38)	0.0001 (0.43)	0.0001 (0.47)
Relationships with friends and relatives	0.0014 (0.09)	0.0011 (0.08)	0.0004 (0.03)	0.0012 (0.08)	0.0005 (0.03)
Relationships with neighbors	−0.0006 (-0.65)	−0.0004 (−0.47)	−0.0005 (−0.53)	−0.0005 (−0.52)	−0.0005 (−0.56)
Money lending	−0.0001 (−0.00)	−0.0042 (−0.11)	−0.0055 (−0.15)	−0.0004 (−0.01)	−0.0003 (−0.01)
Financial products	−0.1687 (−1.05)	−0.1689 (−1.05)	−0.1683 (−1.05)	−0.2353 (−1.44)	−0.1731 (−1.07)
Sample size	546	546	546	546	546

*Note: ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively. The values in parentheses are the t values.*

operatives is significantly positive at the 10% level, with low-income farmers' membership of co-operatives improving their ability to adapt their livelihood strategies. The core explanatory variable agricultural subsidies is significantly positive at the 5% level, showing that government-granted agricultural subsidies also have a significant positive impact on the adaptability of livelihood strategies of low-income farmers.

Table 6 shows the regression results for the middle-income farm household sample. The core explanatory variables soil testing and fertilizer technology, organic pesticide technology, agricultural insurance, cooperatives and agricultural subsidies all positively affected the adaptation of farmers' livelihood strategies, but none of them passed the significance test. For middle-income farmers, the scale of their agricultural production is high relative to that of low-income farmers, but not yet at the scale of production of high-income farmers, and therefore the adoption of soil-formulation fertilizer technology and organic pesticide technology is low, and the marginal benefits of purchasing agricultural insurance are low. The core explanatory variable enterprise help was significantly and positively correlated with the explanatory variable livelihood strategy adaptation at the 5% level, indicating that middle-income farmers' access to enterprise help can significantly improve their ability to adapt their livelihood strategies. Since middle-income farmers do not have a complete production and marketing process, seeking help from enterprises to share and transfer risks can effectively improve their productivity and livelihood strategy adaptability.

Table 7 shows the regression results for the sample of high-income farmers. The core explanatory variable soil testing and

TABLE 7 | Regression results for the high-income sample.

	Livelihood Strategy Adaptation (High -Income Sample)				
Soil testing and fertilizer application techniques	–0.1007** (-2.44)	—	—	—	—
Organic pesticide technology	0.0387 (1.19)	—	—	—	—
Agricultural insurance	—	0.0692** (2.23)	—	—	—
Cooperatives	—	—	0.0556 (1.04)	—	—
Enterprise's help	—	—	—	-0.0481 (-0.74)	—
Agricultural subsidies	—	—	—	—	0.0138*** (3.12)
Average education level of household members	0.0216*** (3.08)	0.0190*** (2.76)	0.0197*** (2.83)	0.01867*** (2.68)	0.0206*** (3.02)
Labor proportion	0.1643** (2.23)	0.1240* (1.70)	0.1494** (2.05)	0.1449** (1.98)	0.1371* (1.92)
Proportion of the trained workforce	-0.0135 (-0.86)	-0.0189 (-1.20)	-0.01875 (-1.18)	-0.0161 (-1.00)	-0.0144 (-0.92)
Land area	0.0015* (1.71)	0.0005 (0.58)	0.0007 (0.82)	0.0010 (1.11)	0.0005 (0.63)
Housing area	0.0006 (1.60)	0.0008** (2.23)	0.0007** (2.12)	0.0008** (2.16)	0.0007** (2.06)
Relationships with friends and relatives	–0.0150 (–0.71)	–0.0123 (-0.58)	–0.0135 (–0.63)	–0.0122 (–0.57)	–0.0158 (–0.75)
Relationships with neighbors	–0.0007 (–0.39)	-0.0005 (-0.30)	-0.0006 (-0.33)	-0.0001 (-0.06)	-0.0002 (-0.11)
Money lending	0.0179 (0.40)	0.0238 (0.53)	0.0164 (0.36)	0.0223 (0.48)	0.0034 (0.08)
Financial products	0.1506* (1.83)	0.1135 (1.36)	0.1042 (1.14)	0.1580* (1.85)	0.1408* (1.73)
Sample size	213	213	213	213	213

*Note: ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively. The values in parentheses are the t values.*

fertilizer application technology is significantly negatively related to the explanatory variable livelihood strategy adaptation at the 5% level, probably because high-income farmers tend to emphasize the application of inorganic fertilizers in soil testing and neglect the use of organic fertilizers, which to a certain extent tends to lead to a decrease in crop yield and quality, which is not conducive to livelihood strategy adaptation. The core explanatory variables agricultural insurance and agricultural subsidies are significantly positive at the 5 and 1% levels respectively, indicating that both the purchase of agricultural insurance and the receipt of agricultural subsidies by high-income farmers increase their ability to adapt their livelihood strategies. For high-income farmers, the larger scale of agricultural production and the generally higher losses caused in the event of environmental risks, the higher demand for agricultural insurance by farmers and the higher marginal benefits of purchasing agricultural insurance. In addition, the government grants more agricultural subsidies, etc. to high-income farmers with larger agricultural production, which plays an important role in the long-term stability of their agricultural production. The variables organic pesticide technology, cooperatives and enterprise help did not pass the significance test. The reason for this is that high-income farmers are mostly equipped with complete production materials due to the requirements of the development of their production scale, have better production and marketing processes, and have a lower need to participate in collective actions such as cooperatives and to obtain help from enterprises.

5 CONCLUSION AND DISCUSSION

With the increasing problems of rising temperatures, uneven precipitation and the frequency of extreme disaster weather brought about by global climate change, agricultural production is facing more severe challenges. Unlike the existing literature, this paper is based on a sustainable livelihoods framework, using micro research data on the livelihoods of farm households in Hubei Province, China in 2020, and using the Simpson Index to measure the adaptability index of farm households' livelihood strategies and analyze the benefits of different environmental risk management approaches of farm households on the adaptability of livelihood strategies. Heterogeneity analysis was also conducted by classifying farm households according to their household income. The results showed that 1) the higher the risk management capacity of farmers, the more adaptable their livelihood strategies. (2)The core explanatory variables organic pesticide technology, agricultural insurance, cooperatives, enterprise help and agricultural subsidies all had significant positive effects on the livelihood strategy adaptability of farm households in both Honghu city and Qichun county in Hubei province. This is consistent with the findings of previous studies that risk management has a positive effect on farmers' livelihood adaptation. 3) Soil testing and fertilizer application technology did not pass the significance test on livelihood strategy adaptation because soil testing and fertilizer application technology has not been widely used in both Honghu city and Qichun county in Hubei Province, and farmers' acceptance of soil testing and fertilizer application technology is low due to fertilizer application perceptions. 4) For low-income farmers, soil-formula fertilizer technology, organic pesticide technology, agricultural insurance and enterprise assistance all have insignificant effects on the adaptability of farmers' livelihood strategies. Joining cooperatives and receiving agricultural subsidies had a significant positive effect on the adaptation of livelihood strategies of low-income farmers. 5) For middle-income farmers, the effects of soil testing and fertilizer technology, organic pesticide technology, agricultural insurance, cooperatives and agricultural subsidies were not significant on the adaptation of farmers' livelihood strategies. The positive effect of enterprise assistance on livelihood strategy adaptation was significant, so middle-income farmers can effectively improve their productivity and livelihood strategy adaptation by seeking the help of enterprises for risk sharing and transfer. 6) For high-income farmers, soil testing and fertilizer application technology was significantly and negatively related to the explanatory variable of livelihood strategy adaptation, which is inconsistent with the findings of some existing studies. For example, Zhang et al. (2021) showed that the adoption of soil testing and fertilizer application technology can significantly improve the productivity of apple growers and also contribute to the improvement of planting profit. This paper suggests that the reason for this may be that high-income farmers tend to emphasize the application of inorganic fertilizers in soil testing and fertilizer application, neglecting the use of organic fertilizers, which to a certain extent tends to lead to a decline in crop yield and quality and is not conducive to the adaptation of livelihood strategies. In contrast, the purchase of agricultural insurance and access to agricultural subsidies can have a significant positive effect on the adaptation of livelihood strategies of high-income farming households with larger agricultural production. The marginal benefits of purchasing agricultural insurance are higher for high-income farmers, and the agricultural subsidies granted by the government play an important role in the long-term stability of their agricultural production.

6 POLICY IMPLICATIONS

Based on the above findings, the following recommendations are made with the objective of improving the adaptive capacity of farmers' livelihood strategies and achieving optimal livelihood outcomes: 1) Publicity on the risks posed by climate change to agricultural production should be strengthened to enhance farmers' perception of climate change, and farmers themselves need to strengthen their risk perception and prevent risk uncertainty caused by environmental disasters in advance, so as to increase the adoption of adaptive livelihood strategies by farmers This will increase the adoption of adaptive livelihood strategies and enhance the adaptive capacity of farmers' livelihood strategies. 2) The government should increase its policy support, strengthen the promotion of ecological technologies such as soil testing and fertilizer application, provide more technical training opportunities for farmers, improve their technical awareness, and improve the continuous technical formulation for farmers through technical training to facilitate the promotion of adaptive technologies. Improve agricultural insurance policies and strengthen the promotion of agricultural insurance policies to increase the demand for purchase by farmers. 3) Give full play to the collective role of village collectives, companies and co-operatives to create a good organizational climate for farmers, improve their ability to cope with risk and play an important role in improving the adaptability of livelihood strategies. 4) Farmers should adjust their livelihood strategies in a timely manner according to the way they allocate their capital and the proportion of their structure to enhance the sustainability of their livelihood outcomes. 5) To improve the adaptability of diversified livelihood strategies for farmers with a single livelihood activity, actively create more livelihood options, increase the proportion of farmers' wage, property and transfer income, promote the transformation and upgrading of livelihood options, raise farmers' income, improve the quality of life and further improve the adaptability of livelihood strategies (Barham et al., 2014; Xu and Hu, 2018a; Xu and Hu, 2018b; Yang et al., 2018; Zhang et al., 2021).

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

Conceptualization, WW and CZ; methodology, CZ, XL, and JS; software, ZF and ZH; validation, WW and CZ; formal analysis, CZ; resources, XL; data curation, JS and WW; writing—original draft preparation, ZF; writing—review and editing, ZH; visualization, CZ; supervision, WW and JS; funding acquisition, WW. All authors have read and agreed to the published version of the manuscript.

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Vulnerability Assessment and Spatio-Temporal Dynamics Analysis of Agricultural Flood in China

Yinong Liu, Jiaxi Zheng, Honggang Lu* and Xijian Li*

School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China

Flood is one of the main problems faced by agricultural production in China. The research of agriculture's floods vulnerability is the premise of scientifically dealing with floods. Based on the vulnerability assessment framework of "sensitivity-exposure-adaptability," this paper selects 14 evaluation indicators from three aspects: sensitivity, exposure, adaptability, and the index weights which are determined by the entropy weight method to evaluate the sensitivity, resilience, and vulnerability of flood In terms of time, China's overall flood vulnerability shows a trend of increasing first and then decreasing. From a spatial point of view, the number of highly vulnerable areas is relatively small which are mainly concentrated in Henan, Hubei, Anhui and other provinces, and most areas of the country are at low and mild levels. From the factor analysis model, the main contributing factors of agricultural flood exposure, sensitivity and adaptability are soil erosion control area, forest coverage rate, total reservoir capacity and total power of agricultural machinery. Therefore, controlling soil erosion, increasing forest coverage, further improving water conservancy facilities and strengthening agricultural mechanization level are the keys to reduce vulnerability of agricultural floods.

Keywords: agricultural flood vulnerability, exposure, sensitivity, adaptability, entropy method

Edited by:
Dingde Xu,
Sichuan Agricultural University, China

Reviewed by:
Tongchao Zhang,
Chongqing Academy of Governance, China
Huang Kai,
University of Chinese Academy of Sciences, China

****Correspondence:***
Jiaxi Zheng
470507355@qq.com
Honggang Lu
879144704@qq.com

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INTRODUCTION

In recent years, global climate change has intensified, and extreme climate events have also increased significantly, which has increased the instability of agricultural production. The security of agricultural production has been threatened and challenged. The report "Climate Change 2022: Impacts, Adaptation, and Vulnerability" published by group II of the Intergovernmental Panel on Climate Change (IPCC) pointed out that the current global temperature rise is only 1.1°C, but it has caused great damage on a global scale. Record floods have seriously threatened agricultural security and the livelihoods of tens of millions of people around the world. The increasing risk of flood disasters has become a global problem accompanied by climate change. The rising sea level and the increasing frequency of catastrophic storms caused by the increase in global average surface temperature have increased the threat of future flood disasters.

Affected by the factors such as monsoon, geographical location, topography and landform, China is a country with frequent and serious flood disasters in the world. Flood disasters not only have a wide range, frequent occurrence, strong suddenness, but also create huge losses. According to the statistics, from 1991 to 2020, an average of 2,020 people died or went missing due to floods in China, with a total of more than 60,000 deaths, resulting in an average annual direct economic loss of 160.4 billion yuan, totaling about 4.81 trillion yuan.

Floods have a wider impact on farmland than in cities and other systems. Especially for China's agriculture with small farmers as the main production unit, the construction of rural infrastructure is insufficient, the popularity of agricultural insurance is not high (Xu et al., 2019), and the ability of farmers to deal with flood disasters is limited. Flood disasters directly lead to the reduction of crop yields, the reduction of people's income, and the shortage of food. The reduction of crop productivity and the deterioration of the ecological environment have severely restricted the agricultural development.

China is a big agricultural country, and agriculture is the foundation of the national economy. The safety of agricultural production is related to food security, social and economic development, and more importantly, social stability. From 2000 to 2020, the average area affected by agricultural floods in China was 0.851 million hectares, and the harvest area was reduced by 0.129 million hectares. After 2006, the economic losses caused by flood disasters to China's agricultural production have been increasing year by year. In 2006–2009, the annual economic loss caused by floods in China was about 46.6 billion yuan, and after 2010, this figure soared to 91.3 billion yuan. In 2012, China's grain output decreased by 40 million tons due to floods, which was close to 6.8% of the total grain output in that year. Therefore, in the face of more and more frequent flood disasters, assessing the vulnerability of China's agricultural floods has practical value for formulating disaster prevention and mitigation strategies and improving the ability of agriculture to cope with flood disasters.

LITERATURE REVIEW

The concept of vulnerability originated in the social sciences, firstly used by O'Keefe et al. (1976), to describe concepts related to natural disasters. Vulnerability is defined as a measure of the unfavorable degree to which the socioeconomic system of human groups is damaged by natural disasters, and is determined by sensitivity, exposure, and resilience (IPCC, 2001). Now, it is widely used in disaster research (Sahana and Sajjad, 2019). IPCC (2014) believed that vulnerability is mainly the result of socio-economic processes and social conditions, that is, the socio-economic pathways, adaptation and mitigation actions, and management practices of the assessed area need to be considered. Vulnerability is often related to disasters, aggravated by human activities (Aroca-Jiménez et al., 2020), and will reduce the ability of human beings and regions to respond to threats (Fatemi et al., 2017). Climate change has an increasing impact on production and people's lives. In order to effectively reduce the losses caused by floods, it is necessary to understand the vulnerability of floods (Lian and Morimoto, 2019). In recent years, the issue of flood vulnerability has gradually become the focus and research hotspot of scholars from all over the world.

In the past few decades, a large number of scholars have measured and evaluated the vulnerability of floods. From the research field, researchers divide the vulnerability of flood into many types, including social vulnerability, economic vulnerability and environmental vulnerability., including social vulnerability, economic vulnerability and environmental vulnerability. Munyai et al. (2019) measured the social vulnerability of communities in South Africa, and found that the social and economic components of the flood disaster vulnerability index system scored higher than the natural environment score. Li et al. (2022) evaluated the vulnerability of China's agricultural ecosystem by multi-index method. From the perspective of research scope, the existing research focuses on flood vulnerability from both micro and macro perspectives. At the micro level, the research objects are mainly individuals, families, and communities. Mahmood et al. (2017) used seven integrated methods to assess the impact of flash flood events in the Sudanese capital Khartoum in 2013 and 2014, assessing vulnerability to mountain flooding. Tessema and Simane (2019) calculated the livelihood vulnerability index from the aspects of ecology, agriculture, society, community, wealth, technology and infrastructure, and evaluated the vulnerability of Ethiopia's agricultural system based on farmer's interview and questionnaire. Percival and Teeuw (2019) took a systematic approach to study flood hazard vulnerability in mountainous Nepal. It is found that the high vulnerability level stems from higher flood risk and lower adaptive capacity, and the ordinal response model is used to analyze the micro-factors affecting the flood vulnerability level. Nazeer and Bork (2021) assessed the integrated indicators of flood vulnerability in Khyber Pakhtunkhwa, Pakistan, from a microscopic perspective through a household survey, setting relative indicators and a color matrix. At the macro level, researchers collect regional statistical data to obtain research data. Muqtada et al. (2014) assessed flood vulnerability using indicators such as population mortality, economics, and agriculture. Ahmed and Balica (2019) developed a new flood vulnerability index from six dimensions: climatic, physiographic, land use, anthropogenic, economic and access to services. Thereby evaluating the flood vulnerability index of the Pre-Saharan Region. Kociper et al. (2019) analyzed the agricultural vulnerability of Slovenia. At present, the main methods of vulnerability measurement are mainly divided into Indicator based approach and Multi-Criteria Approach. At the same time, GIS methods are more and more used in vulnerability research. Desalegn and Mulu (2021) used GIS method to analyze the economic vulnerability of flood in Fetam basin. Guo et al. (2021) established 12 indexes, measured drought vulnerability in China by comprehensive index method, and studied spatial change by GIS software.

Based on the above literature, there are abundant researches on flood vulnerability, including research fields, research angles, research methods and so on. However, the existing research still has some shortcomings. First of all, the existing research mainly focuses on the vulnerability assessment and analysis of flood disasters in cities and river basins, and the research on the vulnerability of floods in agriculture is insufficient. Especially for China, a big agricultural country, there is a lack of evaluation and discussion on the vulnerability of agricultural floods in China. In addition, another problem of the existing research is that the research period is short, and the long-term spatio-temporal evolution analysis of flood vulnerability is lacking.

TABLE 1 | China's agricultural flood vulnerability evaluation index system.

	Indicators and units	Character
Exposure	E1:Flood-affected area of crops (khm^2)	+
	E2:Population density (person/km2)	+
	E3:Annual precipitation (mm)	+
	E4:Soil erosion control area (khm^2)	-
Sensitivity	S1:Agriculture in GDP proportion (%)	+
	S2:Annual sunshine duration (h)	-
	S3:Crop sown area (khm^2)	+
	S4:The forest coverage rate (%)	-
Adaptability	A1:GDP per capita (yuan/per)	-
	A2:Net income per capita of rural residents (yuan/per)	-
	A3:Food production per capita (kg/per)	-
	A4:Total reservoir capacity (100 million m^3)	-
	A5:Total power of agricultural machinery (10 MW)	-
	A6:Flood-free arable land area (khm^2)	-

Drawing on the definitions of vulnerability of IPCC (2001) and IPCC (2014), this paper adopted the vulnerability assessment framework of "exposure-sensitivity-adaptability" (Li et al., 2015; Gurri et al., 2018) selected meteorological and socio-economic indicators, combined the natural ecosystem with the socio-economic system, collected and sorted out the statistical data of 31 provinces (cities) in China for 21 years, established an evaluation model of agricultural flood vulnerability, and analyzed the vulnerability of agricultural flood in different provinces. This will provide a reference for the prevention and control of agricultural floods in China.

METHODS AND DATA

Model Settings

This study is based on the vulnerability concept and analytical framework proposed by the Intergovernmental Panel on Climate Change (IPCC). According to the existing research (Rehman et al., 2019; Moreira et al., 2021), 14 meteorological and socio-economic indicators were selected from the three aspects of exposure, sensitivity and adaptability to construct a vulnerability assessment system for agricultural flood vulnerability. The flood vulnerability evaluation index system established in this study is shown in **Table 1**.

(1) In the vulnerability assessment of agricultural floods, exposure is the degree to which agriculture is faced with flood disaster, including the affected area of crop floods, population density, annual precipitation, and soil erosion control area. The flood-affected area of crops reflects the scale of the region affected by floods and floods for a long time. The larger the affected area, the higher the vulnerability of flood. Population density reflects the regional population status, and a larger population density means greater economic losses when suffering from floods. Precipitation is the main natural cause of flood disasters, and annual precipitation reflects regional agricultural conditions and has a positive impact on vulnerability to flood disasters. In addition, soil erosion often aggravates the frequency and scale of flood disasters and increasing the area of soil erosion control is one of the means to alleviate flood vulnerability.

(2) Sensitivity is the degree to which agriculture is vulnerable to floods, including the proportion of agriculture to GDP, annual sunshine hours, crop sown area, and forest coverage. The proportion of agriculture in GDP reflects the position of agriculture in the national economy. The higher the proportion, the greater the impact of agricultural natural disasters on the economy. Annual sunshine duration are the sum of the time when the direct solar radiation is equal to or more than 120 w/m^2 in a year. More sunshine duration mean that the possibility of flood disaster is low. The larger the sown area of crops, the greater the losses in the event of floods, thus increasing the vulnerability. The forest coverage rate reflects the ecological level of the environment, and a higher forest coverage rate is helpful to improve the soil water storage capacity and reduce the flood disaster.

(3) Adaptability is the ability to cope with and reduce the losses caused by floods, which helps to reduce the vulnerability of agricultural floods, including per capita GDP, per capita disposable income of rural households, per capita grain production, total reservoir capacity of the reservoir, the total power of agricultural machinery, and the area of flood control.

GDP per capita can objectively reflect a country's economic level. Compared with underdeveloped countries, countries with higher GDP per capita often have stronger infrastructure and social resources to cope with floods. The net income per capita of rural residents reflects farmers' economic affordability and disaster prevention and recovery ability (Zhou et al., 2021). Increasing people's net income can effectively improve rural residents' ability to cope with floods (Xu et al., 2017). The per capita grain production reflects the level of agricultural productivity, and higher agricultural productivity naturally has a stronger ability to resist natural disasters. Water conservancy facilities such as reservoirs are important facilities for alleviating and weakening flood disasters. The total power of agricultural machinery represents the degree of modernization of agricultural production, and modern agricultural production methods are more conducive to dealing with sudden natural disasters such as floods. The flood-removed area is the area of land that is managed in an area and is not affected by flood disasters and has a negative impact on flood vulnerability.

TABLE 2 | Descriptive statistics of the sample.

Indicators	Obs	Mean	Std. Dev	Min	Max
Flood-affected area of crops	651	274.587	412.104	0	3204
Population density	651	422.081	623.0776	2.146012	3924.29
Annual precipitation	651	940.619	448.2305	200.8411	2231.668
Soil erosion control area	651	3453.729	2873.445	0	15221.5
Agriculture in GDP proportion	651	11.835	6.587329	0.3	37.9108
Annual sunshine duration	651	2077.531	500.4262	932.9999	3156.375
Crop sown area	651	5167.48	3671.55	88.6	14910.1
The forest coverage rate	651	29.575	17.73673	2.94	66.8
GDP per capita	651	36004.07	28497.04	2661.557	164889
Net income per capita of rural residents	651	7964.299	5951.785	1330.8	34911.3
Food production per capita	651	408.945	299.6235	13.3529	2347
Total reservoir capacity	651	232.036	212.7197	4.9	1263.894
Total power of agricultural machinery	651	2763.183	2685.304	93.97	13353.02
Flood-free arable land area	651	714.5034	977.4855	0	4483

(4) It is necessary to explain the character of indicators (**Table 1**). For the indicators whose character is "+", the vulnerability degree increases with the increase of the index value. However, for the indicators whose character is "–", the vulnerability degree decreases with the increase of the index value.

Source of Data

The historical data used in this article are the climate and economic data of 31 provincial-level administrative units in China (except Hong Kong, Macao, and Taiwan) from 2000 to 2020. The climate data includes annual total rainfall and annual sunshine hours, all from the National Meteorological Science Data Center (http://data.cma.cn). Economic data are from the National Bureau of Statistics of China (http://www.stats.gov.cn) and the China Statistical Yearbook. **Table 2** shows the relevant characteristics of the sample data.

Entropy Weight Method

Referring to Guo et al. (2020), in order to make the evaluation results more objective, this study selected entropy weight method to calculate the vulnerability of agricultural floods. The entropy weight has the following methods and steps:

The first step of entropy weight method is to standardize the index data to eliminate the differences in units between different data. The entropy weight method specifies the standardization methods of positive and negative indicators, as shown in **Formula 1** and **Formula 2**.

In this paper, i is the number of provinces, i=1,2,... ,31, j is the number of evaluation indexes, and j=1,1,2,... ,14.X_{ij} represents the value of j index of ith province. $X_{\max}$ and $X_{\min}$ represent the maximum and minimum values of X_{ij}. Y_{ij} is the normalized value of X_{ij}.

$$\text{Positive indicator:} \quad Y_{ij} = \frac{X_{ij} - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

$$\text{Negative indicator:} \quad Y_{ij} = \frac{X_{\max} - X_{ij}}{X_{\max} - X_{\min}} \tag{2}$$

Calculate the weight index P_{ij}, m=31

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{m} Y_{ij}} \tag{3}$$

Calculate the information entropy of the jth index E_j:

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} P_{ij} \ln\left(P_{ij}\right) \tag{4}$$

Calculate the coefficient of variance of the jth indicator H_j:

$$H_j = 1 - E_j \tag{5}$$

Calculate the weight of the jth indicator $W_{j:}$

$$W_j = \frac{H_j}{\sum_j^m H_j} \tag{6}$$

Vulnerability Assessment Model

According to Yuan et al. (2021), agricultural flood vulnerability is a function of exposure, sensitivity, and adaptive capacity. This paper constructs a vulnerability evaluation model to measure the vulnerability index of agricultural flood in China.

$$V = E + S + A \tag{7}$$

Where V represents vulnerability, E represents exposure, S represents sensitivity, and A represents adaptive capacity. E, S and A are calculated as follows:

$$\begin{aligned} E &= \sum_{j=1}^{4} W_{ej} Y_{eij} \\ S &= \sum_{j=1}^{4} W_{sj} Y_{sij} \\ A &= \sum_{j=1}^{6} W_{aj} Y_{aij} \end{aligned} \tag{8}$$

Where W_{ej}, W_{sj}, and W_{aj} are the weights of the jth indicators of exposure, sensitivity, and adaptive capacity, respectively; Y_{eij}, Y_{sij}, and Y_{aij} are the standardized values of the jth indicators of exposure, sensitivity, and adaptive capacity, respectively.

$$C_j = \frac{I_j \times W_j}{\sum_{j=1}^{14} \left(I_j \times W_j\right)} \times 100\% \tag{9}$$

Factor Contribution Model

The premise of effectively reducing vulnerability is to identify and analyze its main influencing factors. In the research of influencing factor identification, factor contribution models are widely used. This paper analyzes the main factors affecting the vulnerability of agricultural floods in China. the calculation equation is as follows:

Cj is the contribution of the jth index to vulnerability, I_j is the index deviation, usually expressed as the difference between 1 and the pu value Y_{ij} of each index; W_j is the weight of index j calculated by **Formula 6**.

RESULTS AND DISCUSSION

Vulnerability Assessment of Agricultural Floods in China

According to **Formula 8**, the agricultural flood vulnerability index, exposure index, sensitivity index, and adaptability index in China from 2000 to 2020 is calculated in this paper, and lists the data in **Table 3**.

TABLE 3 | Average vulnerability of agricultural floods in China from 2000 to 2020.

Year	Vulnerability	Exposure	Sensitivity	Adaptability
2000	0.365	0.111	0.125	0.128
2001	0.399	0.136	0.131	0.133
2002	0.394	0.137	0.128	0.129
2003	0.370	0.133	0.120	0.118
2004	0.403	0.154	0.123	0.126
2005	0.392	0.140	0.123	0.128
2006	0.382	0.129	0.123	0.130
2007	0.384	0.135	0.126	0.124
2008	0.361	0.118	0.124	0.120
2009	0.343	0.111	0.121	0.111
2010	0.382	0.130	0.130	0.122
2011	0.382	0.117	0.135	0.130
2012	0.389	0.122	0.139	0.128
2013	0.328	0.095	0.118	0.114
2014	0.351	0.112	0.122	0.118
2015	0.371	0.125	0.125	0.121
2016	0.352	0.109	0.121	0.122
2017	0.352	0.114	0.121	0.116
2018	0.327	0.099	0.121	0.108
2019	0.327	0.099	0.121	0.108
2020	0.338	0.112	0.123	0.103

From 2000 to 2020, China's agricultural flood vulnerability showed a fluctuating downward trend, reflecting the improvement of China's overall flood vulnerability. The national average flood vulnerability increased from 0.365 in 2000 to 0.403 and in 2004, reaching the highest value, and then began to fluctuate and decrease to 0.338 in 2020. The possible reason is that since 2005, China's Central Document No. 1 of the Central Government has continuously paid attention to the construction of agricultural infrastructure. The corresponding increase increases the ability of agriculture to resist natural risks, resulting in a lower vulnerability index.

In the existing research, there is no clear level standard of agricultural flood vulnerability. Based on the researches of Kociper et al. (2019), Yuan et al. (2021), Guo et al. (2021) and Li et al. (2022), this study graded the vulnerability index, exposure index, sensitivity index and adaptability index of agricultural floods in China from 2000 to 2020. The classification range is shown in **Supplementary Data Sheet S2**. Among them, all the indicators that constitute the adaptability index are negative (as shown in **Table 1**), and reverse normalization is carried out, that is, the smaller the adaptability index, the higher the adaptability.

Spatio-Temporal Dynamics Analysis of Agricultural Flood Vulnerability in China

After calculating the vulnerability index of agricultural floods in China, this study used Arcgis10.5 software to visualize the data, and the results of a temporal and spatial variation of agricultural flood vulnerability in China from 2000 to 2020 were shown in **Figure 1**.

The vulnerability of agricultural floods in China is weakening from the central and southern regions to the northwest regions. Compared with the northwest provinces, the central and southern provinces have relatively more annual precipitation, high population density, and high intensity of agricultural and economic activities.

The number of highly and moderate vulnerable areas is relatively small, mainly concentrated in south-central and southwest areas, including Henan, Hubei, Hunan, Anhui, Sichuan, Guangxi, Jiangxi, Guizhou and Shanghai. The first is geographical factors. There are problems such as instability, flooding, short river channels, concentrated rainstorms, and poor circulation in the Yellow River (Wu et al., 2012), so the Henan near the Yellow River is more vulnerable to floods. Hunan and Hubei are located in the middle and lower reaches of the Yangtze River, the largest river in China. The topography of Sichuan, Guizhou and Guangxi is mainly mountainous and hilly, with frequent floods in mountainous areas (Zeng et al., 2021). Secondly, compared with other regions, these regions are provinces with higher population density in China, and their cultivated land area ranks among the top in the country. The natural conditions for agricultural development are good, and the exposure and sensitivity to flood disasters are relatively high. Therefore, the vulnerability is high.

Low and mildly vulnerable areas maintain an absolute majority in aggregate, accounting for more than two-thirds of all areas in the country. Mainly concentrated in the Northeast and West. Among them, Jilin, Heilongjiang and Liaoning in the northeast have long been in low and mild vulnerability levels, with high forest coverage, per capita grain production, total power of agricultural machinery, and total reservoir capacity, and have strong adaptability to flood disasters. Xinjiang, Tibet, Gansu, Qinghai, Ningxia, Inner Mongolia, Shaanxi, and other regions in the western region have been in low vulnerability level for a long time. These regions have relatively arid climate, low precipitation, many sunshine hours, and weak sensitivity to flood disasters.

Spatio-Temporal Dynamics Analysis of Agricultural Flood Exposure in China

Figure 2 shows the evaluation results of agricultural flood exposure and the spatial distribution of exposure index levels in each province in China from 2000 to 2020.

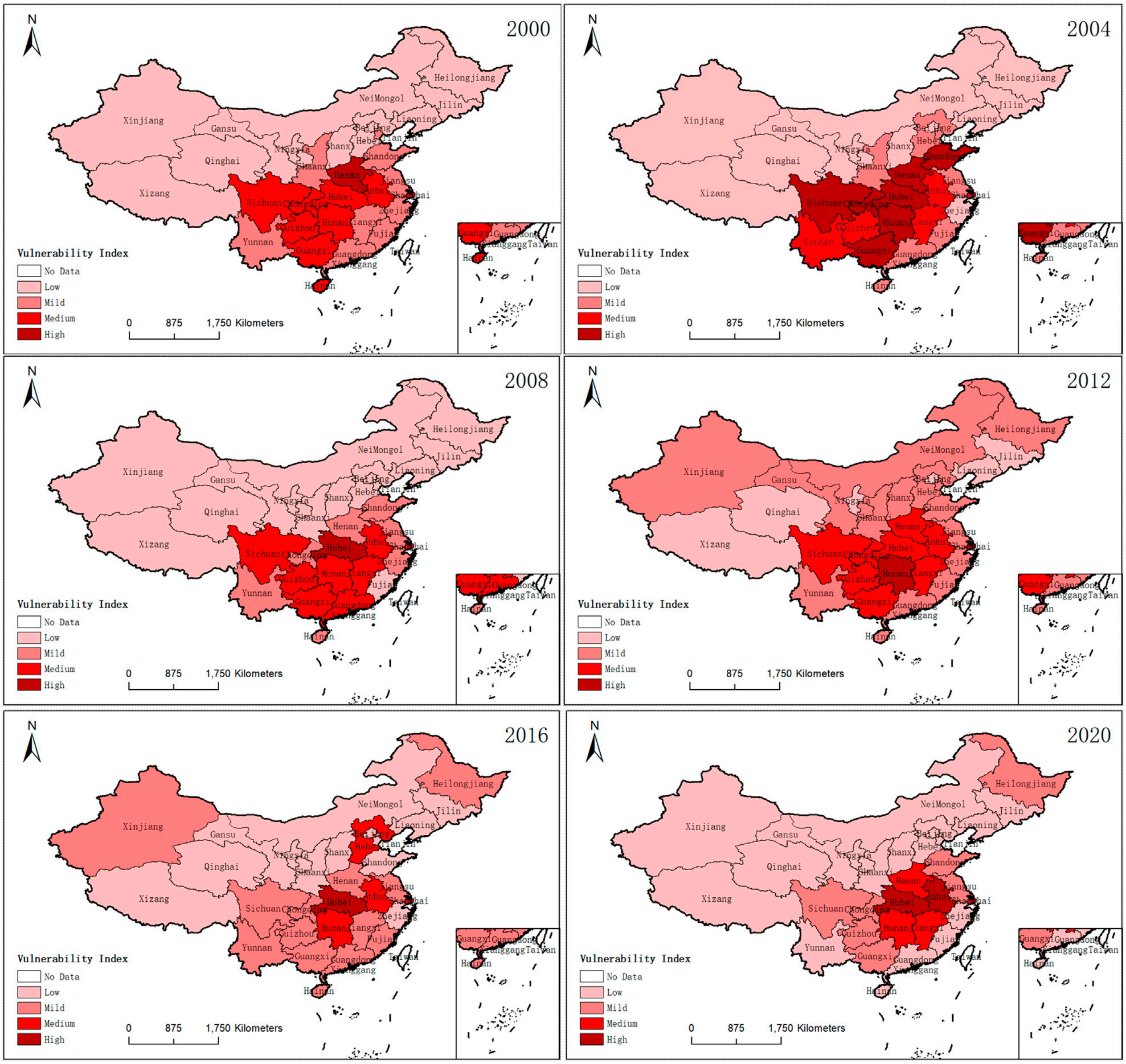

FIGURE 1 | Temporal and spatial variation of agricultural flood vulnerability in China.

From 2000 to 2020, China's overall agricultural flood exposure showed a trend of increasing first and then decreasing. Xinjiang, Tibet, Gansu, Qinghai, Ningxia, Inner Mongolia and other places have the lowest exposure to agricultural floods, belonging to low-exposure areas, concentrated in the western region and west of the Huyong line, which may not only be arid and less rainy, but also have a small population density. related. The lightly exposed areas were concentrated in the southwest and southeast coastal areas, mainly in Sichuan, Yunnan, Guizhou, Fujian, and Guangdong. Similar to the vulnerability index distribution, low and mild exposures account for the vast majority of the national area. Anhui, Henan, Hunan, Hubei and Shanghai have the highest exposure to agricultural floods. This may be due to the fact that these places are located in the Yangtze River and Yellow River basins, with abundant water resources, and the scale of agricultural production and population are at the forefront of the country. Among them, Shanghai is located in the coastal area, and typhoons are frequent., easy to bring heavy rain, resulting in high exposure.

Spatio-Temporal Dynamics Analysis of Agricultural Flood Sensitivity in China

Figure 3 shows the results of agricultural flood sensitivity evaluation and the spatial distribution of sensitivity index levels in various provinces in China from 2000 to 2020.

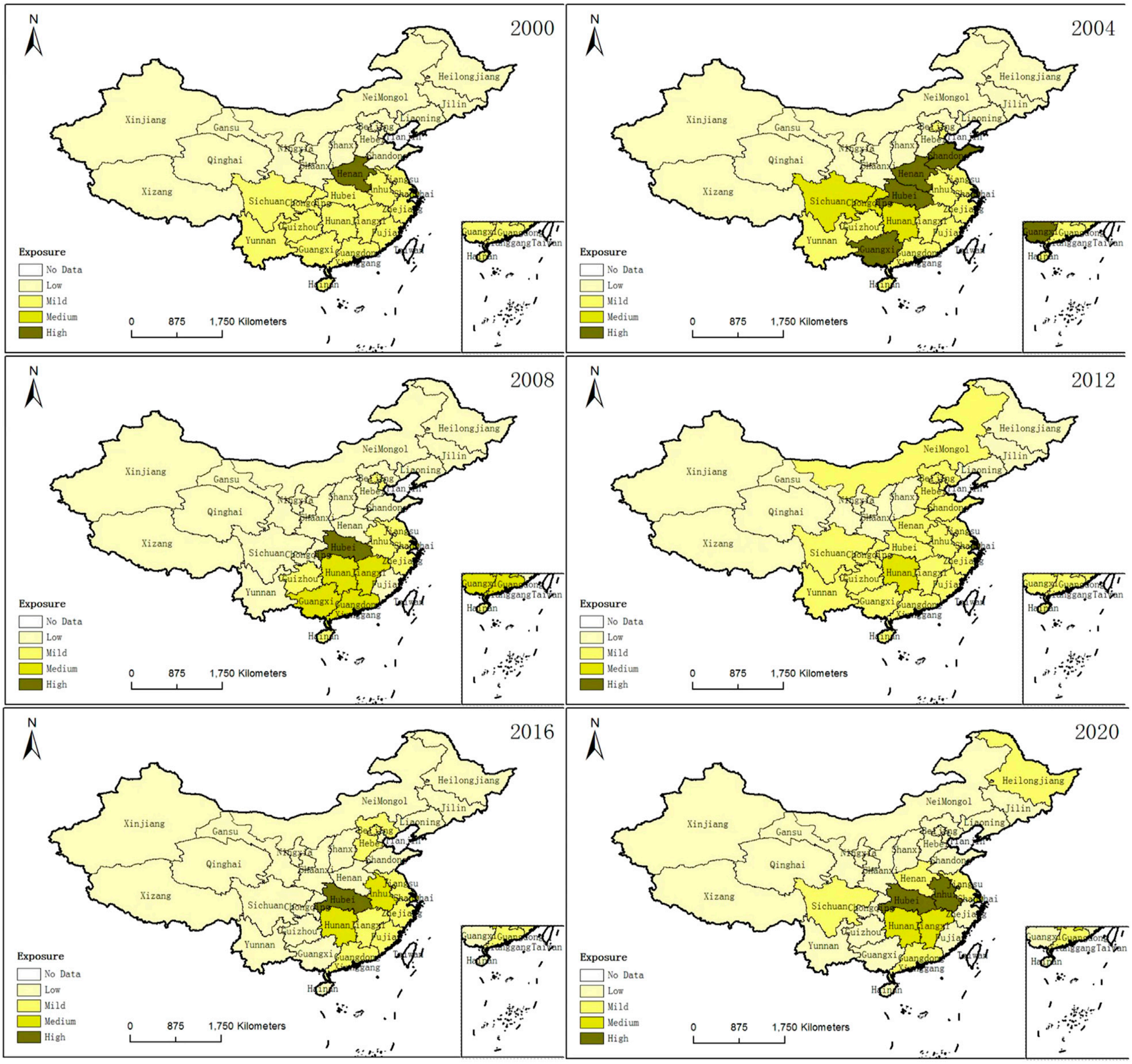

FIGURE 2 | Temporal and spatial variation of agricultural flood exposure in China.

From 2000 to 2020, the main distribution areas of high-value and medium-value areas of agricultural flood sensitivity in China are similar to the exposure, mainly in Shandong, Henan, Hubei and Anhui. Shandong, Henan and Hubei are major agricultural provinces in China. Agriculture accounts for the proportion of gross domestic product and the sown area of crops is relatively high. Once a flood disaster occurs, agriculture suffers huge losses. Mild flood-sensitive areas are mainly distributed in western China, including Qinghai, Ningxia, Tibet, Gansu, Shaanxi, Xinjiang, Shanxi, and Inner Mongolia. These areas are deep inland, not easily affected by monsoons, and have little rainfall. In addition, more than two-thirds of the provinces in China are at the level of mild and low flood sensitivity.

Spatio-Temporal Dynamics Analysis of Agricultural Flood Adaptability in China

Figure 4 shows the results of agricultural flood adaptability evaluation and the spatial distribution of adaptability index levels in various provinces in China from 2000 to 2020.

From 2000 to 2020, the adaptability of agricultural floods in China's provinces has shown a significant improvement trend. The number of provinces with high adaptability has increased from 5 in 2000 to 10 in 2020. The adaptability of agricultural floods in China has been significantly enhanced. Over time, the adaptive index of the central and western provinces improved significantly. At present, the areas with mild adaptability to

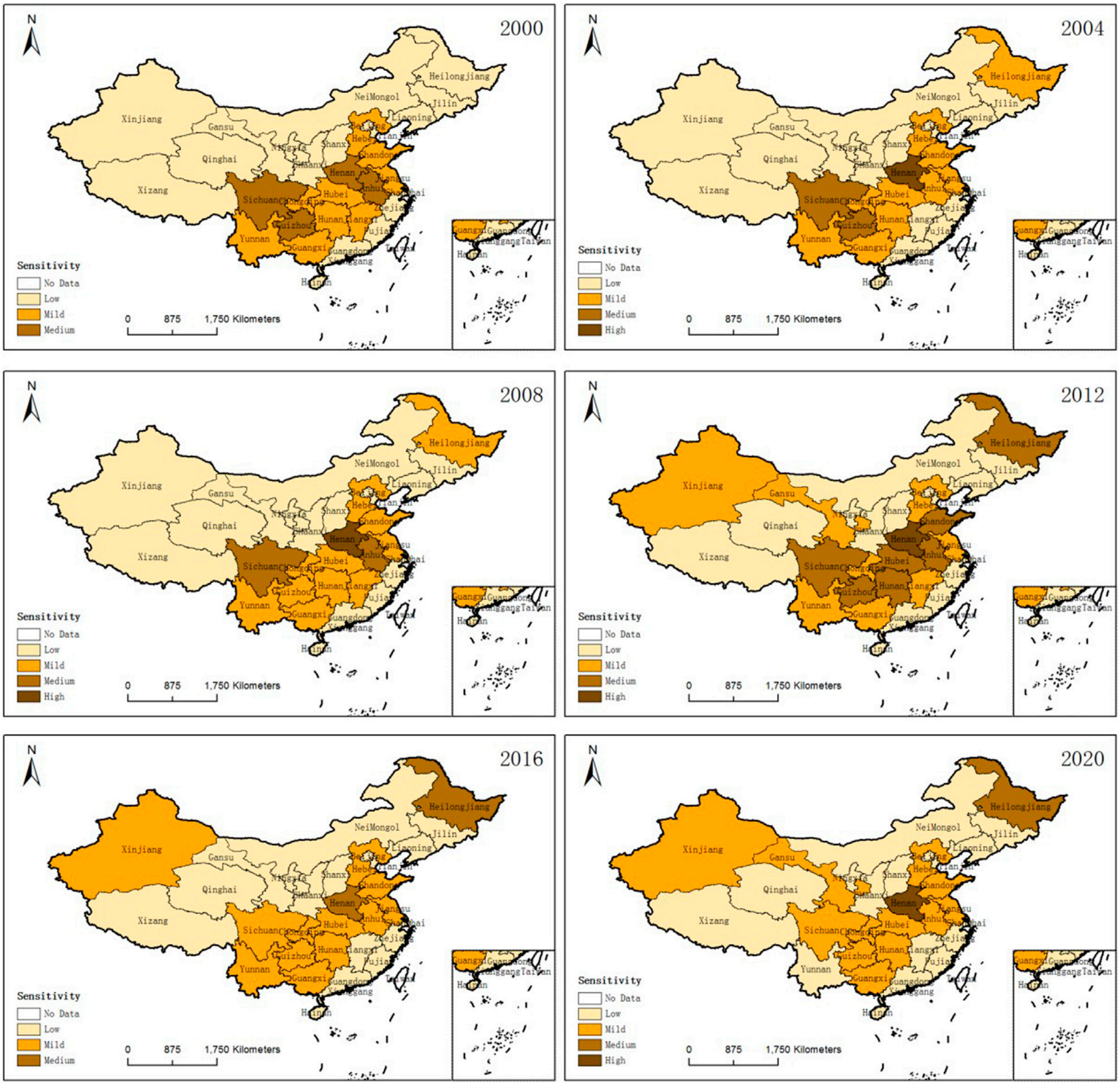

FIGURE 3 | Temporal and spatial variation of agricultural flood sensitivity in China.

agricultural floods are mainly in Gansu, Qinghai, Tibet, Hainan and other places, which may be related to the backward agricultural development and low agricultural investment in these places.

Factor Contribution Analysis of Agricultural Flood Vulnerability in China

In order to further analyze the factors that affect the vulnerability of agricultural floods in China, this study uses the factor contribution model to calculate the contribution of each factor to the vulnerability to agricultural floods and lists the top three factors with the largest contributions in 2020 in **Supplementary Data Sheet S3**.

It is noted that in **Supplementary Data Sheet S3** that the main contributing factors of agricultural flood exposure in China are E4 (Soil erosion control area) and E3 (Annual precipitation). Therefore, it is necessary to improve the ecology and environment, restore forest and grass vegetation, and adjust the land use structure to continuously increase the area of soil erosion control. The main contributing factors to my country's agricultural flood sensitivity are S4 (The forest coverage rate) and S2 (Annual sunshine duration). The principle of adapting measures to local conditions, combined with climate and soil

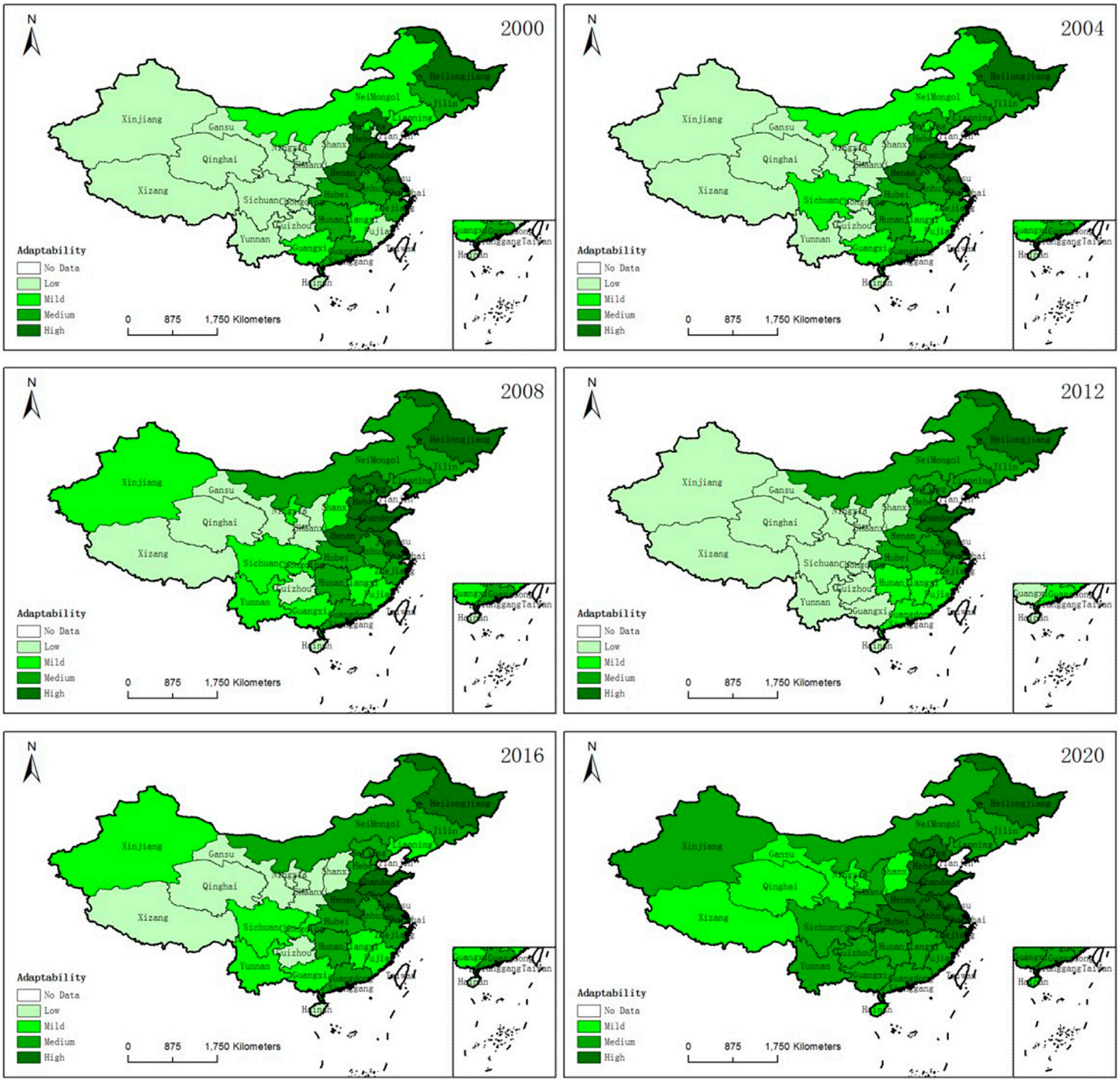

FIGURE 4 | Temporal and spatial variation of agricultural flood adaptability in China.

conditions, restores forest and grass vegetation in ecologically fragile areas, and gives full play to the role of forests in conserving water and soil and weakening flood disasters. The main contributors to China's agricultural flood resilience are A4 (Total reservoir capacity) and A5 (Total power of agricultural machinery). It is necessary to strengthen the construction of agricultural infrastructure such as water conservancy, improve the level of agricultural mechanization and ensure China's food security.

At the same time, from the perspective of regional characteristics. Soil erosion control area is the main exposure factor and annual sunshine duration is the main sensitivity factor that affect the vulnerability of agricultural floods in western provinces such as Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The main factors affecting the exposure, sensitivity and adaptability of Yunnan, Guizhou and Sichuan are annual precipitation, forest coverage rate and total reservoir capacity respectively.

CONCLUSION AND DISCUSSION

This study constructed the vulnerability evaluation system of agricultural flood in China. The vulnerability, exposure, sensitivity and adaptability of agricultural floods in China from 2000 to 2020 were calculated by entropy weight method, and their temporal and spatial evolution was analyzed. The main conclusions are as follows:

1) From the perspective of the whole country, from 2000 to 2020, the vulnerability of China's agricultural floods showed a fluctuating downward trend. Specifically, the vulnerability to agricultural flooding decreases from the central south to the northwest. Central regions such as Hunan, Henan, Hubei, and Anhui have long-term high vulnerability to floods, while northwestern provinces such as Gansu, Ningxia, and Shaanxi, and northern provinces such as Beijing and Hebei are mildly vulnerable, and Heilongjiang Province in northeastern China has increased vulnerability to agricultural floods over time.
2) The number of highly and moderately vulnerable areas is relatively small, mainly concentrated in south-central and southwest areas. The main distribution areas of high-value and medium-value areas of agricultural flood sensitivity in China are similar to the exposure, mainly in Shandong, Henan, Hubei and Anhui. The areas with mild adaptability to agricultural floods are mainly in Gansu, Qinghai, Tibet, and Hainan.
3) Henan, Hubei and Anhui, which are located in central China, are big agricultural provinces and important agricultural producing areas to ensure national food security. However, in the past 21 years, their vulnerability to agricultural flooding has been high and medium. For food security and sustainable agricultural development, the central provinces should take effective measures to reduce the vulnerability of agricultural floods.
4) The main contributing factors of agricultural flood exposure ar soil erosion control area and annual precipitation. The main contributors to sensitivity are the forest coverage rate and annual sunshine hours. The main contributors to resilience are total reservoir capacity and total power of agricultural machinery.

This study expanded the research scope of agricultural vulnerability, and based on the vulnerability analysis framework, the vulnerability assessment system of agricultural floods in China was constructed from three aspects: exposure, sensitivity and adaptability. This paper analyzes the vulnerability of agricultural floods in China from two dimensions of time and space, and points out the provinces that are still in high vulnerability, providing reference for the formulation of disaster prevention and mitigation planning. Secondly, this paper calculates the factor contribution of different indicators, so as to better identify the main indicators that affect the vulnerability of agricultural floods. This has certain policy significance for reducing the vulnerability of agricultural floods in China and realizing the sustainable development of agriculture. However, this paper also has shortcomings. For example, due to the consideration of data availability, the vulnerability index selected in this paper mainly comes from social and economic factors, without taking topographic structure, climatic conditions, soil and other factors into account. It is necessary to further study it in the future.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: http://data.cma.cn and http://www.stats.gov.cn.

AUTHOR CONTRIBUTIONS

Conceptualization, JZ and YL; methodology, HL; software, HL; validation, YL, HL and XL; formal analysis, JZ and YL; investigation, JZ and YL; resources, JZ and XL; data curation, YL; writing—original draft preparation, YL; writing—review and editing, JZ; supervision, HL; project funding acquisition, JZ. All authors have read and agreed to the published version of the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.902968/full#supplementary-material

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Households' Earthquake Disaster Preparedness Behavior: The Role of Trust in and Help From Stakeholders

Yibin Ao[1], Liyao Tan[1], Ling Tan[1], Jinglin Zhong[1], Hongying Zhang[1], Yan Wang[2] and Tong Wang[3]**

[1]College of Environment and Civil Engineering, Chengdu University of Technology, Chengdu, China, [2]Sichuan College of Architectural Technology, Chengdu, China, [3]Delft University of Technology, Delft, Netherlands

Earthquake is one of the most serious natural disasters. Taking scientific and reasonable earthquake preparedness measures can effectively reduce casualties and economic losses caused by earthquakes. It is important to understand how residents choose such earthquake preparedness measures to guide them accordingly. However, the current research has failed to address rural areas in developing countries and has inconsistency conclusions for two aspects related to stakeholders involved: the assistance the victims can get from stakeholders for applying earthquake preparedness measures and the trust in stakeholders' disaster relief abilities. In this study, the rural residents affected by Wenchuan earthquake, Ya'an earthquake and Yibin earthquake were taken as the research objects, and 674 valid questionnaires were obtained through field household surveys. A Multinominal Logit Model (MNL) was constructed to explore the influence of villagers' trust in the disaster relief ability of stakeholders and the help they can get from stakeholders on their preparedness behavior. The results show that the less trust the villagers have on the government and the community, and the more help they can get from the outside while preparing measures, the more inclined they are to take the disaster preparedness measures. Furthermore, the education level of villagers in earthquake-stricken areas has significant positive impacts on people's earthquake preparedness behavior. People who are not born in rural areas are more likely to take earthquake preparedness measures. In addition, male, young and married villagers are more likely to take earthquake preparedness measures in their daily lives. This study enriches the theory of rural disaster prevention and mitigation, and provides reference for the practice of disaster prevention and mitigation in earthquake-stricken rural areas.

Keywords: multi-stakeholders, MNL model, trust, help, villagers earthquake preparedness behavior

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Dingde Xu,
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Reviewed by:
Bingjie Yu,
Southwest Jiaotong University, China
Jinbao Yao,
Beijing Jiaotong University, China

****Correspondence:***
Yan Wang
wangyan@scac.edu.cn
Tong Wang
t.wang-12@tudelft.nl

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INTRODUCTION

China is one of the countries with the most serious earthquake disasters in the world, with many wide distributed, highly intense earthquakes, which causes serious disaster consequences (Imirbaki, 2018). Three recent earthquakes in Sichuan Province in China have caused huge damage. Wenchuan M8.0 earthquake in 2008, Lushan M7.0 earthquake in Ya'an in 2013 and Changning M6.0 earthquake in Yibin in 2019 have caused more than 70,000 deaths, with losses exceeding one trillion yuan, especially in rural areas. It is clear to see that in Sichuan region, earthquakes happen frequently and it is important to be prepared for residents for the next coming earthquake.

Existing research shows that scientific and reasonable disaster preparedness behavior can reduce the negative impact of earthquake disasters (Li et al., 2017). Xu et al. systematically analyzed the influence relationship between risk perception and residents' disaster preparedness behavior (Xu et al., 2019). Zhou believed that improving residents' livelihood resilience and adjusting residents' livelihood strategies were effective means to deal with disaster risks (Zhou et al., 2021). Ma explored the correlation between community resilience and residents' disaster preparedness by establishing a Tobit regression model (Ma et al., 2021). However, existing studies mostly focus on the driving factors of disaster-preparedness behaviors among urban residents, while few studies consider such factors among rural residents (Lian et al., 2021).

Furthermore, effective disaster preparedness behavior also needs the participation of other stakeholders, including the government, communities, families and individuals (Han et al., 2020). Existing research shows that perceived stakeholder characteristics, such as trust, responsibility and help affect people's judgment of disasters, could affect people's disaster preparedness behavior (Wei et al., 2016a; Han et al., 2021). Among the perceived characteristics of stakeholders, the public's trust in the ability of relevant government departments and social organizations to cope with disasters has received great attention in recent years (Deyoung and Peters, 2016; Wei et al., 2019). The help from different stakeholders that local residents can get when preparing for earthquake disaster is another emerging factor that affects their disaster preparedness behavior (Wei et al., 2019). However, the current research results are not always consistent on these two factors. Therefore, it is necessary to explore the impact of stakeholders on residents' disaster preparedness behavior in rural China.

Therefore, this study takes the three rural earthquake-stricken areas in Sichuan Province as the case areas, and controls the socio-demographic variables of the villagers in the disaster areas to explore whether the villagers' trust in stakeholders' disaster relief ability and the assistance they can get from stakeholders affect their earthquake preparedness behavior. In such way, this work contributes to systematically investigate the disaster situation and influence factors of rural residents and reveal the differences between them. The significance of this study is to supplement and improve the understanding of influencing factors of rural farmers' earthquake preparedness behavior, further enrich the theoretical framework of disaster prevention and mitigation, provide theoretical support for the formulation of disaster prevention and mitigation guidelines, and promote the development of disaster prevention and mitigation in China. At the same time, the awareness of disaster preparedness has been effectively spread to residents and farmers to advocate them to take effective disaster preparedness behavior.

LITERATURE REVIEW

There is a growing body of empirical research that explores the relationship between preparedness behavior and demographic factors. And such factors include residents' age, gender, education level, earthquake experience and so on. With the increase of age, the probability of residents taking disaster preparedness measures will decrease (Tang and Feng, 2018; Wu et al., 2018). Some studies find that men had higher levels of preparedness than women (Chen et al., 2021; Wang et al., 2021). Some studies believe that education level has a positive impact on disaster preparedness (Mabuku et al., 2018; Zheng and Wu, 2020). For example, Hoffmann et al. (Hoffmann and Muttarak, 2017) find that education can increase disaster preparedness actions. Atreya et al. (Atreya et al., 2017)also confirm that people with higher education levels were more active in disaster preparedness. In addition, there is a significant correlation between residents' disaster preparedness behavior and their disaster experience (Bronfman et al., 2016). People who have experienced an earthquake are more likely to take disaster preparedness measures than people who have not. Another study finds out that migrants are more prepared than locals (Green et al., 2021).

Stakeholders involved in disaster control and prevention have significant influence on residents' disaster preparedness behavior (Kim and Jae, 2020). Stakeholders refer to the individuals and groups that have important interests in an organization's decisions or activities, or all the individuals and groups that are influenced by an organization in realizing its goals. Stakeholder theory is one of the dominant approaches for analyzing the normative obligations of those engaged in business (Hasnas, 2013), and is widely applied in the study of earthquake preparedness behavior (Wei et al., 2016). Stakeholders in earthquake preparedness are individuals or groups that have an important influence on residents' disaster preparedness behaviors (Deng et al., 2015; Wu et al., 2020). In most cases, the government and its relevant parts act as stakeholders, and the stakeholder characteristics include the trust in varied stakeholders, feeling of responsibility, etc., (Wu et al., 2018). In the event of an earthquake, the participation of stakeholders is very important in disaster response decision-making (Coppola, 2018), and stakeholders can support the resilience of buildings and infrastructure, the delivery of health and human services, and the restoration of transport and transportation systems (Taeby and Zhang, 2019). Existing research shows that people's trust in stakeholders' disaster relief ability (Deyoung and Peters, 2016; Cheng and Tsou, 2018) and the help they can get from stakeholders (Wei et al., 2019) for preparing are two factors that significantly affect their earthquake preparedness behaviors.

Even though stakeholders have an important influence on residents' disaster preparedness behavior, there are different results about this aspect of the research. One study has found that the public confidence in local governments' ability to respond to disasters enhances their willingness to prepare for disasters, but has no significant impact on their actual preparedness behavior (Basolo et al., 2009). Another evidence shows that residents' confidence in government disaster relief cannot predict the degree of disaster preparedness measures they take (Deyoung and Peters, 2016). In Chile, researchers find that trust in authorities is a strong predictor of environmental hazards risk perception (Bronfman et al., 2016). However, lessons from

TABLE 1 | Selection and explanation of social demographic variables.

Variable		Variable declaration
Demographic characteristic	City and county	1 = Wenchuan County; 2 = Lushan County; 3 = Changning County
	Gender	1 = Man; 2 = Woman
	Age	The corresponding numerical value is the corresponding age. For example: 25 = 25 years old
	Is the current place of residence the birthplace?	1 = No; 2 = Yes
	Education Level	1 = Uneducated; 2 = Primary School; 3 = Junior High School; 4 = Senior High School; 5 = University and above
Architectural features	Year of residence	The corresponding value is the corresponding year. For example, 2008 = 2008
	Residential structure type	1 = Bamboo-grass structure, 2 = Stone-wood structure; 3 = Masonry structure; 4 = Brick-concrete structure; 5 = Steel-concrete structure
	Type of house	1 = Own house; 2 = Rent house; 3 = Other

the Netherlands show that the trust in government reduces the public's risk perception of flooding, and in turn, discourages individual's preparedness intention (Terpstra, 2011). Similarly, scholars also find out that the Chinese residents' trust in the government's ability of disaster prevention and mitigation can reduce their judgment on the degree of disaster impacts, thus reducing the disaster preparedness behavior (Han et al., 2017a; Han et al., 2017b); while American residents' confidence in Federal Emergency Management Agency (FEMA) is positively correlated with their probability of taking disaster preparedness measures (Kim and Oh, 2015).

Similarly, facing different natural disasters, the research conclusions on the influence of the help and support that residents can get from stakeholders on their disaster preparedness behavior are not completely consistent. For example, the emergency information that individuals can get through social networks such as family, friends and neighbors (Rooney and White, 2017) as well as learning about other people's disaster experiences can help individuals understand the consequences of disasters and thus facilitate their disaster preparedness behaviour (Becker et al., 2017). However, some studies have found that if a person thinks that the help they can get is enough to resist threats, the probability that they take the initiative to prepare for disasters will be reduced (Mulilis et al., 2010). Therefore, more related empirical research is very necessary to provide context-specific recommendations, especially for areas like rural China that have not received much attention until recently.

METHODS

Based on the literature review, the questionnaire designed in this study consists of three parts, namely, social and demographic variables (control variables), villagers' trust in disaster relief ability of stakeholders and help from stakeholders variables (explanatory variables) and disaster preparedness behavior variables (dependent variables).

Control variables: Demographic variables studied by Wei et al. (2019), Goltz and Bourque (Goltz and Bourque, 2017) include gender, age, education, birthplace and other factors. In addition, the type of housing structure (Liu et al., 2007), geographical location (Sim et al., 2021) and residence year (Zhou et al., 2009) also have an impact on disaster preparedness behavior. Combined with the pre-investigation, this study adds the housing type index, and finally designed eight sociodemographic variables (shown in **Table 1**):

Explanatory variables: In previous studies, different stakeholders are considered as residents, peers, government officials, media and other forms (Apatu et al., 2015). Bo et al. (Fan and Zhan, 2013) conduct a systematic stakeholder analysis on the government, military, non-governmental organizations, enterprises, victims and media. And Basolo's (Basolo et al., 2009) study finds that the ability of local government to deal with disasters is positively correlated with the willingness of residents to prepare for disasters. Therefore, this study takes the government as a typical stakeholder. Babcicky and Seebauer (Babcicky and Seebauer, 2017) believe that more forms of social capital or social network should be added, such as kinship and connection with external resources. In general, individuals can access all kinds of urgent information through social networks such as family, friends and neighbors (Rooney and White, 2017), therefore, this study also considers the role of family members, relatives, friends and neighbors as stakeholders in residents' disaster preparedness behavior. To sum up, this study mainly considers the following six kinds of social stakeholders: 1) Government; 2) Family members; 3) Relatives; 4) Friends; 5) Neighbors; 6) Other social relations.

Trust in disaster relief ability and available help in disaster preparedness measures are considered as two independent variables. The question is set to: How much do you trust the ability of six different groups of stakeholders to respond to disasters. For each kind of stakeholders and the responses are measured by Likert 5 sub-scale, ranging from 1 to 5, representing no confidence at all to very confident. As such, the range of measurement value is 6–30. Another question is: the degree of help that can be obtained from six different stakeholders in earthquake preparedness. Similarly, for each kind of stakeholders, Likert 5 sub-scale is used, with 1 representing no help and 5 representing all-round help, so the range of measurement value is 6–30.

In addition, risk perception has a certain relationship with residents' disaster preparedness behavior (Xu et al., 2018a; Qing

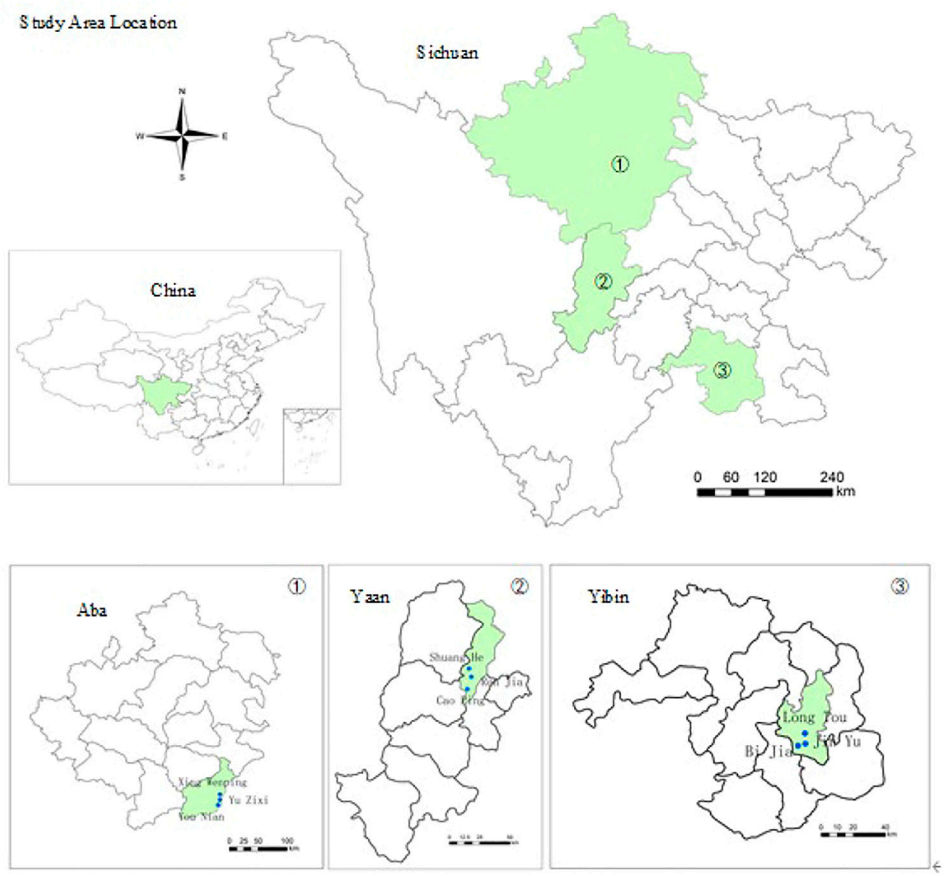

FIGURE 1 | Location of sample villages.

et al., 2021), this study sets a question of perceived disaster preparedness degree: How do you think you are prepared for the earthquake with the help of Likert 5 sub-scale. 1 means completely unprepared, and 5 means completely ready.

Dependent variables: According to the existing research, the most common disaster preparedness behaviors are preparing emergency disaster kits (Lindell and Perry, 2000; Doyle et al., 2018), buying insurance (Xu et al., 2018a; Xu et al., 2018b), making escape plans (Sudo et al., 2019) and learning knowledge (Yong et al., 2020) etc. Based on the characteristics of villagers in Sichuan earthquake-stricken areas, this study considers six specific earthquake preparedness measures: 1) purchasing disaster insurance; 2) preparing valuables for carrying; 3) preparing sufficient food, medicine and other storage materials; 4) participating in evacuation drills; 5) making an escape plan; 6) learning disaster prevention knowledge. Respondents have selected the above six disaster preparedness activities according to the actual disaster preparedness measures. The research design questionnaire is included in the **Supplementary Appendix**.

Sample Selection and Data Collection

Sichuan Province is located in the hinterland of southwest China, with an area of 486,000 square kilometers. In Southwest of China, especially in Sichuan Province, There are high frequency and magnitude of earthquakes, causing great damages. At 14: 28 on 12 May 2008, an earthquake measured 8.0 on the Richter scale occurred in Wenchuan County, Sichuan Province and it left 89,000 people dead and missing (Guo, 2009); At 21: 19 on 8 August 2017, an earthquake measured 7.0 on the Richter scale occurred in Jiuzhaigou County, Aba Prefecture, Sichuan Province, caused 20 people's lives and injured about 500 others (Liang, 2019); At 22: 55 on 17 June 2019, an earthquake measured 6.0 on the Richter scale occurred in Changning County, Yibin City, Sichuan Province, killed 13 compatriots (Jia, 2019). Therefore, this study takes the villagers in rural areas seriously affected by these three earthquakes as the research objects, and randomly selects three sample villages in each earthquake-stricken area, counting totally nine sample villages, namely: Younian Village, Yuzixi Village and Xingwenping Village in Wenchuan County, Aba Autonomous Prefecture; Renjia Village, Shuanghe Village and Caoping Village in Lushan County, Ya 'an City; Bijia Village, Jinyu Village and Longtou Village in Changning County, Yibin City. The geographical locations of the villages is shown in **Figure 1** and the spatial distribution of respondents is shown in **Figure 2**.

The questionnaire survey was carried out by three groups, each with six people, during January 5th and 10 January 2020.

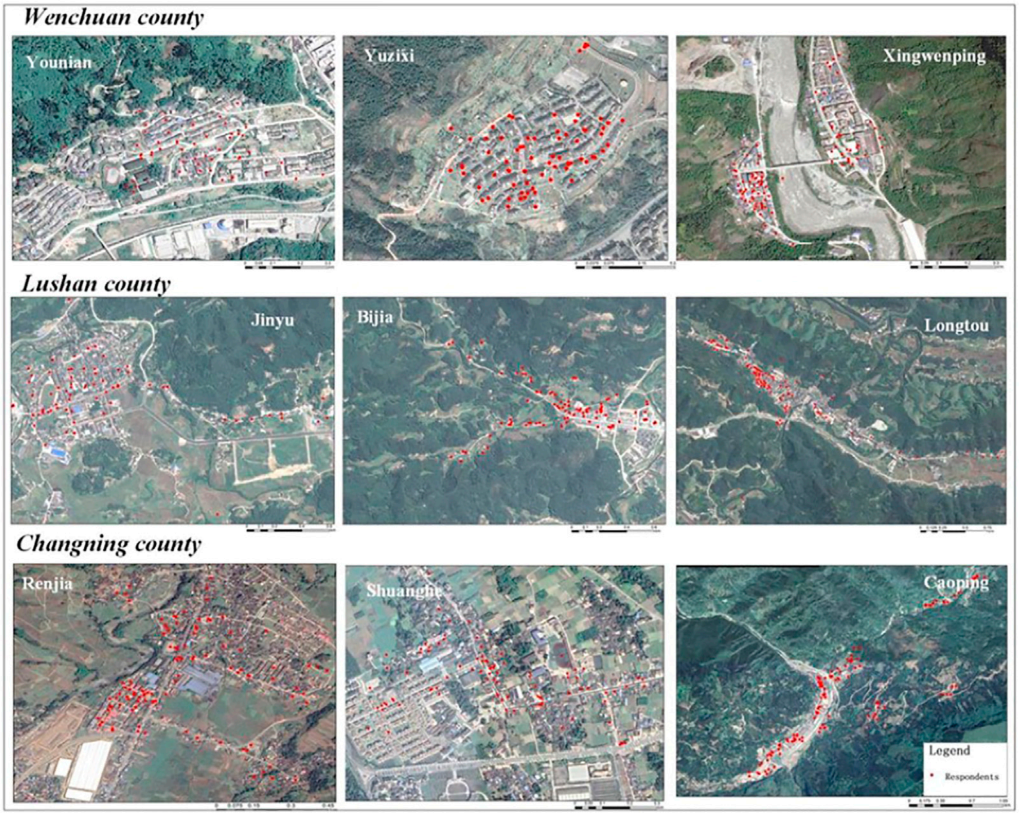

FIGURE 2 | Spatial distribution of respondents.

TABLE 2 | Number and proportion of questionnaires collected by villages.

City and county where the sample village is located	Sample village	Number of valid returned questionnaires	Percentage%
Wenchuan County, Aba Autonomous Prefecture	Younian village	78	11.57
	Yuzixi village	71	10.53
	Xingwenping village	65	9.64
Lushan County, Ya 'an City	Renjia village	76	11.28
	Shuanghe village	83	12.31
	Caoping village	68	10.09
Changning County, Yibin City	Bijia village	78	11.57
	Jinyu village	71	10.53
	Longtou village	84	12.46
Total		674	100.00

The researchers randomly selected households to carry out the questionnaire survey. In order to obtain the accurate geographical location of the respondents' households, the researchers used Ovi map software to locate the geographical location with the consent of the respondents. A total of 714 questionnaires were collected during this survey period, of which 674 were valid, with an effective rate of 94.40%. The number of valid returned questionnaires are shown in **Table 2**. The socio-demographic information of interviewees is shown in **Table 3**.

Model Specification

Multinominal Logit Model (MNL) is widely used in the research of multiple choices, mainly through the calculation of utility functions to determine the item to obtain the probability of individual different choices. Different disaster preparedness behaviors as discrete variables with general models will cause deviation. Therefore, this study chooses MNL to establish the model, and explores the relationship between villagers' trust in the disaster relief ability of stakeholder, the disaster preparedness help available from stakeholder and the daily

TABLE 3 | Socio-demographic information of respondents.

Variable	Variable definition	Frequency	Percentage%
City and county	Yibin	210	31.2
	Ya'an	254	37.7
	Wenchuan	210	31.2
Gender	Man	311	46.1
	Woman	363	53.9
Age	35 below	152	22.6
	36–60	380	56.4
	61 above	142	21.1
Birthplace	Not local	441	65.4
	Local	233	34.6
Academic degree	Primary school and below	340	50.4
	Junior school	223	33.1
	Senior high school	72	10.7
	University and above	39	5.8

TABLE 4 | Scale reliability test.

Variables	Items	Cronbach's alpha
Trust in stakeholders	6	0.904
Help available for disaster preparedness	6	0.865
Disaster preparedness behaviour	6	0.732

TABLE 5 | Scale validity test.

KMO	Bartlett's test of sphericity		
	Approx.Chi-square	df	Sig.
0.886	7038.737	171	0.00

disaster preparedness behaviors of the topic, by controlling the demographic variables of respondents.

Suppose that the nth respondent chooses the effect of the ith disaster preparedness behavior as U_{ni}, J_n is the scheme set, then i $\in J_n$, $U_{ni} = V_{ni}+\varepsilon_{ni}$, and $V_{ni} = \beta' X_{nk}$. Among them, ε_{ni} is the random error term; X_{nk} is the kth factor which affects the nth disaster preparedness behavior; β' is the parameter to be estimated. Then the probability that the nth respondent chooses the ith disaster preparedness behavior is:

$$\begin{aligned} P_n(i) &= \mathrm{Prob}\left(U_{ni} \geq U_{nj}, j \in J_n, i \neq j\right) = \mathrm{Prob}\left(V_{ni} + \varepsilon_{ni}, j \in J_n, i \neq j\right) \\ &= \mathrm{Prob}\left[V_{ni} + \varepsilon_{ni} \geq \max_{j \in J_n}\left(V_{nj} + \varepsilon_{nj}\right)\right] \end{aligned} \tag{1}$$

If each random term ε_{ni} obeys independent identical distribution, then:

$$f(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n) = \prod_n g(\varepsilon_n) \tag{2}$$

Where $g(\varepsilon_n)$ is the distribution function corresponding to the nth respondent. Assuming that $g(\varepsilon_n)$ obeys the double exponential distribution, the probability of choosing the ith disaster preparedness behavior in J_n is:

$$\begin{aligned} p_{in} &= \frac{\exp(V_{in})}{\sum_{j \in J_n} \exp\left(V_{jn}\right)} = \frac{1}{\sum_{j \in J_n} \exp\left(V_{jn}\right) - \sum_{j \in J_n} \exp(V_{in})} \\ &= \frac{\exp(\beta' X_{nk})}{\sum_{j \in J_n} \exp(\beta' X_{nk})} \end{aligned} \tag{3}$$

RESULTS AND DISCUSSION

Reliability and Validity Test

SPSS software was used to test the reliability and validity of the questionnaire. As shown in the **Table 4**, Cronbach's Alpha of all scales was greater than 0.7, indicating that the scales had good reliability.

As shown in **Table 5**, the KMO value of the scale was greater than 0.7, and the p value of Bartlett's Test of Sphericity was lower than 0.05, indicating that the scale had good validity.

Collinearity Analysis

In this study, Variance Inflation Factor (VIF) is used to test multicollinearity. When VIF value is greater than 10, it is considered that there is strong multicollinearity among variables, which will seriously affect the model fitting (Wu and Pan, 2014). After inspection, the VIF values of the variables in this study are all less than 2, which indicates that there is no multicollinearity among the variables, and model analysis can be carried out. The results of multicollinearity detection are shown in **Table 6**.

Model Result Fitting

MNL model was established by SPSS to fit the above data. Options for disaster preparedness are defined as: purchasing disaster insurance, preparing valuables, preparing sufficient materials, participating in disaster drills, making an escape plan, learning disaster prevention knowledge, and nothing as the reference group. The model fitting significance P *is* 0.008 (<0.05) and *Nagellkerke* R^2 is 0.235, which indicates that the model fitting effect is good. It can be seen from **Table 6** that the likelihood ratio test p values of all variables are less than 0.05, which indicates that these variables have a significant impact on the choice of disaster preparedness behavior of villagers in earthquake-stricken areas in the selected sample villages. The fitting results of MNL model are shown in **Table 7**.

Socio-Demographic Variables

As shown in **Table 7**, compared with the villagers living in Yibin, the villagers in Ya'an (−1.040) and Wenchuan (−0.507) are less likely to take part in disaster preparedness drills, and there is no significant difference in other measures (p > 0.05). In addition, other variables have significant influence on disaster preparedness behavior. Gender has significant difference in disaster preparedness behavior. Compared with women, men

TABLE 6 | Multiple collinearity and independent variable likelihood ratio test.

Variable	Model fitting condition	Likelihood ratio test			Collinearity test	
	The-2 log-likelihood of the reduced model	Chi square	Degree of freedom	*p*-value	Tolerance	VIF
Intercept distance	3300.279	0	0			
City and county	3328.695	28.417	12	0.005	0.858	1.166
Gender	3321.374	21.096	6	0.002	0.901	1.11
Age	3312.988	12.709	6	0.048	0.627	1.595
Birthplace	3319.238	18.96	6	0.004	0.93	1.075
Level of education	3318.778	17.499	6	0.013	0.63	1.586
Years of residence	3320.605	20.327	6	0.002	0.986	1.014
Structure type	3339.503	39.224	24	0.026	0.93	1.075
Type of house	3314.546	12.981	6	0.043	0.972	1.028
Perceptual preparation	3348.043	99.226	6	0.000	0.846	1.181
Trust in disaster relief ability	3317.278	16.999	6	0.009	0.674	1.483
Help available for disaster preparedness	3316.801	16.522	6	0.011	0.663	1.507

TABLE 7 | MNL model parameter estimation (ref = reference group; β= intercept).

	Purchasing disaster insurance		Preparing valuables		Preparing sufficient materials		Participate in evacuation drills		Making an escape plan		Learning disaster prevention knowledge	
	β	*p*-value	β	*p*-value	β	*p*-value	β	*p*-value	β	*p*-value	β	*p*-value
Intercept distance	−43.616	0.125	−7.786	0.685	−5.492	0.576	−62.402	0.020	−75.370	0.002	−58.826	0.007
City and county (Yibin = ref)												
Wenchuan	−0.041	0.908	0.500	0.141	−0.032	0.921	−0.507	0.041	0.108	0.689	−0.046	0.861
Ya ' an	−0.572	0.107	−0.326	0.374	−0.55	0.105	−1.04	0.000	−0.302	0.263	−0.176	0.489
Male (Female = ref)	0.786	0.004	0.827	0.002	0.695	0.007	0.775	0.000	0.812	0.000	0.686	0.001
Age	−0.592	0.017	−0.517	0.036	−0.646	0.008	−0.545	0.005	−0.316	0.097	−0.464	0.011
Not born locally (Local birth = ref)	0.450	0.109	0.822	0.002	0.771	0.003	0.808	0.000	0.701	0.001	0.657	0.002
Level of education	0.324	0.040	0.322	0.034	0.298	0.049	0.223	0.075	0.207	0.092	0.292	0.013
Years of residence	0.021	0.133	0.003	0.734	0.002	0.664	0.031	0.020	0.037	0.002	0.029	0.007
Type of house (other = ref)												
Own house	0.056	0.941	−0.311	0.638	0.522	0.543	0.692	0.296	0.74	0.272	0.643	0.298
Rent a house	−2.167	0.093	−0.317	0.688	−0.032	0.974	−0.24	0.763	0.349	0.654	0.032	0.965
Type of structure (steel concrete structure = ref)												
Bamboo and grass structure	0.693	0.592	1.37	0.207	0.674	0.603	0.788	0.423	−0.202	0.873	0.770	0.406
Stone and wood structure	0.089	0.939	−0.744	0.542	0.169	0.857	−19.672		−1.539	0.173	−0.974	0.265
Masonry structure	2.039	0.000	1.672	0.001	1.022	0.052	1.290	0.004	1.364	0.001	1.182	0.004
Brick-concrete structure	0.315	0.301	0.395	0.178	0.284	0.318	−0.151	0.516	0.110	0.628	0.061	0.782
Perceptual preparation	1.039	0.000	0.979	0.000	1.260	0.000	0.716	0.000	0.810	0.000	0.764	0.000
Trust in disaster relief ability	0.230	0.728	0.335	0.208	1.040	0.117	−0.882	0.048	−0.784	0.009	−0.855	0.068
Help available for disaster preparedness	0.088	0.894	0.036	0.956	−0.508	0.441	1.200	0.017	1.085	0.027	1.112	0.018

are more likely to purchase disaster insurance (0.786), prepare valuables (0.827), prepare sufficient materials (0.695), participate in evacuation drills (0.775), make an escape plan (0.812) and learn disaster prevention knowledge (0.686). All the six measures: purchasing disaster insurance (−0.592), preparing valuables (−0.517), preparing sufficient materials (−0.646), participating in evacuation drills (−0.545), making an escape plan (−0.316), and learning disaster prevention knowledge (−0.464) are negatively correlated with age. Non-native-born residents are more inclined to prepare valuables (0.822), prepare sufficient materials (0.771), participate in evacuation drills (0.808), make an escape plan (0.701), and learn disaster prevention knowledge (0.657). Among them, the probability of preparing valuables is the highest, and the probability of learning disaster prevention knowledge is the lowest. The education level of villagers in earthquake-stricken areas is significantly positively correlated with purchasing of disaster insurance (0.324), preparing valuables (0.322), preparing sufficient materials (0.298), participating in evacuation drills (0.223), making an escape plan (0.207), and learning disaster prevention knowledge

(0.292). The length of residence has a positive impact on participation in disaster drills (0.031), development of escape plans (0.037) and learning disaster prevention knowledge (0.029). The seismic capability of rural buildings is negatively correlated with residents' disaster preparedness behavior. Compared with steel-concrete structure, villagers living in masonry structures are more likely to purchase disaster insurance (2.039), prepare valuables (1.672), prepare sufficient materials (1.022), participate in evacuation drills (1.290), make an escape plan (1.364), and learn disaster prevention knowledge (1.182).

Explanatory Variables

As shown in **Table 7**, there is a significant positive correlation between the perceived level of earthquake preparedness and the actual probability of taking measures such as purchasing disaster insurance (1.039), preparing valuables (0.979), preparing sufficient materials (1.260), participating in evacuation drills (0.716), making an escape plan (0.810), and learning disaster prevention and reduction knowledge (0.764). That is, the self-perception of earthquake preparedness level of rural residents is consistent with the actual disaster preparedness behavior, and there is no obvious deviation in perception. There is a significant negative correlation between the degree of trust of villagers regarding stakeholders' disaster relief ability and the probability of participating in evacuation drills (−0.822), making an escape plan (−0.784), and it has no significant effect on other disaster preparedness behaviors ($p > 0.05$). The degree of help that villagers in earthquake-stricken areas can get from different stakeholders in disaster preparedness is significantly positively correlated with the probability of participating in evacuation drills (1.200), making an escape plan (1.085), and learning disaster prevention knowledge (1.112). The more help rural residents can get from stakeholders in earthquake preparedness, the higher the degree of disaster preparedness actions they take.

In addition, the degree of help that villagers in earthquake-stricken areas can get from different stakeholders in earthquake preparedness measures has significant positive impacts on their preparedness measures. The more help rural residents can get from six different stakeholder groups in earthquake preparedness measures, the higher the degree of disaster preparedness actions they would take. This is consistent with the previous conclusion that when faced with disasters, the degree of social support has a positive impact on the perception of residents in disaster areas, thus promoting them to take disaster preparedness actions (Han et al., 2017a). In an emergency, people depend on each other to get help and information (Perry and Lindell, 2003), which will promote the transformation of preventive measures into concrete actions (Kim and Kang, 2010).

DISCUSSION

In this research, we analyze the disaster preparedness behavior of rural residents from typical disaster areas in Sichuan Province. We classify six specific disaster preparedness behaviors and explore their influencing factors.

There is no significant difference in the residents' disaster preparedness behavior in the three regions except in the participating in evacuation drills. This is because these three areas have experienced many earthquakes, and the residents have similar earthquake experiences. Disaster experience is regarded as an important driving factor of disaster preparedness behavior (Atreya et al., 2017) and one of the key predictors of disaster preparedness behavior (Hoffmann and Muttarak, 2017). Therefore, we believe that similar disaster experiences can motivate residents to take similar disaster preparedness behaviors. Becker et al. (Becker et al., 2017)find that disaster experiences, life accidents, and other people's disaster descriptions can help individuals understand the consequences of disasters and facilitate disaster-preparedness interactions in communities as well.

There are though significant differences between individuals with different demographic characteristics. Men are more active in disaster preparedness than women. This could be cause by that women have more family activities and they are less aware of crisis, so their cognition of earthquake disaster ability is lower than that of men, and the corresponding possibility of disaster preparedness is also lower (Yue and Ou, 2005; Su et al., 2007). Older people are less likely to take disaster preparedness measures, and people with higher levels of education are more likely to take disaster preparedness measures, which is consistent with the conclusion of Wu et al. (Wu et al., 2018). While it is not possible to improve disaster preparedness by changing the nature of the public, disaster preparedness education can be more targeted to women, the elderly, the less educated population and other groups. Non-native residents are more likely to take a range of preparedness measures. This is consistent with the conclusion of Paul et al. (Paul and Bhuiyan, 2010). Compared with native people, non-native people have a weaker sense of belonging. Yang et al. point out the connection between belonging and sense of security. Non-natives have a sense of crisis due to their weak sense of belonging, so they are more likely to take disaster prevention measures.

The characteristics of houses can also affect residents' disaster preparedness behavior, the younger the age of the house, the more likely the villagers of the house to prepare for disaster. Zhou et al. (Zhou et al., 2009)also find that residential year significantly affected residents' disaster preparedness level. Villagers living in masonry structures were more likely to adopt a range of disaster preparedness measures than those living in steel-concrete structures. According to the statistics of Ming et al. (Ming et al., 2017), in the earthquake, masonry structure and civil structure of the damage rate of the damage rate is relatively high. The seismic performance of buildings is negatively correlated with villagers' disaster preparedness measures.

This study finds that trust in government is negatively correlated with individual disaster preparedness behavior. By surveying survivors of the Yushu earthquake, Han et al. find that trust in government tends to decrease the respondents' perceived consequences of and reported preparedness for future potential earthquakes (Han et al., 2020). However, there are many conflicting results on the relationship between government trust and disaster preparedness. Through a survey of residents in North Carolina, Deyoung et al. (Deyoung and Peters, 2016) find that there is no significant relationship between trust in the government and individual disaster preparedness behavior. Wang (Wang and Han, 2018) also finds that in the United States, where individualism prevails, the more the general public trusts the government, the higher the disaster preparedness level is. Although it is positively correlated with the actual emergency preparedness level, it is not significant. He believes that this is a result of cultural differences. The general public in China have a much higher degree of trust in government than the citizens in western countries (Li, 2016). For disasters and emergency management, China has no policy made clear that the public should take their own responsibility facing emergencies. On the contrary, the government often gives a person a kind of impression that the government can save you in disaster (Han et al., 2020). as a result, Chinese residents are highly dependent on the government, which makes them less prepared for disasters. Therefore, we need to recognize that disaster reduction is not entirely a matter of the government, nor can the government cover all aspects of disaster reduction (Wang and Han, 2018). While emphasizing the leading role of the government, we must also advocate the participation of social forces.

CONCLUSION

To understand how residents in rural areas of China choose various earthquake preparedness behavior to reduce damages, it is desired to understand how these behaviors are related to their perception of the help they can get in preparation and their trust in the different stakeholders in reducing and preventing earthquake damages. Since there is no consistent conclusion regarding these two explanatory variables, it is necessary to carry out related research in rural earthquake-stricken areas with control variables like socio-demographic variables. Through theoretical and empirical research, this paper investigates several villages in Sichuan province that have experienced major earthquakes. A Multinominal Logit (MNL) model is used to explore and analyze the influencing factors of rural residents' disaster preparedness behavior, especially the influence of stakeholders on residents' disaster preparedness behavior. The results of this study show that stakeholders play a very important role in residents' disaster preparedness behavior, which is manifested in that trust and available help to stakeholders will reduce residents' willingness to take disaster preparedness behavior. In addition, the willingness of residents to take disaster preparedness behavior is affected by age, gender, educational background, housing type and years of residence. The main findings of the study areas are as follows:

(1) Among the sociodemographic variables, males and young villagers are more inclined to actively take disaster preparedness measures. The villagers' education level and residence years significantly affect their disaster preparedness activities.
(2) The villagers' trust in disaster relief ability of different stakeholders has significant negative impacts on their disaster preparedness behavior. In addition, the relationship between trust and disaster preparedness may be different in different regions and cultures. On the contrary, the degree of disaster preparedness assistance that villagers can get from stakeholders significantly affects their daily disaster preparedness behavior positively.

This study further confirms the importance of earthquake education and disaster preparedness assistance. Due to the differences in residence, age, education level and social experience, different groups of people face different risks during the earthquake. Therefore, it is necessary to formulate targeted publicity and education measures according to the different characteristics of the publicity objects (Peng and Huang, 2020). Some recommendations are given in this context: Organizing regular earthquake education and disaster preparedness measure publicity through village speakers; Setting up early warning devices and equipment in places with large crowds such as squares or commissary; Posting comprehensive earthquake preparedness behaviors and implementation methods on community bulletin boards; and establishing community disaster preparedness work boxes to obtain specific disaster preparedness assistance that residents want, etc. In addition, because the villagers' high trust in the disaster relief ability of stakeholders will reduce the villagers' daily vigilance in disaster prevention, it is necessary to further objectively emphasize the uncertainty of earthquake disasters and the importance of self-prevention in daily publicity and education, so as to promote disaster prevention and mitigation for all people. While relying on the government, we must also advocate the participation of social forces, not only social organizations, but also enterprises and the public.

To summarize, this research sheds lights on the rural residents earthquake preparedness behavior, and provide practical guidance for rural disaster prevention planning and construction, especially from the stakeholder perspective in Rural China.

While empirical results for rural areas in Sichuan have been found in this research, there are limitations. These may be taken up in subsequent research work:

(1) The scope of the study is limited. The selected villages are all from Sichuan province, and most of them are near the epicenter. Although these locations are representative to some extent, they cannot represent other earthquake-affected areas in China, and the general applicability of the conclusions needs further study. This paper has some limitations in regional distribution.
(2) This study does not deeply explore the specific impact path and intermediary effect between each influencing factor and residents' disaster preparedness behavior. This will be further studied in the future research.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding authors.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

Manuscript draft: HZ, LiyT, LT, YA, and TW; Research design and methods: HZ, YA, and TW; Data collection and analysis: YW and JZ; Revision: All authors.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.926432/full#supplementary-material

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Effects of Climate Changes on the Pasture Productivity From 1961 to 2016 in Sichuan Yellow River Source, Qinghai-Tibet Plateau, China

Lv Zhang[1], Pengfei Xiao[2], Hui Yu[3†], Tao Zhao[4*], SiYuan Liu[5†], Li Yang[1*], Yu He[6], Yong Luo[5*], Xiao Wang[7], Wei Dong[1,5], Hui He[8], Duyang Wang[5], Keli Liu[5] and Yi Lu[5]*

[1] Sichuan Institute of Land Science and Technology (Sichuan Satellite Application Technology Center), Chengdu, China, [2] Information Center of Department of Natural Resources of Sichuan Province, Chengdu, China, [3] Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu, China, [4] Sichuan Land Consolidation and Rehabilitation Center, Chengdu, China, [5] College of Earth Sciences, Chengdu University of Technology, Chengdu, China, [6] Sichuan Environment and Engineering Appraisal Center, Chengdu, China, [7] China Southwest Geotechnical Investigation and Design Institute Co. Ltd., Shanghai, China, [8] Chongqing Jiaotong University, Chongqing, China

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Edited by:
*Dingde Xu,
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*Yu Liu,
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Li Xuedong,
Shandong Jianzhu University, China*

***Correspondence:**
*Hui Yu
yuhui@imde.ac.cn
Tao Zhao
462782265@qq.com
Li Yang
398920637@qq.com
Yong Luo
luoyong2014@cdut.edu.cn*

† These authors share first authorship

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Meteorological station data from 1961 to 2016 in the Sichuan Yellow River Source (SYRS) was used to analyze the trends in precipitation and temperature. The Thornthwaite Memorial model and GIS technology were used to calculate the response of pasture productivity to climate change. A climate prediction model of pasture productivity was established to predict its response to precipitation and temperature. The results showed that: (1) the annual precipitation presents a slight downward trend, at a rate of -10.16 mm$\cdot$(10a)$^{-1}$. The average annual temperature exhibited an upward trend, at (10a)$^{-1}$, and the productivity of herbage exhibited a linearly increasing trend, with a rate of increase of 80.07 g$\cdot$m$^{-2}\cdot$(10a)$^{-1}$. (2) In terms of spatial distribution, the pasture productivity decreased from southwest to northeast. The influence of temperature on pasture productivity was greater than that of precipitation in the SYRS. (3) The "warm-wet" climate was conducive to increasing pasture productivity. The annual average temperature was predicted to increase by 1 or 2°C, and the annual average precipitation was predicted to increase by 10 or 20% with an average increase between 7.15 and 14.30%. (4) Grassland degradation continues to occur and ecological restoration measures should be implemented to control grassland degradation.

Keywords: pasture productivity, climate change, Sichuan Yellow River Source (SYRS), climatic productivity, spatiotemporal variation

INTRODUCTION

Since the twentieth century, the world has experienced significant effects of global warming. According to the Fifth Assessment Report of the IPCC, the average temperature of the world has increased by 0.85°C from 1880 to 2012. In the Northern Hemisphere, the 30 years with the highest temperature in the past 1,400 years was 1983–2012 (Shen and Wang, 2013). Short- and long-term fluctuations in the temperature and moisture of the surrounding environment are the main reasons for changes in the pasture productivity in a given region (Wu, 2002). It is important to notethat even low levels of climate change can lead to functional destruction and structural changes in vegetation and vegetation zones (Song et al., 2012). Yi et al. (2012) adopted the total deficit method to identify climatic factors affecting pasture productivity from observed data, exploring how extreme climate events change the productivity of an ecosystem.

Grassland accounts for 1/3 of China's land area and is an important barrier in terrestrial ecosystems. As an important part of the ecological barrier of the Qinghai-Tibet Plateau and the "Water tower of China," the source region of the Yellow River is one of 34 hotspots with the richest biodiversity in the world. It plays an extremely important role in maintaining national ecological security. The models used to calculate the climatic pasture productivity include the biogeochemical ecosystem model, Jiang Ai-liang model, Miami model, and Thornthwaite Memorial model (Zhao, 2007; Berberoglu et al., 2021; Huang et al., 2021). Berberoglu et al. (2021) used a biogeochemical ecosystem model, the Carnegie–Ames–Stanford Approach (CASA) model, to forecast the annual net primary productivity (*NPP*) changes for the periods 2000–2010 and 2070–2080. Cheng and Yin (2022) used the Thornthwaite Memorial model to analyze the climatic productivity, population carrying capacity, and its index in eastern Gansu. They revealed the relationship between population and grain growth in eastern Gansu. Huang et al. (2021) estimated the potential and actual *NPP* in Anji based on the Thornthwaite Memorial model, CASA model, and multiple linear regressions. HANPPluc significantly increased from 1984 to 2014. The comprehensive estimation model of climatic productivity is also used to analyze the spatiotemporal distribution of climatic productivity in China (Cao et al., 2020). On the Tibetan Plateau, the climatic productivity has shown significant spatiotemporal differences over the past 50 years. From 1965 to 2013, the climatic productivity of herbage on the Qinghai-Tibet Plateau increased from northwest to southeast. The climatic productivity of herbage in the northern and southern parts of Qinghai Province increased significantly, while that in the eastern part of Tibet increased only slightly, and the differences between the northern and southern regions were large (Zhao et al., 2016). In Ningxia, with increases in temperature and precipitation, the climatic production exhibited an increasing trend (Duan et al., 2014). The Three-River-Source experiences a dry climate, and precipitation is the key factor affecting grassland climate production in the region (Guo et al., 2008).

The Miami model considers precipitation and temperature as climate factors, while the Thornthwaite Memorial model considers temperature, precipitation, and evapotranspiration (Zhao, 2007). The Thornthwaite Memorial model results are consistent in that precipitation and temperature are the key factors affecting the growth and development of herbage in this area. The objectives of this study are as follows: (1) to elucidate the spatiotemporal variations in the pasture productivity in the study area based on long-term climate factors, and (2) to establish a climate prediction model for pasture productivity, clarifying the impact of climate change on the pasture productivity and proposing measures to improve the productivity of grassland vegetation.

MATERIALS AND METHODS

Study Area

The SYRS is located on the east margin of the Tibetan plateau (**Figure 1**). The research location is the SYRS, which primarily comprises the Hongyuan, Aba, and Zoige counties of the Aba Tibetan and Qiang Autonomous Prefecture, covering an area of 29,161 km^2. The main geomorphic types are alpine, hilly plateau, and terrace. Natural grassland is the main type of grassland, covering an area of 16,735 km^2 and accounting for 79.85% of the total grassland area. Meanwhile, marsh grassland covers 3,964 km^2, accounting for 20.12%. The study area experiences a sub-humid monsoon climate in the cold temperate zone of the plateau, which is a typical ecologically fragile area, sensitive to local and global climate change.

Data Source

The meteorological data are obtained from the China Meteorological Data Sharing Service Network[1] ground climate data, including the monthly average temperature, average precipitation, etc. from 1961 to 2016.

[1] http://data.cma.cn/wa

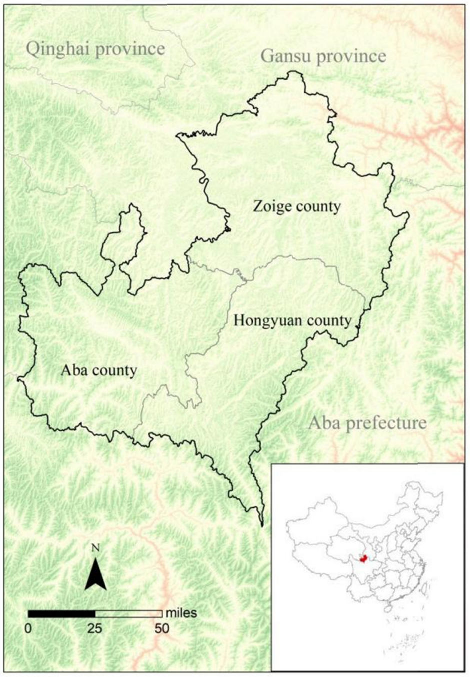

FIGURE 1 | Location of the study area.

Methods

First, the meteorological data for the past 56 years were collected. Second, the data were processed to analyze the trends in precipitation and temperature in the source area of the Yellow River. Then, a model was used to calculate the evapotranspiration, while calculating the pasture productivity. A model was constructed to describe the relationship between climate and pasture productivity, which is an important part of this research. Finally, we analyzed the impact of climate change on pasture productivity (**Figure 2**).

The Pasture Productivity

The pasture productivity is affected by the joint action of the pasture's genetic traits and environmental factors during the growth period. If other factors remain unchanged, the climatic conditions during the growth period have the greatest influence on the yield (Zhao, 2007). The Thornthwaite Memorial model (Yang and Piao, 2006; Liu et al., 2014) estimated the pasture productivity in the study area as follows:

$$T_P = 30000 * [1 - e^{-0.0009695(v-20)}]$$

$$V = \begin{cases} 1.05P/\sqrt{1 + (1.05P/L)^2} & (P >= 0.316L) \\ P & (P < 0.316L) \end{cases}$$

$$L = 300 + 25T + 0.05T^3$$

Where T_P is the pasture productivity, g.m^{-2}.a^{-1}; V is the annual average actual evapotranspiration, mm; T is the annual average temperature, °C; L represents the empirical function of the annual average temperature; and P is the average annual precipitation, mm.

Grassland Degradation Index

Grasslands have many service functions, including soil and water conservation and biodiversity maintenance (Tang et al., 2022). Furthermore, their carbon sequestration is huge, which has an important regulatory effect on the global climate and ecosystem carbon cycle (Zhao et al., 2018). Based on remote-sensing data and meteorological data, the *NPP* in the study area was calculated. From the perspective of the carbon sequestration status of the ecosystem, the issue of grassland degradation in the region was discussed, the optimal productivity value in the region was selected as the reference ecosystem, and the grassland productivity NPP_{real} in the study area was compared with the NPP_{max} of the reference ecosystem productivity to obtain the degree of degradation.

The grassland degradation index (*GDI*) was calculated as follows:

$$GDI = \frac{NPP_{real}}{NPP_{max}} \times 100\%$$

where NPP_{real} represents the *NPP* within the assessment unit and NPP_{max} is the ideal *NPP* or maximum *NPP* of the intact grassland within the unified physical geographic zone and the assessment unit.

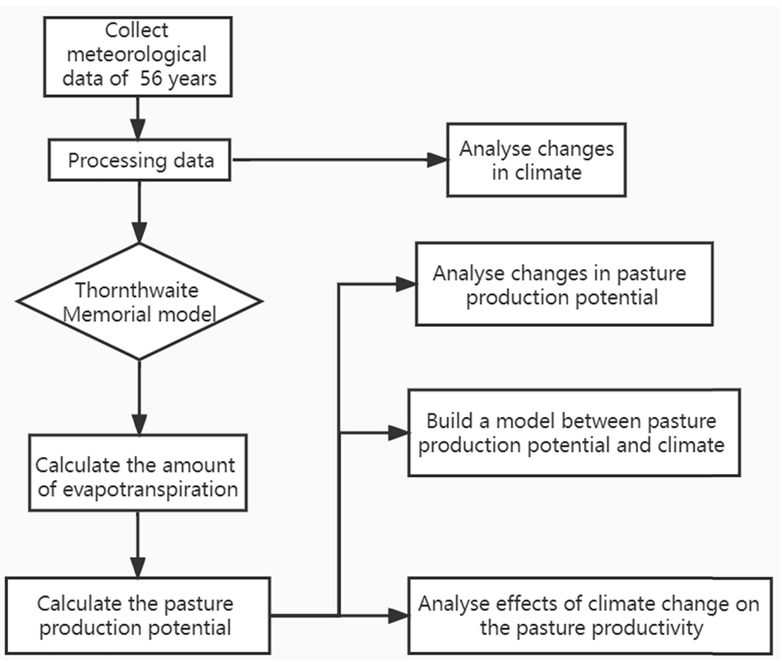

FIGURE 2 | Technical process.

RESULTS

Spatial and Temporal Trends in Climate

Temporal Trends in Climate

Over the past 56 years, the temperature has exhibited an increasing trend (**Figure 3**), with a warming of 0.32°C·$(10a)^{-1}$ in the SYRS. From the trend line, it can be seen that the temperature generally lies below the average from 1961 to 1997, and has been increasing since 1997. Precipitation displayed a decreasing trend in general. However, this decrease was small, with a propensity rate of 10.16 mm·$(10a)^{-1}$. The precipitation in 2002 reached the minimum value of 476 mm.

Spatial Variation of Climate

The spatial distribution of average annual precipitation (**Figure 4**) and average annual temperature (**Figure 5**) from 1961 to 2016 showed a decreasing trend from southwest to northeast. Within the study location, Aba County had the highest temperature, with an increase of 1.46°C in the average temperature from 2011 to 2016 compared to the 1961–1970 average temperature. The overall precipitation was generally above 500 mm, with a decrease in the twenty-first century compared to the 1960s. Precipitation was most abundant in Hongyuan, but the temperature was low. Aba County had sufficient precipitation to meet the needs of forage growth and higher temperature, showing a trend of warming and humidification; this is to say, a "warm-wet" climate.

Spatial and Temporal Variation in Pasture Productivity

Interannual Variation in Pasture Productivity

Over the past 56 years, the pasture productivity in the SYRS exhibited an overall upward trend (**Figure 6**). The overall change was from 6891.95 to 8073.16 g·m^{-2}, with an increase of 80.07 g·m^{-2}·$(10a)^{-1}$, and the average value was 7491.56 g·m^{-2}. The pasture productivity increased the most from 1997 to 1998, with a change of 1044.17 g·m^{-2}. Since 2008, the pasture productivity has been higher than the average, but the increase has been slow.

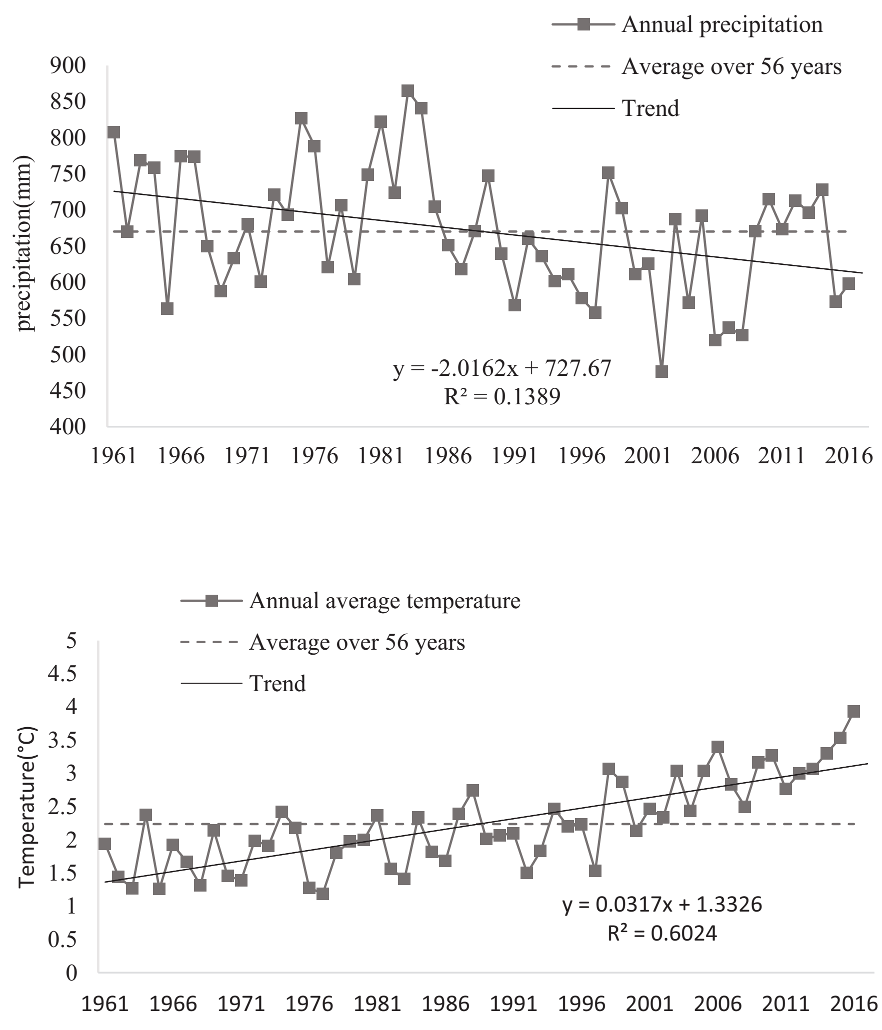

FIGURE 3 | Trends in temperature and precipitation in the SYRS from 1961 to 2016.

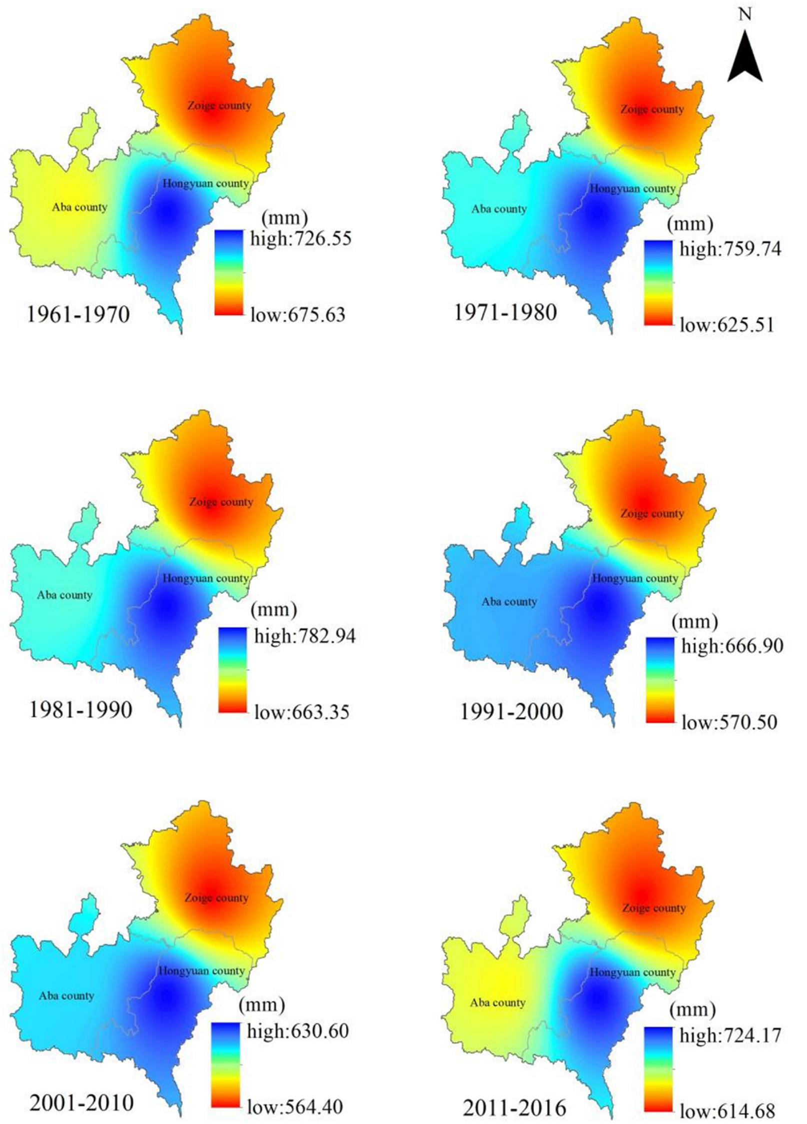

FIGURE 4 | Average annual precipitation from 1961 to 2016.

Interdecadal Variation in Pasture Productivity

From the 1960s to 2016, the pasture productivity in the SYRS exhibited an overall increasing trend (**Figure 7**). It was negative in the 1990s. Since the twenty-first century, the pasture productivity has increased significantly. In comparison to the average value over the past 56 years, the pasture productivity in the 1960s, 1970s, and 1990s was 2.1, 1.3, and 1.2% lower than the average value, respectively, and 0.5% higher than the average value in the 1980s, 0.8% higher than the average value in the 2000s, and 5.3% higher than the average value from 2011 to 2016 (**Table 1**).

Interdecadal Spatial Variation in Pasture Productivity

The spatial distribution of pasture productivity in the SYRS was significantly different (**Figure 8**), decreasing from southwest to northeast. The area with the highest value was in Aba County, with a maximum of 7978.01 $g{\cdot}m^{-2}{\cdot}a^{-1}$ in the 1960s and a maximum of 8180.47 $g{\cdot}m^{-2}{\cdot}a^{-1}$ from 2011 to 2016. The lowest value occurred in Zoig County, with a minimum of 6898.83 $g{\cdot}m^{-2}{\cdot}a^{-1}$ in the 1960s and 7449.12 $g{\cdot}m^{-2}{\cdot}a^{-1}$ from 2011 to 2016. A comparison of pasture productivity in 1961–1970 and 2011–2016 indicated an increasing trend due to the significant increase in temperature, but this increase was restrained by the faint decrease in precipitation. Pasture productivity in the SYRS was increased overall.

Effects of Climate Change on the Pasture Productivity in Climate Scenarios

From the meteorological data over 56 years, it can be seen that the temperature in the SYRS exhibited an overall upward trend while the precipitation fluctuated from year to year. Therefore, this

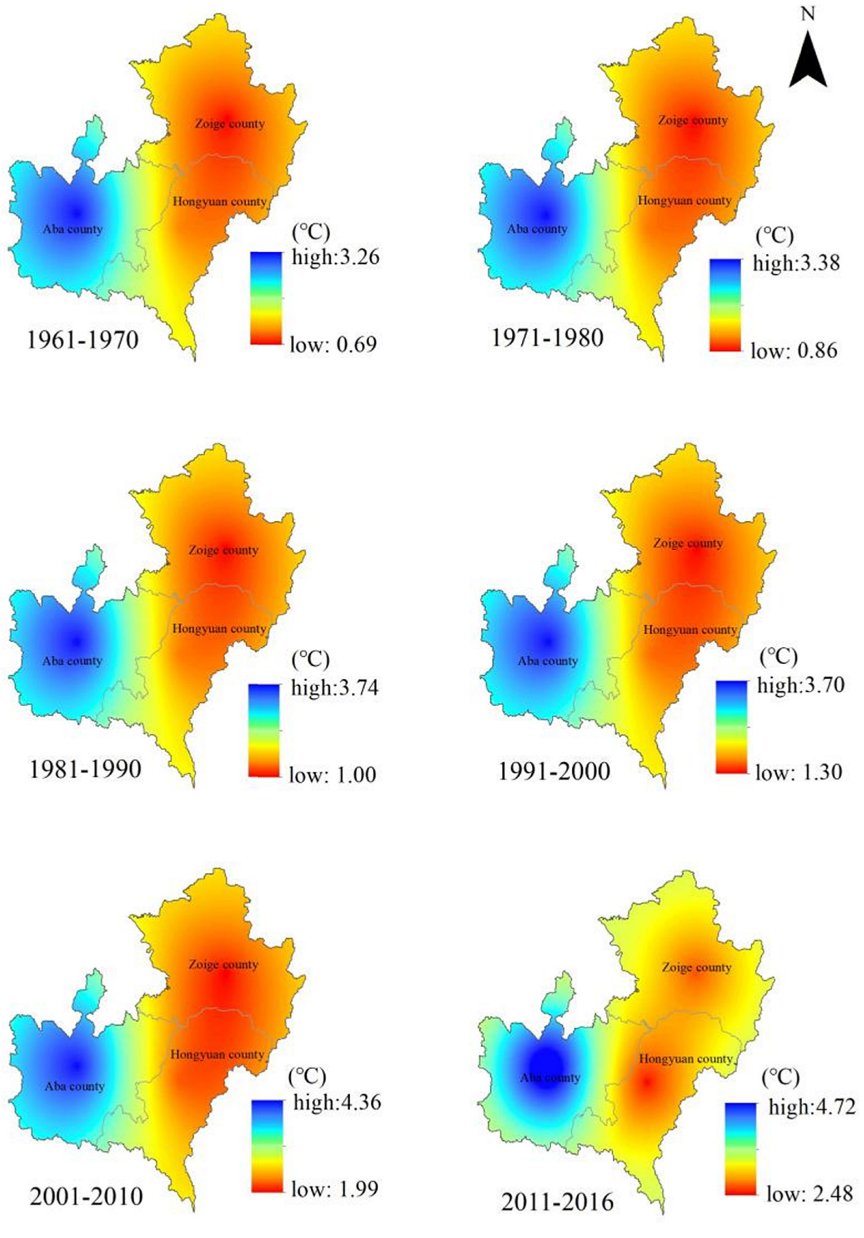

FIGURE 5 | Average annual temperature from 1961 to 2016.

study assumes that, in the SYRS, the annual average temperature increases or decreases by 1 or 2°C, and the annual average precipitation increases or decreases by 10 or 20%. Given these assumptions, the percentage change in pasture productivity was predicted (**Table 2**).

Effects of Precipitation Change on the Pasture Productivity in Climate Scenarios

Assuming that the average annual temperature remained unchanged at the average level over 56 years, the pasture productivity would increase by 1.67 and 3% when the precipitation increased by 10 and 20%, respectively. The pasture productivity was predicted to decrease by 2.14 and 4.91% when the precipitation decreased by 10 and 20%, respectively (**Figure 9**).

Effects of Temperature Change on the Pasture Productivity in Climate Scenarios

If the average annual precipitation remains unchanged at the average level over 56 years, the pasture productivity will increase by 5.20 and 10.26% when the temperature increases by 1 and 2°C, respectively. The pasture productivity was predicted to decrease by 5.39 and 11.04% when the temperature decreased by 1 and 2°C, respectively (**Figure 10**). This shows that the influence of

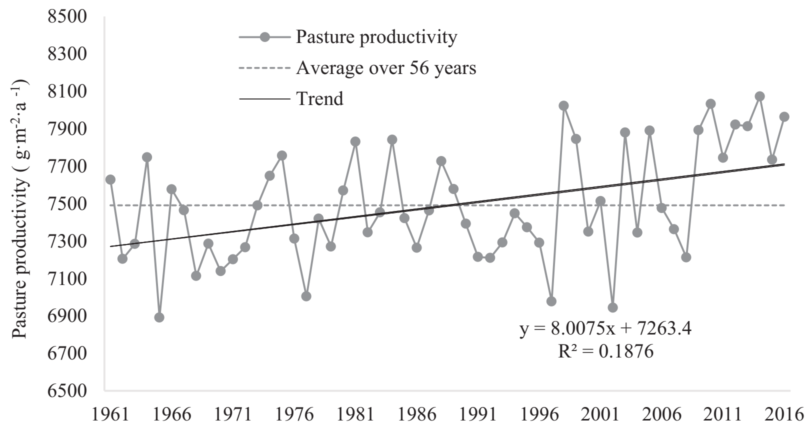

FIGURE 6 | Interannual variation in pasture productivity from 1961 to 2016.

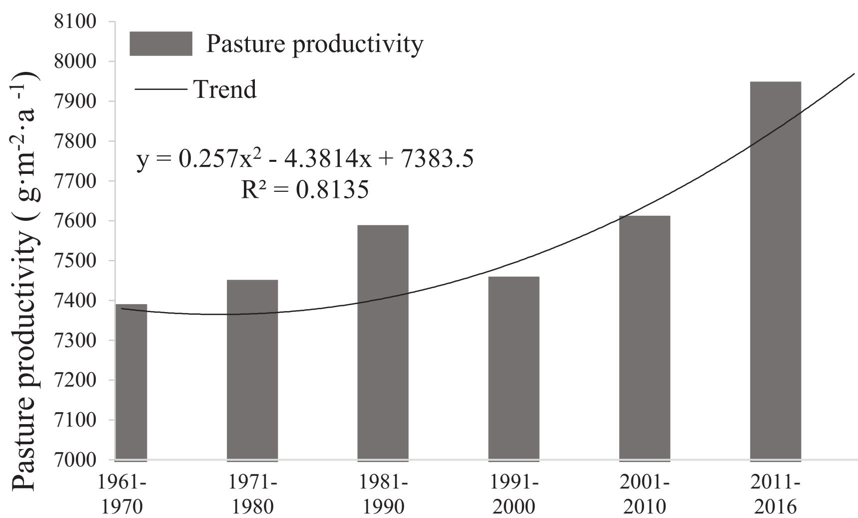

FIGURE 7 | Interdecadal variations in pasture productivity in the SYRS.

temperature change on the pasture productivity was greater than that of precipitation in the SYRS.

Combined Effects of Precipitation and Temperature on Pasture Productivity in Climate Scenarios

If the annual precipitation increased by 10% and the annual mean temperature increased by 1°C, the pasture productivity would increase by 7.15%. Meanwhile, if the annual precipitation increased by 20% and the annual mean temperature increased by 2°C, the pasture productivity would increase by 14.30% (**Figure 11**). Therefore, the "warm-wet" climate is beneficial to improving the pasture productivity.

Given a 10% decrease in the annual precipitation decreased and a 1°C decrease in the annual mean temperature, the pasture productivity would decrease by 7.22%. If the annual precipitation decreased by 20% and the annual mean temperature decreased by 2°C, the pasture productivity would decrease by 14.59% (**Figure 11**). This shows that a "cold-dry" climate has significant negative effects on the pasture productivity in the SYRS.

If the precipitation decreased by 10% and the average annual temperature increased by 1°C, the pasture productivity would decrease by 0.45%. If the precipitation decreased by 20% and the average annual temperature increased by 2°C, the pasture productivity would increase by 3.82%. If the precipitation increased by 10% and the annual average temperature decreased

TABLE 1 | Interdecadal anomalies in the pasture productivity in the study area.

Age	Average annual *NPP*	*NPP* anomaly percentage (%)
1661–1970	7333.72	−2.1
1971–1980	7394.26	−1.3
1981–1990	7531.97	0.5
1991–2000	7402.76	−1.2
2001–2010	7555.03	0.8
2011–2016	7891.71	5.3

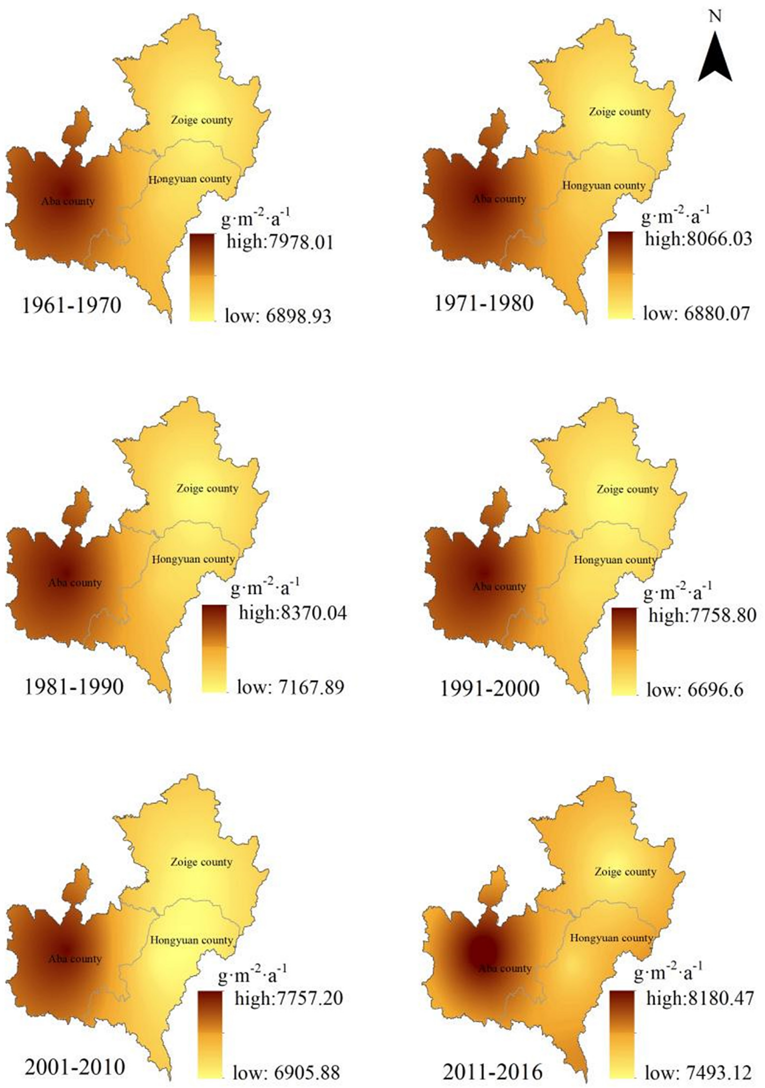

FIGURE 8 | Pasture productivity during 1961–2016.

by 1°C, the pasture productivity would decrease by 3.98%. If the precipitation increased by 20% and the annual mean temperature decreased by 1°C, the pasture productivity would decrease by 2.86% (**Figure 11**). Compared to the "warm-wet" and "cold-dry" climates, the "warm-dry" and "cold-wet" climates have less influence on pasture productivity in the SYRS.

TABLE 2 | Predicted percentage change on pasture productivity based on changes in the annual mean temperature and annual precipitation in the SYRS.

Variation in precipitation (%)	Temperature change (mp)				
	-2	-1	0	+1	+2
-20	-14.59	-9.60	–4.91	–0.45	3.82
–10	–12.57	–7.22	–2.14	2.73	7.43
0	–11.04	–5.39	0	5.20	10.26
+10	–9.85	–3.98	1.67	7.15	12.50
+20	–8.92	–2.86	3.00	8.70	14.30

DISCUSSION

The rising global temperatures and decreasing precipitation have significant impacts on terrestrial ecosystem productivity and its spatiotemporal distribution (Cao et al., 2020). From the analysis of spatial and temporal variations in climate and pasture productivity, it can be concluded that over the past 56 years, precipitation demonstrated a decreasing trend and temperature exhibited an increasing trend, with a warming of $0.32°C{\cdot}(10a)^{-1}$. The spatial distribution of average annual precipitation and average annual temperature showed a decreasing trend from southwest to northeast in the SYRS.

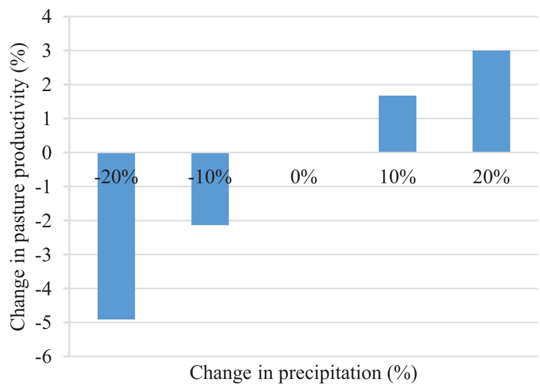

FIGURE 9 | The compared graph of precipitation changes on pasture productivity.

The temperature has a significant influence on the Tibetan Plateau at high altitudes and latitudes (Cao et al., 2020). The research results of Guo et al. (2008) show that the 1960s and 1970s experienced a "cold-wet" climate, the 1980s experienced a "warm-wet" climate, the 1990s experienced a "warm-dry" climate, and the first 6 years of the twenty-first century experienced a "warm-wet" climate in Yellow River Source. In terms of the response of pasture productivity to climate change, many researchers have found that climate change has an impact on the pasture productivity (Gao et al., 1994; Zhou et al., 1997; Yao et al., 2004). The Aba-Hongyuan-Zoige grassland is one of the three major grassland pastoral areas in China and is also one of the best natural pastures in Asia. According to the climate prediction model of pasture productivity, it can be concluded that the influence of temperature change on the pasture productivity was greater than that of precipitation in the SYRS. The "warm-wet" climate is good for herbage growth and will be favorable for improving the pasture productivity, while the "cold-dry" climate is detrimental to herbage growth and will be the most unfavorable for pasture productivity in the SYRS. Due to global climate change and human activities, pasture productivity has changed significantly and exhibited a linearly increasing trend, with an increase rate of 80.07 $g \cdot m^{-2} \cdot (10a)^{-1}$ in the SYRS over the past 56 years.

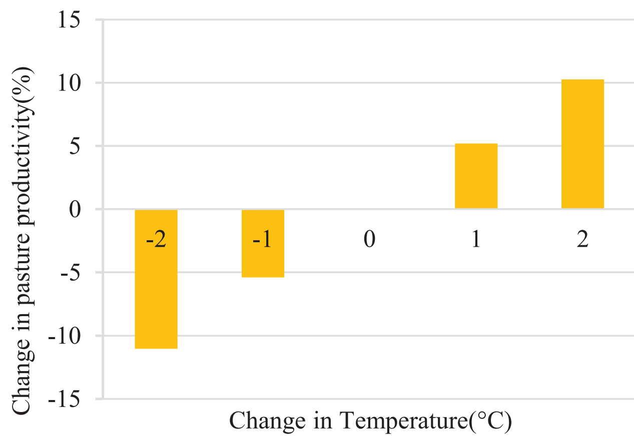

FIGURE 10 | The compared graph of temperature changes on pasture productivity.

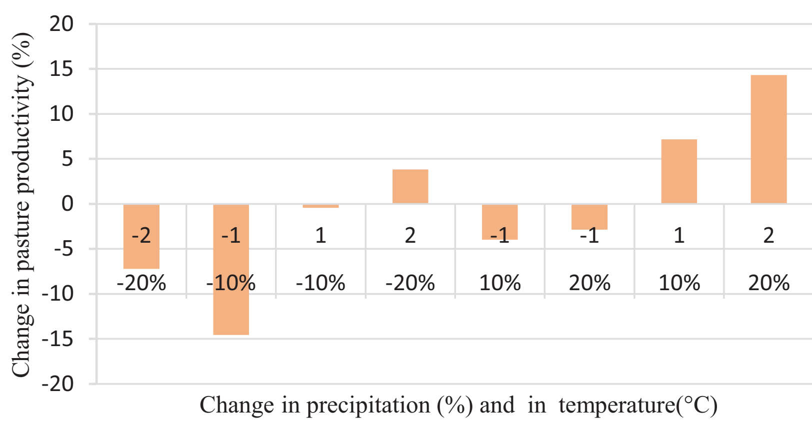

FIGURE 11 | The compared graph of precipitation and temperature changes on pasture productivity.

Owing to the significant increase in temperature, the potential pasture productivity of the entire region exhibited an increasing trend; however, this trend was restrained by the decrease in precipitation. Furthermore, in recent decades, due to the influence of natural and human factors such as global temperature increases and overgrazing, grassland degradation has continued and there is a risk of reverse succession into rat wasteland and sandy land. The grassland carry the survival and life of local residents (Yu et al., 2020a), and bearing pressure on the grasslands has been steadily increasing with the development of the social economy (Yu et al., 2021). This not only affects the livestock industry but also poses challenges for ecological security (Pan and Li, 1996; Ren et al., 2011; Zhou et al., 2014). Restoring degraded grassland ecosystems plays an important role in improving grassland ecosystem service functions (Yu et al., 2020b). Therefore, ecological restoration measures should be implemented in the region as soon as possible to control grassland degradation, with the restoration of grassland vegetation as the main goal. This will improve the grassland structure and the pasture productivity.

CONCLUSION

Based on the Thornthwaite Memorial model, the pasture productivity over the past 56 years was calculated and the key factors affecting the pasture productivity were obtained in the SYRS. A regression model between the climatic factors and pasture productivity was established to predict the effects of specific changes in precipitation and temperature on pasture productivity. The main conclusions are as follows.

(1) Over the past 56 years, the annual precipitation exhibited a weak downward trend, with a rate of decrease of 10.16 mm $(10a)^{-1}$. The average annual temperature presented an upward trend, with a rate of increase of 0.32°C $(10a)^{-1}$. The spatial distribution of average annual precipitation and temperature showed a decreasing trend from southwest to northeast in the SYRS.

(2) The pasture productivity exhibited a linearly increasing trend, with a rate of increase of 80.07 $g \cdot m^{-2} \cdot (10a)^{-1}$. The spatial distribution of the pasture productivity was significantly varied, decreasing from the southwest to the northeast. The influence of temperature change on pasture productivity was greater than that of precipitation in the SYRS.

(3) The "cold-dry" climate has negative effects, while the "warm-wet" climate has positive effects on the pasture productivity. According to the climate prediction model of pasture productivity, if the annual precipitation increases by 10% and the annual mean temperature increases by 1°C, the pasture productivity increases by 7.15%. Meanwhile, if the annual precipitation increases by 20% and the annual mean temperature increases by 2°C, the pasture productivity increases by 14.30%.

(4) The SYRS is an important part of the ecological barrier of the Qinghai-Tibet Plateau, with a fragile ecological environment. Grassland degradation continues to occur; therefore, the restoration of degraded grassland is imperative. In addition, desertification control and "three-hazard" prevention are crucial for improving the grassland structure, vegetation productivity, and animal husbandry in the SYRS.

DATA AVAILABILITY STATEMENT

The original contributions presented in this study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

LZ, SL, and YoL: methodology, data collection, data analysis, and writing of all drafts. PX, HY, TZ, and LY: methodology, data collection, review, and editing of drafts. HY, YH, and XW: conceptualization, investigation, and funding acquisition. WD and HH: methodology, review and editing of drafts, and supervision. DW, KL, and YiL: data collection, validation, review, and editing of drafts. All authors contributed to the article and approved the submitted version.

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From Passive to Active: The Paradigm Shift of Straw Collection

Qiang Wang[1,2] *and Yueling Yang*[1,3]*

[1] Business School, Shandong Management University, Jinan, China, [2] Department of Economics and Rural Development, Gembloux Agro-Bio Tech, University of Liège, Gembloux, Belgium, [3] School of Economics and Management, Chongqing Normal University, Chongqing, China

This paper takes the centralized biogas production project in the energy utilization of straw as a hypothetical item in investigation to discuss the straw collection mode based on the wishes of farmers. Through surveys of farmers in Shandong and Hebei provinces, under the current straw collection price, we found that 85% of farmers have the willingness to actively collect and transport straw, and the longest distance for active transportation is 3.22 km. The willingness of farmers to actively transport is not only affected by personal characteristics, family characteristics, and current energy consumption habits, but also the characteristics of behavioral intervention variables such as knowledge, attitude, and practice of environmental protection also significantly affect the distance of farmers' active transportation. The behavioral intervention variables of these non-economic factors can be interfered and improved through multiple conventional propaganda tools. Therefore, it is necessary to establish a collection and storage point construction model based on the willingness of farmers to realize the transformation of the straw collection model from passive to active. This method also has an important reference value for most straw energy utilization projects. It will have an important impact on the planning, design, and operation of the project.

Keywords: paradigm shift, Contingent Valuation Method, willingness to transport, straw collection, centralized biogas production

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Dingde Xu,
Sichuan Agricultural University, China

Reviewed by:
Peng Jiquan,
Jiangxi University of Finance and Economics, China
Bin Guo,
Beijing University of Posts and Telecommunications (BUPT), China
Jun Liu,
Nanjing University of Aeronautics and Astronautics, China

***Correspondence:**
Yueling Yang
dryangyueling@126.com

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INTRODUCTION

In November 2018, the United Nations Intergovernmental Panel on Climate Change (IPCC) issued a "Special Report." The report pointed out that in order to achieve the goal of global warming below 1.5°C by the end of the century, the world must achieve zero carbon emissions around 2050 (Intergovernmental Panel on Climate Change [IPCC], 2018). In order to achieve this ambitious goal, the Special Report pointed out that the only options are to promote biomass energy with negative emission and carbon collection and storage. On September 22, 2020, the Chinese government clearly stated at the 75th United Nations General Assembly that carbon emissions will strive to reach the peak before 2030, and strive to achieve carbon neutrality by 2060. Carbon emissions will be an important binding indicator for China's social and economic development in the future. Carbon reduction in vast rural areas is an important part of China's goal of achieving carbon neutrality. In recent years, with the development of China's rural economy and the improvement of farmers' lives, important changes have taken place in the energy structure of rural life (Han et al., 2018). Traditional cooking energy such as straw has been gradually replaced by coal, natural gas, and electricity (Yan et al., 2020).

Biomass energy is a zero-emission carbon energy throughout the life cycle (Tokimatsu et al., 2017). The development of biogas energy in China's rural areas has obvious economic, social and environmental benefits. Provide clean energy for rural households to replace scattered coal, reduce greenhouse gas emissions. Among them, the biogas is not only "carbon neutral," but also a rare full life cycle carbon negative emission energy (Li et al., 2017). The reason is that the main component of biogas is CH_4. CH_4 is a greenhouse gas with a warming effect much greater than CO_2. In a natural state, organic waste, especially human and animal manure, will be fermented in an oxygen-deficient environment, such as water or accumulation, to produce a large amount of biogas, which is directly discharged into the atmosphere. If engineering measures are taken to collect organic waste and produce biogas in a closed anaerobic fermentation tank, and then use energy, it can effectively block a considerable part of the natural formation and emission of biogas CH_4 (Fu et al., 2021).

The utilization of straw energy is an important way to improve the comprehensive utilization of straw and the clean energy supply in rural areas, and it is an effective way to solve environmental problems. In 2017, the comprehensive utilization rate of straw nationwide exceeded 82%, and including utilization modes of fertilizer, feed, fuel, crop matrix, industrial raw materials (Ma et al., 2019). The main clean energy utilization technologies related to rural energy for straw energy include rural large and medium-sized biogas, biomass pyrolysis gasification, biomass molding fuel and other modes. The centralized biogas production (CBP) mode is the future biogas development model in rural China (Chen et al., 2014).

The CBP mode refers to use crop straw as the primary raw material, and supply biogas to farmers through a pipe network. This model usually uses natural villages as the unit, and the system scale is hundreds of households. Compared with domestic biogas digesters, CBP can provide more stable and sufficient biogas energy and a more complete follow-up service and management method (Hengeveld et al., 2014). Under the premise that natural gas cannot cover rural areas, biogas has the comparative advantage of centralized supply. Wang et al. (2016) pointed out that the development of CBP should be further encouraged and continue to reduce support for domestic biogas digesters. Song et al. (2014) believed that CBP are suitable for developed regions where people live close together. Wang et al. (2017) took the straw biogas project in Gengguantun, Cangzhou City as an example, and calculated that the centralized biogas supply project can reduce a net emission of 3.56 t per ton (dry mass) of straw and 11.50 kg/m^3 of biogas used.

For the straw utilization project represented by CBP, the link of collection, storage and transportation has always been a bottleneck. Straw collection, storage and transportation are the key link for off-field utilization. For farmers, collecting freight is laborious and not motivated. For companies, they have straw utilization technology but suffer from no raw materials available. In addition to speeding up the research and development of straw collection, storage, and transportation technology and related equipment, it is also necessary to establish a complete market operation mechanism for straw collection, storage and transportation and research related incentive mechanisms, and explore new models of straw collection, storage and transportation systems (Gao et al., 2019). At present, farmers can choose to dispose of straw by self-processing, purchase by purchasers, purchase by cooperatives, and purchase by enterprises. Compared with the other three methods, self-processing requires farmers to spend more time and labor costs, which can be regarded as labor-consuming methods, while the other three methods are regarded as labor-saving methods.

Farmers selling straw are facing extremely strong market constraints. Active, is to fully mobilize the enthusiasm and initiative of farmers, so that farmers can participate in straw collection and transportation. Passive, means that farmers are not very enthusiastic about straw collection, and straw collection is mainly driven by third parties such as brokers. Straw storage can adopt two modes: scattered and centralized storage. The decentralized storage model encourages users to actively collect. According to the quality and variety requirements of the biogas plant for raw materials, farmers are allowed to provide raw materials to the fuel plant in stages and quantitatively. The centralized storage mode requires a larger storage space. The production plant centrally stores the raw materials collected from farmers. In order to meet the project's raw material collection volume, it is necessary to establish a collection and storage station within a certain collection and storage radius. There are three ways for farmers to sell straw: one is the door-to-door purchase by an intermediary, the other is transportation and sale by their own tractor, and the third is the sale by hired tractor.

The location of the collection and storage site is the most important link in the straw collection, storage and transportation system. The overall consideration should be given to the support methods in the various links of straw collection, storage, transportation, and use, and in accordance with the principle of nearby utilization, to reduce the cost of collection, storage and transportation, and establish a policy that includes government promotion, straw utilization enterprises and purchasing and storage organizations as the axis, broker participation, market-oriented operation system. The collection cost was found to be the most sensitive factor in the Artificial model. The storage cost was found to be the most sensitive factor in the Mechanical model (Sun et al., 2017). Huo et al. (2016) took the North China Plain (Feicheng, Shandong) as an example to establish a continuous supply model based on field collection-centralized storage-utilization, and determined the location and number of straw collection and storage stations. He also analyzed the cost and energy consumption of 5 links, including field collection, primary transportation, storage at the collection and storage station, secondary transportation, and raw material loading and unloading (Huo et al., 2016). China's rural official organizations to collect agriculture straw in a centralized way and to share benefits with farmers (Luo et al., 2018) we develop a straw collection and transportation model using transfer stations and propose a method to calculate the corresponding transportation costs based on China's specific agricultural and rural transportation conditions in this paper. Transportation cost calculations and location optimization for each transfer station are carried out in ArcMap (Cao et al., 2016). Wang et al. (2021a) suggested that should according to the transportation distance, the requirement of agricultural residue pretreatments and brokers' participation to influence the decision of the centralized transportation patterns.

If the enthusiasm of farmers can be mobilized, the efficiency of purchasing and storage enterprises will be greatly improved. This requires a full understanding of the farmers' willingness to collect and transport and influencing factors, and the construction of a purchasing and storage model based on the wishes of farmers. This requires two issues to be resolved: what is the longest distance of farmers' willingness to transport, and what influencing factors need to be intervened to mobilize farmers' participation. Regarding the survey method of willingness, the Contingent Valuation Method (CVM) is currently commonly used. At first, CVM was mainly used for the investigation and evaluation of the value of ecological products. In recent years, its application scope has been expanded to daily necessities, location selection of public facilities etc. (Choi and Koo, 2018; Zhu et al., 2019). In the study of rural residents' willingness for the CBP project, it is necessary to consider the individual characteristics, socioeconomic factors, and some non-economic factors of rural residents, so we use the CVM method for research. Significant positive behavioral intervention will greatly increase the enthusiasm of farmers. The "Knowledge, Attitude, Practice" model divides human behavior change into three continuums of knowledge, attitude, and behavior, where knowledge (knowledge and learning) is the foundation, attitude (belief and attitude) is the driving force, and practice (behavior change process) is the goal. The "Knowledge, Attitude, Practice" model has conducted a large number of status quo surveys and intervention studies, and has been found to have significant effects in behavioral intervention studies (Sharifzadeh and Abdollahzadeh, 2021).

Based on the above description, we proposes the following hypotheses:

Hypothesis 1 (H1): Families with means of transportation are more motivated.

Hypothesis 2 (H2): Behavioral intervention variables affect farmers' willingness to transport.

METHODOLOGY

Survey Regions

In order to study the straw collection paradigm based on farmers' wishes, we chose to conduct research and data collection in Shandong and Hebei provinces (**Figure 1**). First of all, the two provinces are the most important production provinces in the North China Plain, rich in straw resources, and have built a large number of CBP demonstration projects. Secondly, the population of the two provinces is close to 1/7 of China's population, which is one of the most densely populated areas in China, and the current air pollution problem is relatively serious. The construction of clean energy in this region will be the first area for China to break through in the future.

Survey Methods

We collected the questionnaires from July to November 2018 in Daiyue District and Feicheng City of Shandong Province, Linxi County, Weixian County and Linzhang County of Hebei Province. The survey includes four aspects (**Table 1**).

First, the basic information of respondent's personal characteristics, including: gender, age.

Second, the basic information of respondent's family characteristics, including: family population size, education level,

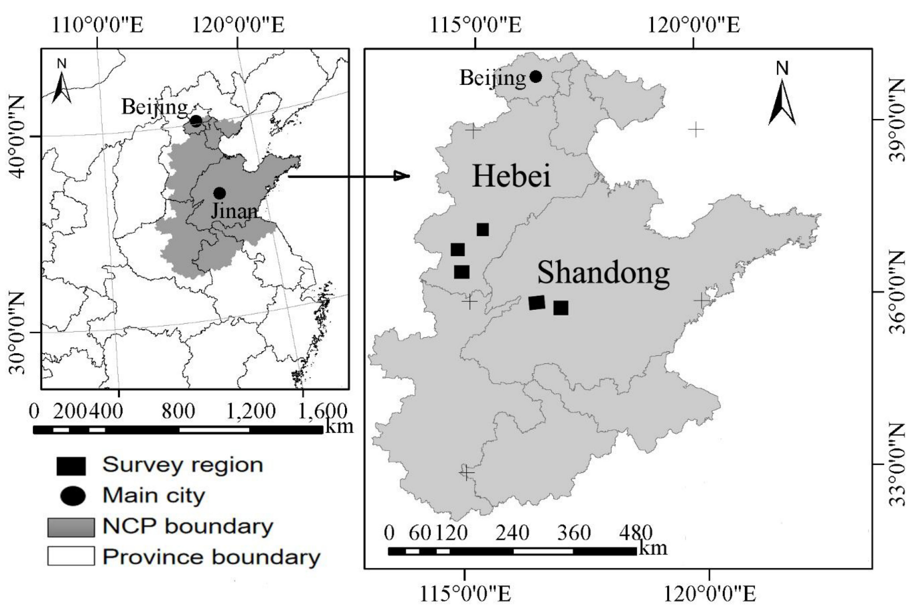

FIGURE 1 | The survey regions.

TABLE 1 | The variables and descriptive statistics.

Variable		Definition	Code	Value setting	Mean value	Std. err.
Dependent variable		WTT	WTT	Number	3.22	2.03
	Individual characteristic	Gender	Gen	Male is 1	0.59	0.49
		Age	Age	Years	50.17	11.45
		Education	Edu	Years	7.43	2.98
Independent variable	Family characteristic	Family population size	Popu	Number	5.78	2.16
		Cultivated land area	Area	Unit: Mu (Chinese land unit, 1 mu = 666.67 m^2)	12.90	41.74
		Children under the age of 10	Age 10	Number	1.26	0.99
		Older people over 65 years of age	Age 65	Number	0.73	0.79
		Is there a village cadre?	Cad	Yes is 1	0.04	0.20
		Family income 2017	Inc	Number	32205	24470
		Household expenditure 2017	Exp	Number	20478	14851
		Transport vehicle	Veh	Yes is 1	0.42	0.49
	Life energy characteristics	Is there solar water heaters?	Sol	Yes is 1	0.59	0.49
		Is there household biogas?	Bio	Yes is 1	0.11	0.31
	Behavioral intervention	Knowledge	Kno	Score	4.98	3.16
		Attitude	Att	Score	3.09	2.12
		Practice	Pra	1 = mainly clean energy 2 = clean and traditional energy half 3 = mainly traditional energy such as coal and firewood	1.95	0.74

cultivated land area, the number of children under 10 years old, whether family members serve as village cadres, the number of elderly people over 65 years old, annual family income in 2017, family expenditure in 2017, whether to have transport vehicle. In particular, transport vehicles, in the survey, we define transport vehicles as: fuel or electric transport vehicles with more than three wheels for agricultural production and life.

Third, household life energy characteristics variable, including: whether to have solar water heater at home, whether to have household biogas at home.

Fourth, the behavioral intervention variable by the survey of environmental protection "Knowledge, Attitude and Practice (KAP)," which is a behavioral intervention theory. "Knowledge" as "understanding of any given topic," "Attitude" as "feelings toward it, along with predetermined opinions" and "Practice" as "ways in which they demonstrate their knowledge and attitude through their actions (Kaliyaperumal, 2004)." Nowadays, the "KAP" have often been used in the consumer and environmental sectors (Ahamad and Ariffin, 2018; Almasi et al., 2019). There are no clear rules on how best to conduct a KAP survey, as the methods vary according to the subject and purpose of the study (Vandamme, 2009).

Fifth, the farmers' willingness to transport (WTT). In order to ensure that the interviewed farmers can accurately understand the question under investigation, we ask the investigator to first spend 1 to 5 min introducing the CBP project and model, the advantages and disadvantages of the project and product to the interviewee. The questionnaire used a double-border dichotomy (Bateman et al., 2001). Each questionnaire takes about 30 min. We mainly lead the team through the staff of the local agricultural authority, and let them provide the respondents according to our requirements.

In the specific investigation work, our first question is "If a CBP project is built to provide residents with concentrated biogas, will it be supported?" The respondents chose the answer "Yes" or "No." If respondents answered "Yes," proceed to the WTT survey section. Before the WTT survey, the respondents were first informed that the current purchase price of straw is 200 yuan/ton. If the respondents themselves or their family members are willing to take the initiative to transport the straw to the straw collection station, he can accept the distance from collecting straw to transporting it to the collection station. What is the maximum distance? The answer option directly answers the kilometers.

Variable Definition

The WTT is chosen as the dependent variables, separately. In the process of investigation, the investigators will make a special explanation that the acquisition price of straw is the current market price.

In the independent variable part, most of the questions come directly from the inquiries of the respondents, and some independent variables are obtained by means of proxy variables.

Income variables and expenditure variables are in the form of proxy variables. Because income is a relatively private issue in China's traditional concept, and most farmers also lack accurate statistics on income and expenditure. Therefore, these two variables are mainly estimates of the main sources of income such as the occupation, planting and breeding of the respondents. Expenditure variables also refer to the number of households to support, household spending on bulk consumer goods, etc.

Regarding the acquisition of the "KAP" variable, a more complex approach is taken. First, for the "knowledge" variable, we set 10 questions about environmental protection, and scored from 0 to 10 according to the number of questions answered by the respondents. Second, for the "attitude" variable, this variable was obtained by the following method: We asked respondents about the importance of environmental protection relative to income and health, and asked respondents to make a comparison and differentiate between income, health and environmental protection, a total of 10 points. For example, if environmental protection is given 3 points, the respondents' attitude score is 3 points. Third, we obtain the "Practice" variable using household energy preference as a proxy variable. Therefore, we use a preference value to represent this practice: if they prefer clean energy, such as liquefied gas/electricity, we define it as 1; if they prefer traditional energy such as coal and firewood, we define it as 3; clean energy and traditional energy, we define it as 2. The lower the preference value, the cleaner the current energy practice.

Descriptive Analysis

We collected 389 questionnaires. Among them, 38 questionnaires have missing data or self-contradictory filling. After detailed statistics, we finally obtained a total of 351 valid questionnaires. The sample efficiency rate is 90.23%.

The surveyed area has a temperate continental climate with four distinct seasons and long sunshine hours. Therefore, in terms of household energy utilization, the installation rate of household solar water heaters is not low, reaching 58.97%. However, due to the temperate zone, household biogas has poor efficiency and high maintenance costs. Only 10.54% of households have household biogas, and most biogas digesters are basically abandoned.

In addition to the hot water provided by solar water heaters, 11.95% of the sources of hot water are electric water heaters, 51.00% are coal-based, 11.68% are fuelwood, and 7.41% are liquefied gas. There is still huge space for improvement.

With the popularization of new media methods, the channels for farmers to obtain information and knowledge are becoming more and more diversified. "TV\Newspaper\Books" channel accounted for 48.22%; "Village Committee" channel accounted for 20.56%; "Mobile and Internet" channel accounted for 13.96%. There are also a small number of channels, such as "relatives and friends," "agricultural technical service personnel," "agricultural material dealers" and so on.

Model

In CVM studies, Tobit econometric model (censored regression model) was used to analyze the determinants of WTT and the maximum amount of distance that individuals are willing to transport. Zero-response data are inevitable in WTT surveys. Tobit model is often assumed as the true distribution of willingness bidding censored at zero and is better suited in case of data with many zeros than ordinary least squares regression analysis which may be biased and inconsistent parameter estimates the regression. Tobit model reveals both the probability of WTT and the maximum WTT of the respondents. Following the Tobit model (McDonald and Moffittt, 1980), a standard one-equation censored model can be defined as:

$$WTT_i^* = X_i\beta + \varepsilon_i,\ \varepsilon_i \sim N(0, \sigma^2),$$
$$WTT_i = \begin{cases} WTT_i^*,\ if\ WTT_i^* > 0 \\ 0,\ if\ WTT_i^* \leq 0 \end{cases} \tag{1}$$

Where for the ith individual, WTT_i is the latent (unobservable) WTT for construction of straw collection site; WTT_i is the observed actually maximum WTT for construction of straw collection site and is censored at 0; X_i is the vector of independent variables that are hypothesized to influence WTT theoretically; b is the unknown parameter vector to be estimated; and εi is the error term which is assumed to be normally distributed with the mean zero and constant variance sigma square (σ^2). The standard Tobit model provides the expected value of WTT_i (Tobin, 1958):

$$\begin{aligned} E(WTT_i) &= \Pr(WTT^* \leq 0) \cdot E(WTT_i | WTT_i = 0) \\ &\quad + \Pr(WTT^* > 0) \cdot E(WTT_i | WTT_i > 0) \\ &= Xi\beta F(Xi\beta/\sigma) + \sigma f(Xi\beta/\sigma) \end{aligned} \tag{2}$$

Where F represents the cumulative distribution function of a standard normal random variable, f represents the normal density function and s represents the standard deviation. In addition, the expected value of WTT for observations with positive WTT bids (Amemiya, 1973) is:

Tobit model can be used to determine both changes in the probability of being above zero (i.e., the discrete decision of whether to pay) and changes in the values of WTT for the whole sample and the observations which are above zero (McDonald and Moffittt, 1980). Afterward, the marginal effect of an independent variable on the expected value of WTT among the entire sample in the model is given by:

$$E\ (WTT_i | WTT_i > 0) = Xi\beta + \sigma\lambda\ |\ (Xi\beta/\sigma) \tag{3}$$

The change in the expected WTT value of those observations with positive WTT bids is:

$$\partial E\ (WTT_i)/\partial Xi = \beta F\ (Xi\beta/\sigma) \tag{4}$$

$$\partial E\ (WTT_i/WTT_i > 0)/\partial Xi = \beta\ [1 - \lambda(Xi\beta/\sigma)\ (Xi\beta/\sigma - \lambda(Xi\beta/\sigma))] \tag{5}$$

Where $\lambda(X_i\beta/\sigma)$ is the inverse Mills ratio, $[f(X_i\beta/\sigma)/F(X_i\beta/\sigma)]$. The change in the probability of eliciting positive bids is:

$$\partial \Pr(WTT_i > 0)/\partial Xi = \partial F(Xi\beta/\sigma)/\partial Xi = f\ (Xi\beta/\sigma)\beta/\sigma \tag{6}$$

RESULTS

Measurement Results

Before conducting the econometric analysis, we first performed a multicollinearity test for each independent variable. The mean variance inflation factor (VIF) is equal to 1.75. Among them, the VIFs of both income and expenditure variables are above 3. Income represents a household's source of income. Consumption level reflects consumption level. Therefore, to avoid multicollinearity, we keep only the expenditure variable.

Relying on the Tobit model and using Stata 15.0 measurement software, the regression analysis of WTT was carried out. The χ value is 148.12, and the *p*-value is 0.0000. The log likelihood is −671.18. The overall effect is good. The measurement results are detailed in **Table 2**.

Calculation of Willingness to Transport

The distance that participants can accept from collecting straw to transporting it to the straw collection station is 3.22 km.

Result Analysis

The measurement results basically verify our previous hypothesis.

The impacts of individual characteristics: According to this survey, considering individual characteristics, the variables of age have significant influence and negative correlation on WTT. This indicates young people have a higher WTT.

The impacts of family characteristics: In terms of family characteristics, "Children under 10 years old" has a significant influence and positive correlation on WTT, which indicates that the child is important to a family's life improvement decision. The more children under the age of 10 in the family, the higher WTT. The "Over 65 years old" is not significant, explaining that families with elderly people are not strong in their desire to improve their lives. The influence of whether has "village cadres in the family" is not significant. However, the family "population" have significant impacts, but the coefficient of "population" is negative.

It is clear that families with transportation vehicles have a higher WTT. This is consistent with the hypothesis.

The impacts of life energy characteristics: The results show that households with solar water heaters have a higher WTT. However, whether the family has biogas or not is not related to the WTT.

The impacts of behavioral intervention theory variable: The three non-economic variables of environmental knowledge, attitude and practice are equally significant in WTT, and the coefficients are in the same direction. The coefficient of knowledge and attitude is positive, indicating that the higher the cognitive score for environmental protection, the more positive the WTT. Cognitive theory shows that all the processes or activities of people to obtain and use information are the first to perceive information, then identifying the content of the information, generating willingness and finally changing the behavior. According to cognitive theory, the influence of knowledge, attitudes and household energy preferences on the purchasing willingness of rural residents should be comprehensive. It can be interpreted from the regression results in **Table 2** that the degree of awareness of environmental protection has a significant positive impact on the WTT, that is, the higher the awareness of environmental knowledge, the higher WTT. Similarly, respondents' emphasis on environmental protection has also increased the WTT. Results can be obtained that it is an effective measure to change household energy preferences and increase residents' WTT by raising public awareness of environmental awareness through publicity activities such as education and attaching importance to cultivate individual attention to environmental protection.

TABLE 2 | Tobit model measurement results.

Classification	Variables	WTT	
		Coeff.	Std. error
Individual characteristic	Gen	0.27	0.19
	Age	−0.02***	0.01
	Edu	0.01	0.03
Family characteristic	Popu	−0.14***	0.05
	Area	0.00*	0.00
	Age 10	0.33***	0.11
	Age 65	0.01	0.12
	Cad	0.22	0.25
	Exp	0.00	0.00
	Veh	0.89***	0.19
Life energy characteristics	Sol	0.63***	0.19
	Bio	−0.07	0.31
Behavioral intervention	Kno	0.08***	0.03
	Att	0.14***	0.05
	Pra	−0.48***	0.13
	_cons	3.70***	0.67

Number of obs. = 351; non-selected = 0; LR chi^2 (14) = 148.12; Prob > chi^2 = 0.0000.
Coeff. is estimated coefficient.
, *, coefficient is significant at 10, 5, and 1% probability levels, respectively.*

DISCUSSION

It is necessary to establish a collection and storage point construction model based on the willingness of farmers to realize the transformation of the straw collection model from passive to active. In the context of the policy of banning straw burning, farmers as rational economic agents (Nie et al., 2021), due to labor cost and time constraints and other restrictive factors, the best choice for farmers in various decentralized utilization behaviors is to directly return straw to the field (Yang et al., 2018). Moreover, most farmers return all the straw to the field directly after harvest, thus avoiding the cost of straw collection. As the executors of these behaviors, farmers need to bear the cost of straw collection (Wang et al., 2021a), and the private benefits they get are less than the social benefits. Under the current cost-benefit accounting of the comprehensive utilization of straw, the private benefits obtained by farmers are even negative, that is, the collection costs are too high and the benefits are too small (Yang et al., 2020).

Therefore, rational farmers will choose not to collect straw (Wang et al., 2021b). The transportation willingness of farmers studied in this article is a rational choice made by farmers on the premise of fully respecting the choices of farmers. It is also the critical point from passive to active.

Intervention in the behavior of farmers can increase initiative awareness and increase willingness. In the process of the utilization of crop straw resources, due to the differences in the goals, understanding and interest orientation of the government, enterprises and farmers in the use of straw resources, there is a game relationship among various stakeholders (Wen and Zhou, 2018). The fundamental driving factor affecting straw collection is the economic benefits of straw collection. In the survey, it was found that the reason why farmers are willing to recycle straw is that they believe that recycling straw can reduce environmental pollution caused by incineration, reduce the use of chemical fertilizers, and increase income. Environmental protection education intervention can significantly improve farmers' cognitive level, improve attitudes and change behaviors. Tools such as TV\newspapers\books have more obvious effects on farmers' intervention. Although the impact of different interventions on farmers is different, the more intervention methods for farmers, the better the effect. These intervention methods are simple, easy to implement, low cost, and effective, and can be widely promoted in rural grassroots.

However, there are still 24.58% of farmers who are unwilling to recycle straw. The reason for their unwillingness is mostly that the amount of straw is too small and they are too old to be able to recycle straw. This has a lot to do with the current aging phenomenon in rural China (Zhan et al., 2021). Most of the young and middle-aged people in rural areas go out to work (Zou et al., 2018). Only the left-behind elderly are left at home, and the elderly do not have enough time and energy to collect straw, so they are unwilling to recycle straw.

This paradigm shift has important reference value for areas with high agricultural vehicle ownership. The transportation fee increases with the increase of the collection radius, which is the most variable factor in the variable cost. The cost of straw supply includes raw materials, labor, fuel collection power, transportation fuel power, equipment depreciation and maintenance, management and other costs (Wu et al., 2021). Analyzed by cost category, labor cost ranks first, followed by raw material cost, and then the cost of collecting and transporting fuel and power (Sun et al., 2017). Labor cost and fuel power increase with the increase of transportation distance. Therefore, in areas where the number of agricultural vehicles is high, the willingness of farmers is relatively high, but the increase in other costs is also an interference factor that needs to be considered in an overall plan.

It has reference value for projects that require straw collection. At present, China's straw as an energy source is mainly used in direct-fired power plants, straw briquette fuel plants, and straw gasification stations. The cost of raw material supply is a common problem for all kinds of straw energy utilization projects. This kind of straw collection, storage and transportation model based on the wishes of farmers, such projects have common reference value. Especially for large straw consuming households such as biomass power plants, the selection and setting of sites at all levels (Cheng et al., 2020), and the distribution of interests of various stakeholders in the process of straw collection, there is great significance for the sustainability of the project by mobilizing the enthusiasm and initiative of farmers.

The development of low-carbon agriculture depends on the awakening of ecological awareness of agricultural producers based on economic incentives. Agriculture has a huge potential for carbon emission reduction and carbon sequestration (Wang et al., 2021c). Due to objective factors such as large straw production, wide coverage, and scattered resources, coupled with the high cost of returning straw to the field, limited local financial investment, and incomplete policy systems, the comprehensive utilization of straw needs to overcome many difficulties. Therefore, it is necessary to adopt a paradigm shift based on the transportation willingness of farmers to explore and strengthen the introduction of market forces and release farmers' willingness to participate in the form of economic incentives (Li et al., 2021). From another point of view, this is also paying for the increase of carbon sinks in the agricultural system by means of ecological compensation (Xiong and Li, 2019).

What is interesting, households equipped with household biogas should be high proportion of clean energy households according to the assumptions, but WTT are not significant. This is because the construction of household biogas is mainly driven by subsidies from the Chinese government (Sun et al., 2014). Ignore the willingness of farmers to participate actively.

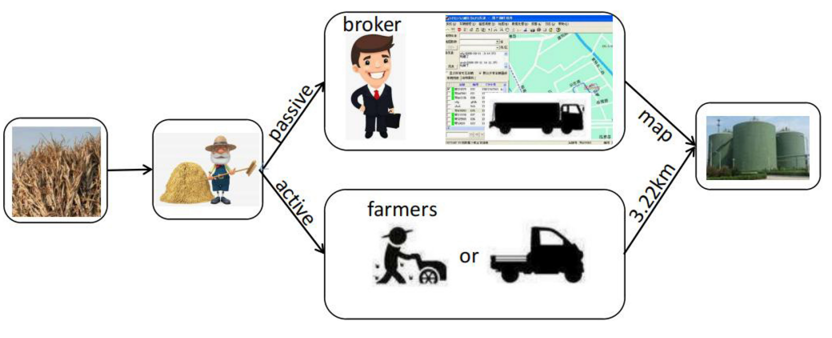

FIGURE 2 | Shift of straw collection mode from passive to active.

As a result, household biogas almost failed in China. This also contradicts the importance of farmers' willingness to the success or failure of the project.

CONCLUSION AND POLICY IMPLICATIONS

This paper takes the centralized biogas production project in the energy utilization of straw as an example to discuss the straw collection mode based on the wishes of farmers. Through surveys of farmers in Shandong and Hebei provinces, under the current straw collection price, we found that 85% of farmers have the willingness to actively collect and transport straw, and the longest distance for active transportation is 3.22 km. The willingness of farmers to actively transport is not only affected by personal characteristics, family characteristics, and current energy consumption habits, but also the characteristics of behavioral intervention variables such as knowledge, attitude, and practice of environmental protection also significantly affect the distance of farmers' active transportation. The behavioral intervention variables of these non-economic factors can be interfered and improved through multiple conventional propaganda tools. Therefore, it is necessary to establish a collection and storage point construction model based on the willingness of farmers to realize the transformation of the straw collection model from passive to active (**Figure 2**).

This research has important policy implications for the construction of most straw energy utilization projects. First, the establishment of a collection and storage point construction model based on the willingness of farmers and the transformation of the straw collection model from passive to active will have an important impact on the planning, design and operation of the project. Secondly, although there are still some farmers who are unwilling to participate, intervening in farmers' behavior can increase their awareness and willingness to take the initiative to transport. Third, the paradigm shift of this collection mode has important reference value for areas with high agricultural vehicles. Fourth, the development of low-carbon agriculture depends on the awakening of farmers' ecological awareness based on economic incentives. Fifth, it also has reference value for other similar projects that require straw collection.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

QW: conceptualization, methodology, validation, formal analysis, investigation, writing—original draft preparation, and visualization. YY: resources, data curation, writing—review and editing, supervision, project administration, and funding acquisition. Both authors were involved in preparing the manuscript.

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Analysis of Agricultural Production Potential and Enhancement Strategy in the Qaidam Basin Based on the Agro-Ecological Zone Method

Hui Yu[1†], Min Huang[1,2], Tao Zhao[3], Jianping Wang[4*], Zihan Li[5†], Dianpeng Chen[5], Pengshan Li[6*], Yong Luo[5*], Haoyu Wang[5], Zhao Jing[5], Dongyang Mou[5], Dan Zhang[1,2] and Xiao Wang[7]*

[1]Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu, China, [2]University of Chinese Academy of Sciences, Beijing, China, [3]Sichuan Land Consolidation and Rehabilitation Center, Chengdu, China, [4]Qinghai Institute of Salt Lakes, Chinese Academy of Sciences, Xining, China, [5]College of Earth Sciences, Chengdu University of Technology, Chengdu, China, [6]Chengdu Land Consolidation and Ecological Rehabilitation Center, Chengdu, China, [7]China Southwest Geotechnical Investigation and Design Institute Co.,Ltd, Shanghai, China

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Edited by:
Dingde Xu,
Sichuan Agricultural University, China

Reviewed by:
Chengchao Wang,
Fujian Normal University, China
Wei Shui,
Fuzhou University, China

***Correspondence:**
Tao Zhao
462782265@qq.com
Jianping Wang
jianpingwang@isl.ac.cn
Pengshan Li
targetlps@163.com
Yong Luo
luoyong2014@cdut.edu.cn

[†]These authors have contributed equally to this work and share first authorship

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The Qaidam Basin has an arid plateau continental climate, with climatic factors strongly influencing agricultural production potential. In the present study, the agro-ecological zone method was applied to study the effects of rainfall, temperature and soil on crop yield, with climatic factors as the main common influencer. By assessing the land production potential, suitable zones for grain production were identified in the Qaidam Basin, and the reasonable current input level was determined, thus, evaluating the population carrying capacity. Strategies for improving crop productivity in these regions were proposed to provide a basis for decision-making by the local government. The results showed that: 1) The photosynthetic and light-temperature production potential was high in Mangya city and the autonomous region; however, the climate production potential was low in Golmud city and the eastern part of Mangya city. After correction based on soil availability, the land production potentials of spring wheat and highland barley were greatly attenuated, and only 15.85 and 16.74% of the photosynthetic production potential, respectively. 2) The current population carrying capacity of the land resources is 595,900 people, which is in a state of human–food balance when the correction coefficient of artificial input is approximately 1.1. If the artificial input can be strengthened to achieve a correction coefficient of 1.2, the population carrying capacity could reach 676,100 people. 3) The suitable area for agricultural production was mainly located in the northeast and west of the Qaidam Basin. These areas can be used as a backup arable land resource. The temperature increase leading to evaporation increase negatively affected the yield per unit area of grain crops in Qaidam Basin. Strengthening water-saving irrigation technology and improving the utilisation rate of chemical fertilisers are good enhancement strategies for the green-oriented agricultural technology system, which would help improve the agricultural productivity potential in the Qaidam Basin.

Keywords: agro-ecological zone method, qaidam basin, land production potential, agricultural production potential, population carrying capacity, enhancement strategy

INTRODUCTION

China is a populous country with a per capita land area lower than the world average. It is currently facing severe problems such as high population growth, a sharp decline in arable land area and scarcity of fresh water resources (Yang and Wang, 2015). Food security is an important foundation for economic development, social stability and national security. Over the past 40 years, climate change has had very different impacts on the northern and southern wheat-producing regions of China. Low-temperature frost damage inhibits the increase in wheat yield during winter in the northern wheat region, and climate warming causes a decline in the potential wheat yield in southern China (Zhang et al., 2015). Due to global warming, the potential yield of rice in most regions of China has demonstrated a decreasing trend, and the rice-growing area has shifted northward (Yin, 2017). In previous literature, appropriate adaptation strategies and measures have been found to mitigate the negative impacts of climate change and significantly increase crop yields (Reid et al., 2007). For example, Easterling et al. (2003) proposed and tested a new approach to simulate the agronomic adaptation of farmers to climate change based on a technological innovation/substitution model improving crop yields. The challenges posed by climate change to food security require unprecedented efforts and the ability to simulate and predict the interactions between crop growth dynamics and environmental and crop management (Brown and Funk, 2008). The crop production potential of an area is the highest theoretical yield that a crop can achieve under ideal conditions (Wang X. et al., 2015). Evaluating crop production potential started with the study of photosynthetic production potential, and in the early 1920s, researchers began to use quantum efficiency theory to study photosynthetic processes, arguing that the magnitude of crop production potential ultimately depends on light and light energy utilisation (Wang X. et al., 2012). After the 1960s, the photosynthetic production potential was revised by considering factors such as temperature, precipitation and soil parameters. These models can be divided into two main categories: process-based crop growth dynamics and agro-ecological productivity models (Tian et al., 2012). Process-based crop models, such as the decision-support system for agro-technology transfer model, simulate processes that occur during the crop growth cycle after parameter calibration using multi-year site-level observations (Zhan et al., 2014). Such models simulate dynamic biophysiological processes occurring during the crop growth cycle in a day-by-day stepwise manner and have been applied to assess crop yield responses to climate change, crop varieties and management (Huang et al., 2009; Xiong et al., 2009). However, the accuracy of such models is influenced by different parameters. Even if the model simulation parameters have been determined, the model performance can be severely affected by altered sowing dates and seasonal changes (Wang J. et al., 2012). Furthermore, parameters often vary over large areas within the same region, and it is almost impossible for researchers to fully understand the variation among parameters; therefore, the model often produces problematic results when used for crop simulations over large areas (Butt et al., 2005; Zhan et al., 2014). In contrast, agro-ecological productivity models such as the agro-ecological zone (AEZ) model use simple and reliable crop models involving standardised calculations to derive crop production potential by determining the limitations imposed by climatic factors on crops (Fischer et al., 2012).

Currently, the AEZ method is the most widely used model for assessing agricultural production potential worldwide (Sun et al., 2020). The AEZ model was developed jointly by the Food and Agriculture Organization of the United Nations and the International Institute for Applied Systems Analysis to calculate suitable growing areas and potential crop yields (Zhao et al., 2015). This standardised crop model and environmental matching procedure uses economic zones and is well suited for crop productivity assessment at regional, national and global scales (Masutomi et al., 2009). The AEZ method operates on the principle of logical partitioning based on the distribution of soil, topography and climate, where the natural production potential of land within the zone is similar (Tong et al., 2018). The AEZ model considers factors affecting crop yields such as light, temperature, water and soil, and the reproductive period length and water requirements of each reproductive stage for different crops, and adjusts the parameters based on the characteristics of the crops so that the estimation results are closer to reality (Wang X. et al., 2012). The basic data from the AEZ model are easy to obtain and convenient to calculate. Therefore, its robustness, ease of use and accurate reflection of regional crop production potential status have led to its high popularity. The AEZ model is widely used to evaluate the grain production potential (Xie et al., 2004) and dynamic assessment of grain production capacity (Zhan et al., 2013), and has been applied in approximately 35% of agricultural production potential assessments in China (Wang X. et al., 2015). In the present study, the parameter selection process depended on previous experience (Jiang, 2008) and focused on analysing the influence of the parameters to guide parameter tuning, resulting in improved accuracy.

The Qaidam Basin is located in the northeastern part of the Qinghai-Tibet Plateau, and is one of the three major inland basins in China. The basin has a plateau continental climate, and the total annual solar radiation is 686.64–741.06 kJ/cm^2, second only to central and southwestern Tibet, and much higher than areas in eastern China at the same latitude. As such, this area is one of the most radiation-rich regions in China. The annual sunshine hours exceed 3000 h, the highest in the country, providing sufficient light for the photosynthesis of crops (Wang et al., 2017). The main crops are spring wheat, rape, barley, potatoes, beans and wolfberries (Wang et al., 2019). The area produces the highest wheat yield in the country (Zhang et al., 2008). The superior climatic conditions provide favourable and reliable conditions for the development of agriculture, which is particularly important in this critical agricultural and livestock production base in Qinghai Province that assures food security in northwest China (Wang et al., 2019; Wang et al., 2020). The Qaidam Basin is located in a climate change-sensitive area of the Tibetan Plateau (Li et al., 2015). It has an arid plateau continental climate, with annual precipitation decreasing from 200 mm in the southeast to 15 mm in the northwest, and an average annual relative humidity of

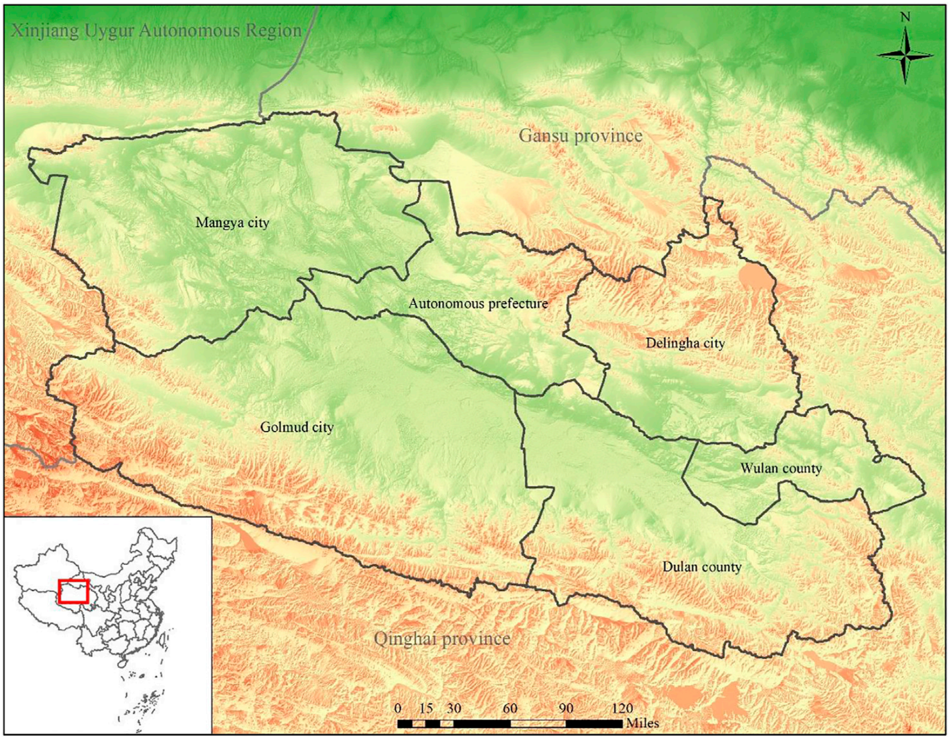

FIGURE 1 | Schematic diagram of the study area.

30–40%. Therefore, it is essential to research the impact of climate change on crop yields in the Qaidam Basin and systematically analyse the main climatic factors (temperature and precipitation) and changing characteristics of crop yields. In the manuscript, by assessing the land production potential, the reasonable current input level was determined, thus, evaluating the population carrying capacity, and proposed the enhancement strategies, which are innovation. Enhancement strategies are critical for optimising the rational use of local climatic resources and improving crop production potential in the Qaidam Basin.

STUDY AREA

The Qaidam Basin is located in the northern part of Qinghai Province, mainly in the Haixi Mongolian and Tibetan Autonomous Prefecture (**Figure 1**). It is a closed plateau-type basin surrounded by the Kunlun Mountains, Arjinshan, Qilian Mountains and other mountain ranges, between 90°16′ E—99°16′ E and 35°00′ N—39°20′ N. The basin is approximately 800 km wide from east to west and 300 km long from north to south, with an area of approximately 240,000 km^2, making it one of the three largest major inland basins in China. The southern edge of the basin is located in the northeastern part of the Qinghai-Tibet Plateau at an elevation of 2767–3191 m. It has oasis agricultural areas, including Golmud, Xiangrid and Chakhan Usu. Suitable agricultural land is mainly distributed in the eastern and southern parts of the basin along the fine soil belt under the flood alluvial fan. The region has significant temperature accumulation and good thermal conditions, and the existing arable land is concentrated in the eastern and southeastern oasis areas, mainly producing grain and oilseeds.

DATA SOURCES AND RESEARCH METHODS

Data Sources and Processing

1) Land use data for 2020 were obtained from the 30 m raster data released by the Ministry of Natural Resources (http://www.globallandcover.com/home.html?type=data). 2) Socioeconomic data such as crop yield and planted area were procured from the Statistical Yearbook of Haixi Prefecture. 3) Soil type and physical and chemical property data were acquired from the World Soil Database. 4) Meteorological data such as rainfall, temperature and sunshine hours were collected from the National Meteorological Science Data Center (http://data.cma.cn/). 5) Atmospheric radiation data were obtained from the National Tibetan Plateau Scientific Data Center (https://data.tpdc.ac.cn). 6) Annual rainfall, average annual temperature and average yield per unit area of spring wheat and highland barley were acquired from the Haixi State Statistical Yearbook. 7)The DEM data were obtained from geospatial data cloud platform (http://www.gscloud.cn/).

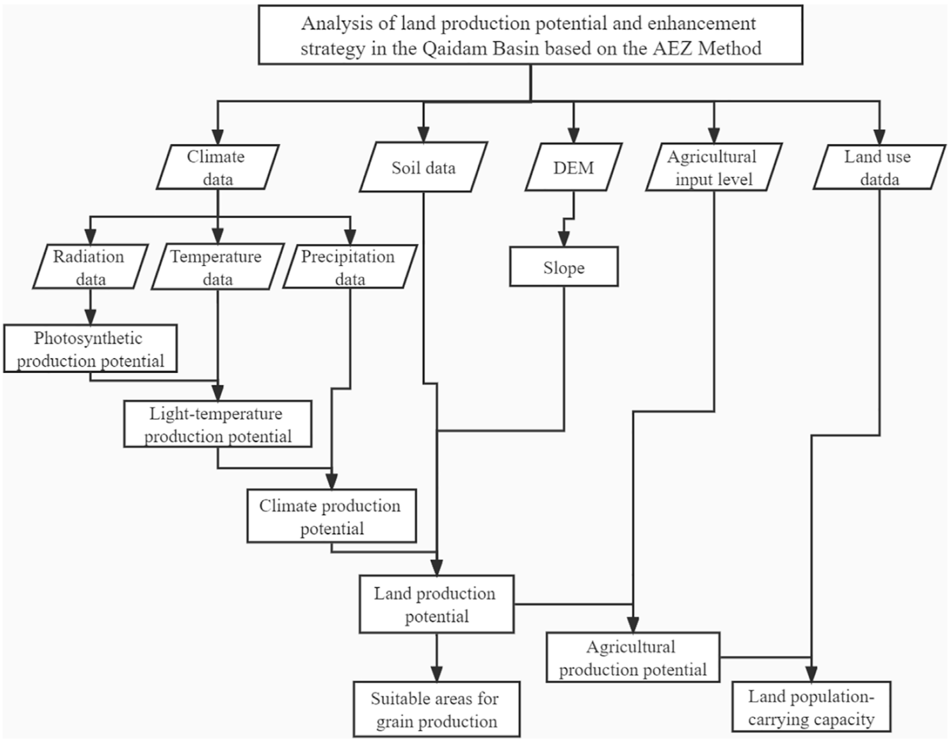

FIGURE 2 | Technical process.

Research Methods

The two main crops, spring wheat and highland barley, were utilised as the research objects. Light, temperature, precipitation and soil texture were the influencing factors. The AEZ model was applied to calculate the photosynthetic production potential. The temperature influence coefficient was used to calculate the light and temperature production potential, which was then revised to obtain the climate production potential by accounting for the influence of precipitation. The land production potential was then obtained by taking soil availability into account. By assessing the range of suitable regions for growing crops, strategies for improving crop productivity in these regions were proposed to provide a basis for decision-making by the local government. The agricultural production potential was determined using the land production potential under various input level coefficients in the Haixi Prefecture. Simultaneously, the land production potential was used to identify suitable areas for agricultural production with spatial analysis technology (**Figure 2**).

The AEZ method was proposed by Kassam et al. with the support of the Food and Agriculture Organization of the United Nations to calculate the crop production potential (Sun et al., 2020). Based on the biomass and total dry matter of standard crops, this method used the following data: climate, land use, soil type and agricultural input level to modify the photosynthesis production potential, light-temperature production potential and climate production potential in a stepwise manner to obtain the agricultural production potential. The calculation formula used was as follows:

$$\begin{aligned} A_P &= Y_Q \times h(T) \times h(W) \times h(S) \times h(M) \\ &= Y_T \times h(W) \times h(S) \times h(M) \\ &= Y_W \times h(S) \times h(M) \\ &= Y_S \times h(M) \end{aligned} \tag{1}$$

where, A_P indicates the agricultural production potential, Y_Q indicates the photosynthetic production potential, Y_T indicates the light-temperature production potential, Y_W indicates the climate production potential, Y_S indicates the land production potential, *h(T)* indicates the air temperature correction coefficient, *h(W)* indicates the moisture correction coefficient, *h(S)* indicates the soil correction coefficient and *h(M)* indicates the input-level correction coefficient.

Photosynthetic Production Potential

The photosynthetic production potential refers to the total dry matter yield of a standard crop as determined by photosynthetically active radiation when all other conditions are ideal. The calculation formula used was as follows:

$$\begin{aligned} Y_Q = Q \times f(Q) = C\Omega\varepsilon\varphi(1-\alpha)(1-\beta)(1-\rho)(1-\gamma)(1-\omega) \\ f(L)\sum Q_i S(1-\eta)^{-1}(1-\delta)^{-1}q^{-1} \end{aligned} \tag{2}$$

where, Y_Q indicates the photosynthetic production potential, *C* indicates the unit conversion coefficient and $\sum$Qi indicates the sum of the total solar radiation during the growth period of the

TABLE 1 | Photosynthetic production potential parameters of crops.

Parameter	Physical Significance	Spring Wheat	Highland Barley
Ω	Ratio of photosynthetic fixation (CO_2) capacity	1.000	1.000
ε	Photosynthetically active radiation ratio	0.490	0.490
φ	Light quantum conversion efficiency	0.220	0.224
α	Plant population reflectance	0.060	0.080
β	Plant population transmittance	0.100	0.100
ρ	Radiation interception rate of crop non-photosynthetic organs	0.100	0.100
γ	Ratio of light beyond the light saturation point	0.030	0.050
ω	Proportion of respiration consumption in photosynthate	0.330	0.330
$f(L)$	Set dynamic change of crop leaf area	0.560	0.440
S	Crop economic coefficient	0.450	0.401
η	Moisture content of mature crops	0.140	0.150
δ	Ash content of crop	0.080	0.080
q	Heat content per unit of dry matter ($MJ.kg^{-1}$)	17.800	17.810

TABLE 2 | Optimum temperature and temperature limits of main crops during the growth period.

Crop Types	T_0	T_1	T_2
Spring wheat	22	3	30
Highland barley	3	– 5	13

crop ($MJ{\cdot}m^{-2}$). The values of other parameters (**Table 1**) were used as previously published (Yang, 2020).

Light-Temperature Production Potential

The light-temperature production potential refers to the productivity potential determined by light and temperature conditions under ideal water and soil conditions, agricultural input level and other conditions. This potential is modified by crop growth and development temperatures and the average temperature in the study area based on the photosynthetic production potential. The specific calculation formula used was as follows:

$$Y_T = Y_Q \times f(T) \tag{3}$$

$$f(T) = \frac{[(T - T_1)(T_2 - T)]^B}{[(T_0 - T_1)(T_2 - T_0)]^B} \tag{4}$$

$$B = \frac{(T_2 - T_0)}{(T_0 - T_1)} \tag{5}$$

where, Y_T indicates the light-temperature production potential; Y_Q indicates the photosynthetic production potential; *f (T)* indicates the temperature correction coefficient*;* T indicates the average temperature during the growth period of the crops and T_0, T_1 and the T_2 indicate the optimum temperature, the lower temperature limit and the upper temperature limit, respectively, in the growth period of the crops. The specific values (**Table 2**) were obtained from the research of Wang X. Y. et al. (2015), Wang et al. (2020).

Climate Production Potential

The climate production potential was revised using the moisture correction factor based on the light-temperature production potential. The specific calculation formula used was as follows:

$$Y_W = Y_T \times f(w) \tag{6}$$

$$f(w) = \begin{cases} \dfrac{P}{ET_c}, & 0 < P < ET_c \\ 1, & P \geq ET_c \end{cases} \tag{7}$$

$$ET_c = K_c ET_0 \tag{8}$$

$$ET_0 = 0.408 \times 0.0014 (T_{mean} + 13.1)(T_{max} - T_{min})^{0.7} R_a \tag{9}$$

where, Y_W indicates the climate production potential; *f(w)* indicates the moisture correction coefficient; P indicates the precipitation during the growth period of the crop (mm); ET_C indicates the theoretical water demand (mm) and K_C indicates the crop water demand coefficient, determined from published literature (Shi et al., 2015). Specifically, the crop water requirement coefficient of spring wheat was 1.12 and highland barley was 0.93. ET_0 indicates the reference crop evapotranspiration; T_{mean}, T_{max} and T_{min} indicate the average temperature, maximum temperature and minimum temperature, respectively and R_a indicates the radiation from the top layer of the atmosphere.

Land Production Potential

The land production potential was based on the climate production potential, which was obtained through correction using the soil availability coefficient. The formula used was as follows:

$$Y_S = Y_W \times f(S) \tag{10}$$

$$f(S) = \prod_i A_i \tag{11}$$

where, Y_s indicates the land production potential, Y_w indicates the climate production potential, f(S) indicates the soil availability coefficient and A_i indicates the raster layer of each factor after scoring.

Based on the literature (Jiang, 2008), the soil pH value, organic matter content and soil texture were combined with the slope to construct a soil availability factor scoring system to obtain the soil availability coefficient (**Table 3**).

Agricultural Production Potential

In addition to natural factors, human factors influence the production potential, especially the amount of fertiliser used and investment in agricultural science and technology (Yin

TABLE 3 | Scoring of soil and slope conditions.

Grading	Soil Texture	pH Value	Score	Organic Matter	Score	Slope	Score
1	L	6.5–7.5	1	≥40	1	≤3	1
2	LS,SL	5.5–6.5	0.9	30–40	0.9	3–7	0.9
3	LC,CL	7.5–8.5	0.7	20–30	0.8	7–15	0.8
4	SLC,SCL	4.5–5.5	0.6	10–20	0.7	15–25	0.6
5	SC,C	8.5–9.0	0.5	6–10	0.6	25–35	0.4
6	S	<4.5,≥9.0	0.4	<6	0.4	>35	0.1

Note: L indicates Loamy; S indicates Sandy; C indicates Clay.

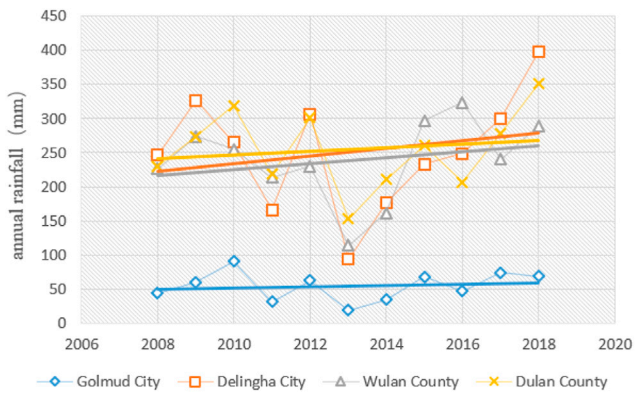

FIGURE 3 | Trend chart of annual average rainfall between 2008 and 2018.

et al., 2005). The latter includes popularising good crop varieties and optimising irrigation techniques. Considering the arid climatic conditions in the Qaidam Basin, methods for developing water-saving irrigation techniques are the main focus of agricultural science and technology investment. Based on the land production potential, the agricultural production potential was achieved after correcting for the positive impact of the level of labour input on production potential; usually, the input level coefficient is between 1 and 1.3. Therefore, the present study calculated the agricultural production potential three times, when the input level coefficient was 1, 1.1 and 1.2, and compared the theoretical grain yield with the actual yield to determine the reasonable current input level and evaluate the agricultural production potential.

RESULTS

Climate and Yield Trends

From 2008 to 2018, the average annual rainfall in Golmud city was approximately 50 mm, and the average annual rainfall in Delingha city, Wulan county and Dulan county was between 100 and 400 mm, with the rainfall in the four counties (cities) all increasing (**Figure 3**). The annual average temperature in Golmud city was approximately 6–7°C, and the average annual temperature of the four counties (cities) increased (**Figure 4**). The yield per unit area of the four counties (cities) showed a downward trend (**Figure 5**). Although rainfall increased, the temperature increase led to evaporation increase, indicating that the temperature increase negatively affected the yield per unit area of grain crops in the Qaidam Basin.

Photosynthetic Production Potential

The photosynthetic potential of spring wheat in 2018 in the Qaidam Basin ranged from 24256.56 kg·hm^{-2}–34353.34 kg·hm-^{2}, with significant spatial differences. The total photosynthetic potential of spring wheat was higher in the northwest and lower in the southeast (**Figure 6A**). The photosynthetic potential in Mangya city in the north was the highest, reaching 31178.11 kg·hm^{-2}. The second-highest value was observed in the autonomous prefectures. The photosynthetic potential of highland barley ranged from 14677.08 to 20771.71 kg·hm^{-2}, with the overall highest value in the north and the lowest value in the east, and the high values were concentrated in the east of Mangya city (**Figure 6B**).

Light-Temperature Production Potential

After temperature effects were taken into account, the production potential was reduced by approximately 13%. The light-temperature production potential of spring wheat ranged from 21208.53 kg·hm^{-2}–30017.95 kg·hm^{-2}, with a high yield in the northwest and a low yield in central regions (**Figure 6C**). The high yield was mainly concentrated in Mangya city in the northwest. The mean value of the light-temperature production potential of spring wheat was the highest in Mangya city. The second-highest value was observed in the autonomous prefecture. The mean values in the other administrative regions showed few differences. The total yield potential of highland barley was between 12865.93 kg·hm^{-2} and 18208.48 kg·hm^{-2}. The overall yield potential was high in the north and low in the east, with the highest values concentrated in the east of Mangya city (**Figure 6D**). The average photosynthetic potential of highland barley in the autonomous prefecture was the highest, followed by Mangya city.

Climate Production Potential

The climate production potential of spring wheat ranged from 3648.54 kg·hm^{-2}–26049.37 kg·hm^{-2}, and both the minimum and maximum values were observed in Mangya city (**Figure 6E**). There were no significant differences among the mean values of different cities and counties; however, there were three low-value clusters in the east of Mangya city, the middle and east of Geermu city, and Dulan county, which showed poor rainfall conditions. The climate production potential of highland barley ranged from

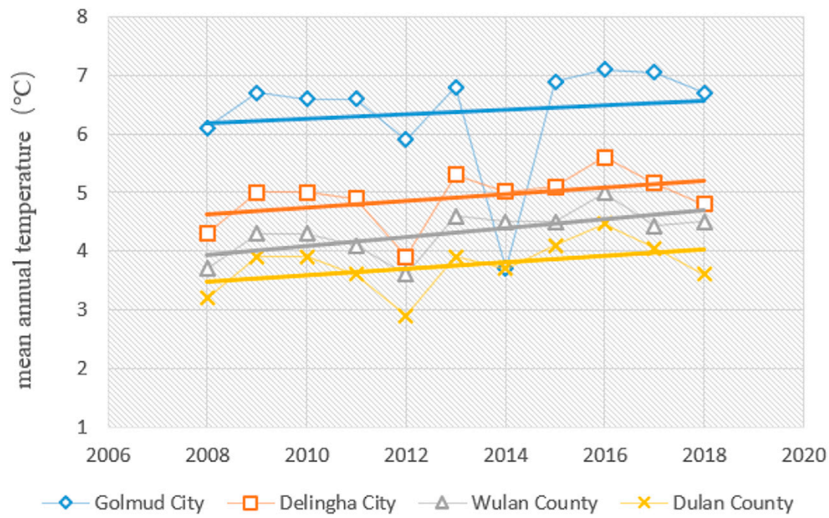

FIGURE 4 | Multi-year mean temperature trend chart.

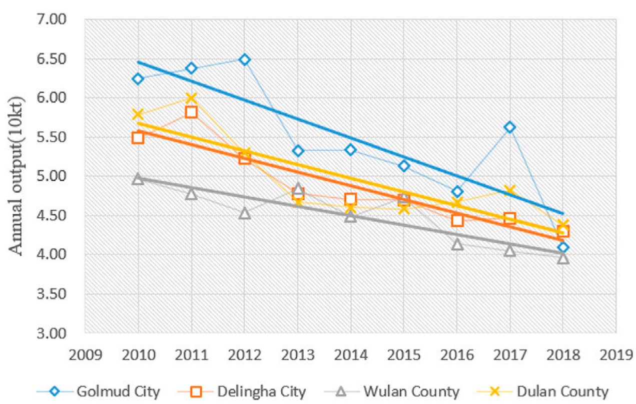

FIGURE 5 | Multi-year production trend chart.

3147.37 $kg{\cdot}hm^{-2}$–15741.97 $kg{\cdot}hm^{-2}$ (**Figure 6F**), and its spatial distribution was similar to that of spring wheat.

Land Production Potential

The land production potential is the lower limit of productive potential under real conditions, which can be obtained by multiplying the soil availability coefficient with the climate production potential. The soil availability coefficient of the Qaidam Basin was between 0 and 0.57. Because there were large areas of bare land and desert in the central and northwestern parts of the Qaidam Basin, the land production potential was greatly attenuated. The land production potential of spring wheat and highland barley was only 15.85 and 16.74% of the photosynthetic production potential, respectively. The average land production potential of spring wheat in cultivated areas was 4908.3 $kg{\cdot}hm^{-2}$ and highland barley was 3084.25 $kg{\cdot}hm^{-2}$ (**Figure 7**).

The highest grade was determined as an appropriate area for grain production in the Qaidam Basin. The areas with high land production potential were mainly distributed in the northeast, southeast and west of the Qaidam Basin. The suitable area in Wulan county was close to Qinghai Lake, in Delingha city it was close to Hala Lake, directly under the autonomous prefecture it was connected to Dachaidan Lake and Xiaochaidan Lake, and in Mangya and Golmud cities these areas were distributed in the Yangtze River originates.

Agricultural Production Potential

More than 85% of the grain crops in the Qaidam Basin are spring wheat and highland barley, and the proportion of their planting area was approximately 4:5 in 2018.

According to (Jiang, 2008), in terms of fertilization level, the input level coefficients corresponding to high fertilization area, medium fertilization area and low fertilization area are 1.2, 1.3 and 1.1 respectively. Based on the land production potential and considering the positive impact of artificial input of agriculture on crop yield, the agricultural production potential was revised, and the average agricultural production potentials of cultivated land areas with input level coefficients of 1, 1.1 and 1.2 were calculated (**Table 4**). By comparing the theoretical yield with the actual yield, it was found that when the input level coefficient was 1, the planting area of grain crops in 2018 was 18.40 thousand hectares and the corresponding agricultural production potential was 71,600 tonnes. This was 0.42 million tonnes lower than the actual yield, indicating that the yield per unit area exceeded the upper limit without artificial intervention. When the input level coefficient was 1.1, the agricultural production potential was 78,800 tonnes, which was closest to the actual output. With an input level coefficient of 1.2, the agricultural production potential reached 8600 tonnes, higher than the actual output of 75,800 tonnes. Therefore, the actual yield was closest to the agricultural production potential when the coefficient of labour input was 1.1.

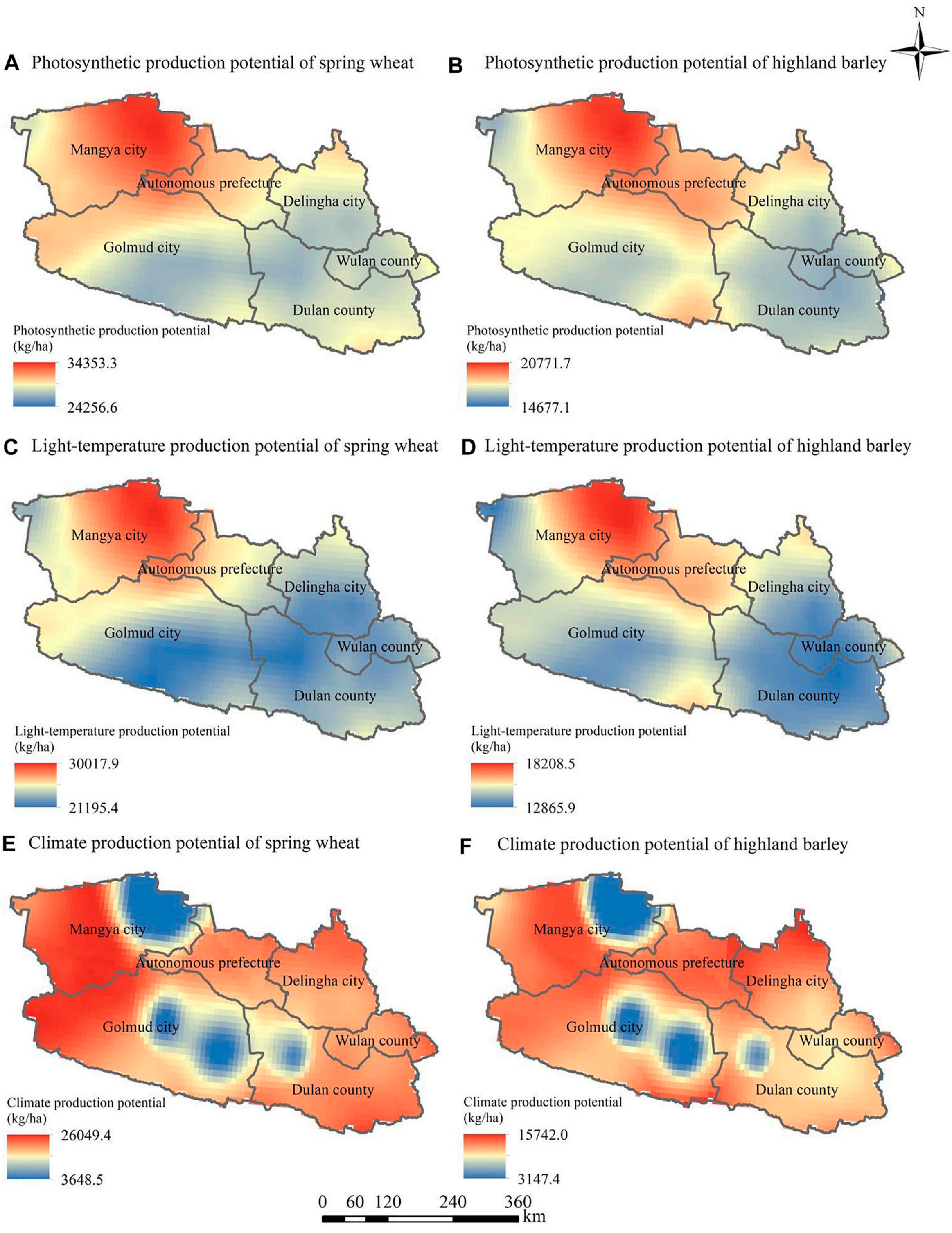

FIGURE 6 | Photosynthetic, light-temperature and climate production potential of spring wheat **(A,C,E)**, respectively and highland barley **(B,D,F)**, respectively. **(A)** Photosynthetic production potential of spring wheat **(B)** Photosynthetic production potential of highland barley **(C)** Light-temperature production potential of spring wheat **(D)** Light-temperature production potential of highland barley **(E)** Climate production potential of spring wheat **(F)** Climate production potential of highland barley.

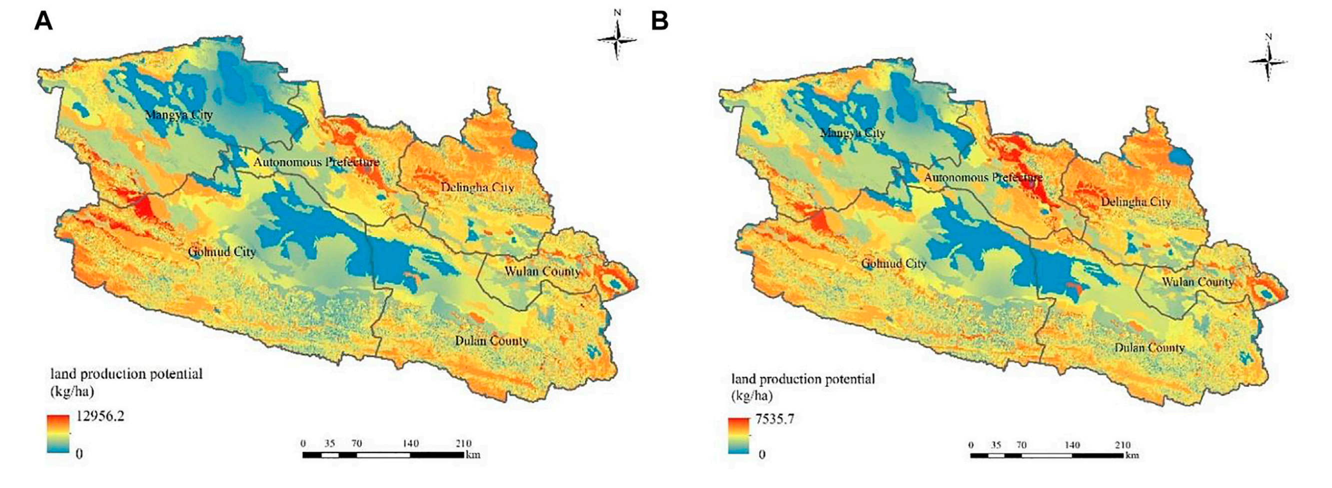

FIGURE 7 | Land production potential of spring wheat **(A)** and highland barley **(B)**.

TABLE 4 | Agricultural production potential and grain yield under different input level coefficients.

Input Level Coefficient	Agricultural Production Potential of Spring Wheat ($kg{\cdot}hm^{-2}$)	Agricultural Production Potential of Highland Barley ($kg{\cdot}hm^{-2}$)	Grain Crop Output (10^4 Tonnes)
1	4908.30	3084.25	7.16
1.1	5399.13	3392.68	7.88
1.2	5889.96	3701.10	8.60

TABLE 5 | Land population carrying capacity under different input level coefficients.

Input Level Coefficient	Population Carrying Capacity of the Land (10^4)
1	56.29
1.1	61.95
1.2	67.61

DISCUSSION

Grain is an important strategic material and its output must continue to expand to maintain social stability (Zhou and Guan, 2000). The present study calculated the land population carrying capacity based on per capita grain consumption (**Table 5**). If all consumed calories were powered by food crops, approximately 400 kg would be needed per person per year. According to the National Bureau of Statistics in 2018, only 36% of the calories in the diet of the Chinese population come from grains. At present, the main grain crops in the Qaidam Basin are spring wheat and highland barley. According to the China Statistical Yearbook in 2018, China's per capita grain consumption was 127.2 kg (most of which was grain). Based on this, the actual grain crop output in the Qaidam Basin in 2018 could support 562,900 people, whereas the permanent population of Haixi was 518,600. Therefore, the carrying rate was 0.87, achieving a sufficient balance between people and food. However, the development potential of the population carrying capacity was insufficient. If the correction coefficient of labour input can reach 1.2, the population carrying capacity can reach 676,100 people, and the carrying rate would be 0.76. In such a scenario, the development potential of the population carrying capacity would have much room for improvement. At present, the grain and oil output of Qaidam Basin could be more than self-sufficient. Taking advantage of the favourable factors of rich land resources, good light and heat, and good water and soil conditions in the Qaidam Basin, the primary position of agricultural development should be to improve the yield per unit area (Zhou and Guan, 2000).

Due to global climate change, the climate of the Qaidam Basin has changed markedly, with considerable warming and a temperature increase significantly higher than the national and global average (Li et al., 2015). The temperature increase has affected crops (Wang et al., 2010; Qin et al., 2013) and directly impacted the climatic production potential of crops (Ding et al., 2006). Many studies have shown that climate change negatively impacts agriculture and may reduce crop productivity in the future (Lobell and Asner, 2003; Tan and Shibasaki, 2003; Ciais et al., 2005) to the extent that it poses some threat to food security (Yin et al., 2008; Xie et al., 2014). Increasing temperature and precipitation have led to the warming and humidification of the climate, causing a significant impact on the crop yield in the Qaidam Basin (Wang et al., 2020). Although rainfall and temperature have increased over the past 10 years, the yield per unit area showed a downward trend in the Qaidam Basin.

The Qaidam Basin is a typical oasis agricultural environment with good hydrothermal conditions and abundant potential arable land resources. The agricultural area is close to natural water sources, and most of the agricultural areas are distributed along the north and south edge of the basin beside the water, which is conducive to good irrigation conditions and development prospects. At present, almost all the cultivated land in the Qaidam Basin is irrigated, with the effective irrigated area exceeding 97%. Developing water-saving irrigation is critical to improving the realistic production potential of crops (Zhou and Guan, 2000). Developing green and efficient water-saving methods and precision agriculture technology can shift the cultivation industry towards pollution-free and environmentally friendly methods (Yu et al., 2021).

In 2018, the grain crop yield per unit area of the Qaidam Basin exceeded the yield ceiling without artificial intervention; therefore, the following enhancement strategies are required to improve the grain crop yield and further improve the population bearing capacity. 1) Strengthen water-saving irrigation technology and improve the utilisation rate of water resources. This should be implemented in light of local conditions to achieve increased water-saving and open source technology in critical areas, vigorous promotion of drip irrigation and other technologies, rational high-level planning and management of surface water and groundwater, and greater water supply and drainage. 2) Improve the utilisation rate of chemical fertilisers and pesticides and replace chemical fertiliser with organic fertiliser. Excessive fertiliser use can inhibit crop growth and cause environmental pollution. The use of chemical fertiliser in Haixi peaked in 2018; however, implementing reduced application and greater efficiency of chemical fertilisers and pesticides in 2019 achieved promising preliminary results, reducing the use of chemical fertilisers by more than 50%. Organic fertiliser should be further promoted to replace chemical fertilisers and a green-oriented agricultural technology system should be constructed.

CONCLUSION

It is important to research the impact of climate change on crop yields in the Qaidam Basin. The present study employed the AEZ method to calculate the production potential of the Qaidam Basin at multiple levels based on photosynthetic capacity, temperature, light, climate and soil availability to ultimately obtain the land production potential. Based on correction using different input coefficients, the potential for agricultural production potential was calculated. These data were then used to calculate the land population carrying capacity. Thus, this study provides a reference for improving agricultural productivity in the Qaidam Basin. The specific conclusions are as follows:

1) By combining the AEZ method with GIS technology, every single factor of land production potential was considered comprehensively through step-by-step correction, ensuring that the results were closer to reality. It is critical to optimise the rational use of local climatic resources and improve agricultural production potential. The research methods have wide application value.
2) The photothermal conditions of the Qaidam Basin are good, and the photosynthetic and photothermal productivity potential of Manya city and the autonomous prefecture in the northern basin is high. The rainfall is low, especially in the eastern part of Golmud city and Mangya city; therefore, the climate production potential of this region is low. After correction using the soil availability coefficient, the land production potential was only approximately 1/6 of the photosynthetic production potential, and the highest values occurred in the northeast and west of the basin margin. The suitable area for agricultural production is a reserve arable land resource to the production potential under natural conditions, and provides a scientific basis for the rational distribution of grain crops.
3) The current population carrying capacity of the land resources is 562,900, which achieves a balance between people and food when the correction coefficient of artificial input is approximately 1.1. If the correction coefficient reaches 1.2 by improving irrigation efficiency and reducing fertiliser use, the population carrying capacity could reach 676,100; hence, there remains potential to increase grain yield. Over the past 10 years, increasing temperature and rainfall have led to warming and humidification, and the grain yield per unit area has shown a downward trend. Therefore, climate change negatively influences agriculture and decreases crop productivity in the Qaidam Basin. Enhancement strategies, such as strengthening water-saving irrigation technology and improving the utilisation rate of chemical fertilisers, are required to improve the agriculture productivity potential in Qaidam Basin, and help advance the green-oriented agricultural technology system.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

HY: Writing original draft. MH: Investigation. TZ: Methodology. JW: Data curation. ZL: Methodology. DC: Formal analysis. PL: Writing -review and editing. YL: Editing. HW: Investigation. ZJ: Validation. DM: Introduction. DZ: Data. XW: Review and editing.

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Do Livelihood Strategies Affect the Livelihood Resilience of Farm Households in Flooded Areas? Evidence From Hubei Province, China

Xin Luo[1], Chongmei Zhang[1], Jiahao Song[2], Zishan Qiu[1], Wenzhuo Li[1] and Wei Wang[1]**

[1] Department of Agriculture and Forestry Economics and Management, College of Management, Sichuan Agricultural University, Chengdu, China, [2] Department of Rural and Regional Development, College of Management, Sichuan Agricultural University, Chengdu, China

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Edited by:
Shaoquan Liu,
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Huawei Zheng,
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Lu Yang,
Nanjing University of Finance and Economics, China

****Correspondence:***
Jiahao Song
sjh799286572@qq.com
Wei Wang
wangwei@sicau.edu.cn

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Hubei Province, located in the middle reaches of the Yangtze River, is a complex area of fragile ecological environment and traditional agricultural production in China. With the further intensification of the impact of global warming, flood disasters have brought a more severe threat to the sustainable development of farmers' livelihoods. This paper therefore examines the livelihood resilience of farmers with different livelihood strategies in the region by constructing a livelihood resilience evaluation system based on three target levels: buffering capacity, Adaptation and restoration, and using a contribution model to identify the main contributing factors affecting the livelihood resilience of fa rmers. The following three conclusions were found: (1). The overall level of livelihood resilience of farmers in flood-affected areas in Hubei Province is not high, and the difference in livelihood resilience indices between farmers with different livelihood strategies is large; (2). Farming-led farmers and part-time balanced farmers can better adapt to external shocks brought about by floods; (3). The main contributing factors affecting the livelihood resilience of various types of farmers have Convergence.

Keywords: livelihood resilience, farmers' livelihood strategies, global warming, flooding impact, farmers' livelihood resilience construction

INTRODUCTION

As global warming intensifies and extreme precipitation events increase, the frequency and intensity of flooding in China is increasing (Hirabayashi et al., 2013; Arnell and Gosling, 2016; Claps, 2017; Bloeschl et al., 2019). Hubei Province, located in the middle reaches of the Yangtze River, has been one of the few provinces in China particularly affected by flooding. Every summer and autumn, when Hubei Province enters the flood season, floods can lead to a lack of security for the lives of local farmers, a reduction in crop production or crop failure, and the resulting adverse effects of health crises, poverty, unemployment, and criminality can seriously threaten the sustainable development of rural areas (De Silva and Kawasaki, 2018; Ma et al., 2021). At the same time, with the rapid transformation of China's economic and social development, farming households have begun to move away from the shackles of the land and choose to go out to work or operate off-farm, and their choice of livelihood strategies has diversified. This has brought unprecedented challenges to the traditional livelihoods of farmers based on land and labor (Li et al., 2019; Ma et al., 2022). Therefore, how to scientifically integrate the advantages of regional resources, reduce the negative impact of natural disasters on the livelihood development of farming households, and improve the resilience of farming households' livelihoods has become an important issue that needs to be addressed for sustainable livelihood development.

As the most basic economic agents in rural ecosystems, the livelihoods of farmers are most directly affected by floods (Tran et al., 2018; Zhou et al., 2021). Since the 1980s, "livelihood," a new perspective for the study of rural economy and the sustainable utilization of natural resources, has become a hot topic of academic attention (Quandt, 2018; Wang et al., 2021; Yang et al., 2021). Many researchers have developed a multi category livelihood development analysis framework based on Srinivasan and Amartya (1983) feasible ability theory, Among them, the most widely used is the sustainable living hood approach (SLA) proposed by the United Kingdom Department for International Development (DFID) (Saxena et al., 2016; Quandt et al., 2017; Tsolakis et al., 2021). This theoretical framework allows researchers to describe how farmers use their capital holdings and external public services to develop livelihoods in risky environments and changing institutions and organizations. However, traditional livelihood theory has focused mainly on the stock of livelihood capital of farmers and how it is combined, neglecting the ability of farmers to adapt and recover under the impact of external shocks (Shikuku et al., 2017; Reyes-Garcia et al., 2019). As threats from climate extremes intensify, more and more researchers are focusing on the role of resilience thinking in the study of livelihoods (Abdul-Razak and Kruse, 2017).

Resilience theory was first applied by ecologist Holling to study the ability of natural ecosystems to recover to their original state in response to external shocks (Holling, 1973). Livelihood resilience is an extension of the socialization and microcosmization of resilience research objects, referring to the ability of farmers to maintain a basic level of livelihood and recover from disturbances and shocks, both internal and external (Ayeb-Karlsson et al., 2016; Quandt, 2018). This concept combines theoretical thinking on resilience with traditional livelihood research models to provide a more comprehensive and accurate description of how farmers can restore their livelihood status to the ability to maintain their basic functions and structures after external disturbances.

Since Speranza et al. (2014) proposed a quantitative analytical framework for livelihood resilience, consisting of three dimensions: self-organizing capacity, buffering capacity, and learning capacity, academic research on livelihood resilience has moved from the exploration of theoretical frameworks to empirical studies (Milestad and Darnhofer, 2003; Alam et al., 2018; Smith and Frankenberger, 2018). Zhou et al. (2021) measured the livelihood resilience of farm households in earthquake-affected areas of Sichuan Province, China, and found that the livelihood resilience of farm households was mainly based on their ability to prevent and mitigate disasters, and that the stronger the buffer capacity of farm households' livelihoods, the more inclined they were to engage in non-farm activities to earn income; Quandt et al. (2017) studied the livelihood resilience of farming households in Isio County, a semi-arid region of Kenya, and found that farming households that adopt agroforestry may be more resilient in terms of livelihood resilience because farming household livelihood capital can be improved through diversification of farming practices; Stanford et al. (2017) used the principles of the sustainable livelihoods approach combined with a rapid assessment of fisheries sustainability (RAPFISH) methodology to construct a livelihoods resilience assessment framework specifically for small-scale fishers to predict the adaptation of fishers to help prevent and alleviate poverty among this group; Sarker et al. (2020) explored the livelihood resilience of riverine islanders in Bangladesh and found that natural disasters, low income and lack of basic sanitation facilities were the main reasons for the lack of livelihood resilience of vulnerable residents in the area.

Our review of the relevant literature shows that research on livelihood resilience in China started late, and there are few empirical studies on farmers' livelihood resilience in the context of climate disasters in particular. In view of this, this paper attempts to make marginal contributions in the following three areas: (1). An attempt is made to enrich and extend the framework for evaluating the livelihood resilience of farm households proposed by Speranza et al. (2014). This paper adds a target layer of resilience to the livelihood resilience evaluation framework based on previous studies, which is used to measure the ability of farmers to recover from a low level of livelihood status to a high level of livelihood status, which is more relevant to the idea of resilience theory proposed by ecologist Holling. (2). The resilience of livelihoods of farmers in flood-affected areas is studied using a theory of livelihoods resilience that is more appropriate to the Chinese context. This paper uses a sample of farmers in flood-affected areas in Hubei Province to provide evidence from China to study the livelihood resilience of affected farmers and its contribution factors in the context of global warming; (3). By classifying farmers who adopt different types of livelihood strategies, this paper attempts to construct pathways for building the livelihood resilience of different types of farmers, in order to provide theoretical support for government-related policy formulation and self-management of farmers' livelihood resilience in disaster-affected areas.

STUDY AREA AND DATA SOURCE

Study Area

Hubei Province (29°01′53″N-33°6′47″N, 108°21′42″E-116°07′50″E) is located in central China, in the middle reaches of the Yangtze River. The total area of the province is 185,900 km^2, accounting for 1.94% of the total area of China.

Hubei Province is located in the subtropical zone of the northern hemisphere, and most of the province, except for the high mountain areas, has a humid subtropical monsoon climate with an average annual precipitation of 750–1,600 mm, with individual areas reaching 2,000 mm. and mostly concentrated in summer and autumn, with typical characteristics of rapid drought and flooding. The terrain of the province is roughly surrounded by mountains to the east, west, and north, while the south-central part is the flat and open Jianghan Plain, forming a "quasi-basin" structure with three rising sides and a low center that opens to the south. The Jianghan Plain in the south-central part of the area is a catchment area for the Yangtze River, Hanshui and Hunan's "four waters," and is a place where surface water and groundwater converge and drain. As a result, prolonged heavy rainfall combined coupled with the unique topographical environment gave birth to the geographical pattern of frequent flood disasters in Hubei Province (Wan et al., 2007).

Hubei Province is one of the regions most severely affected by flood disasters in Chinese history. The fragile ecological environment and the industrial structure, which is dominated by agricultural production, have had a great impact on the agricultural management and livelihood development of farmers in the region (Zhou et al., 2019). In particular, the trend of increased and concentrated precipitation in Hubei Province over the past 50 years due to global warming has intensified, with frequent flooding and the geological disasters it causes, further threatening the production and livelihood of farmers. Therefore, it is of practical significance to promote the sustainable development of farmers' livelihood in the region to study the livelihood resilience of farmers in this area and explore the livelihood construction path to improve livelihood resilience.

Data Sources

The data used in this paper come from a household survey conducted by the research team from July to August 2021 in flood-affected areas of Hubei Province. In order to gain a comprehensive understanding of the livelihoods of farmers in Hubei province, the research team selected 39 administrative villages in 12 townships in Honghu and Qichun counties as sample sites based on the characteristics of topography, population distribution and regional livelihoods, with 30–40 households in each village randomly selected for the survey.

The survey was conducted in the form of structured interviews, and the questionnaire included the impact of the natural environment and new economic and social factors on the livelihood recovery capacity of farmers under the influence of floods. A total of 1,100 questionnaires were distributed, and 1,040 valid questionnaires were finally returned, accounting for 99.05% of the total sample, meeting the requirements of reliability and validity of data use. In this paper, after eliminating missing values and outliers of key variables of the data, we finally obtained 993 valid farm household sample data.

LIVELIHOOD RESILIENCE EVALUATION SYSTEM CONSTRUCTION AND VARIABLE SELECTION

At present, the evaluation system of livelihood resilience in academia is still not unified in terms of evaluation dimensions and evaluation indicators (Sina et al., 2019; Ford et al., 2020). Our understanding of livelihood resilience is how economic activity units can more effectively protect their livelihoods and restore their livelihoods more quickly to their ability to maintain their basic functions under adverse environmental impacts. Therefore, the most important issues in livelihood resilience research should lie in the following three aspects: (1). what factors affect the livelihood resilience of farmers in the context of global warming; (2). how farmers can organize themselves to manage and optimize the use of these factors in order to better adapt to the uncertain natural environment and maintain their livelihoods; (3). what factors influence the development of farmers' livelihood resilience as they adapt and maintain their livelihoods. A more widely used framework for livelihood resilience analysis is that proposed by Speranza et al. (2014). This framework achieves a measure of the role of individual behavior and capabilities of farm households in maintaining livelihood stability in the face of persistent external disturbances.

However, it seems that the application of this framework has been hampered by previous theories of sustainable livelihoods, with scholars focusing on the buffering capacity and self-regulation and Adaptation of farmers in the face of external shocks, while neglecting to consider the restoration that can help farmers recover from unfavorable circumstances to a high level of livelihoods (Alam et al., 2018; Jurjonas and Seekamp, 2018; Phuong et al., 2018). Referring to the concept of resilience proposed by ecologist Holling, we believe that the measurement of livelihood resilience should also focus on the restoration of farmers' livelihoods (Yin et al., 2021). Based on this analysis, we constructed a livelihood resilience evaluation index system based on the existing research results in terms of 3 target layers: buffering capacity, Adaptation, and restoration (see **Figure 1**).

Buffer capacity refers to the ability of farm households to maintain the organizational structure and functional attributes of their livelihood systems by converting the livelihood capital they possess in the face of external risk (Speranza et al., 2014). The first issue to be considered in the study of farmers' livelihood resilience is the use of their own livelihood capital to protect themselves against external risks, and the most important way to improve farmers' buffer capacity is to enrich their livelihood capital endowment (Alam et al., 2017; Cooper and Wheeler, 2017). This paper adopts sustainable livelihood capital to reflect buffer capacity: the human capital of farmers is characterized by the educational level of the workforce, health status. Labor is the most important production factor in agricultural production; physical health is often the first to be affected by external shocks (Xu et al., 2019), and health status of family members is also a key piece of human capital. Cultivated land and Convenient transportation are selected to characterize the natural capital of farm households. Land is the most important means of production for farmers, and the greater the ownership of land, the stronger the natural endowment of agricultural production (Meinzen-Dick et al., 2017); the accessibility of transportation plays a crucial role in the expansion of farmers' social network, affecting the quantity and quality of communication between farmers and the outside world. Living area and Durable goods are selected to represent the physical capital of farmers, which can be transformed into financial capital when farmers'

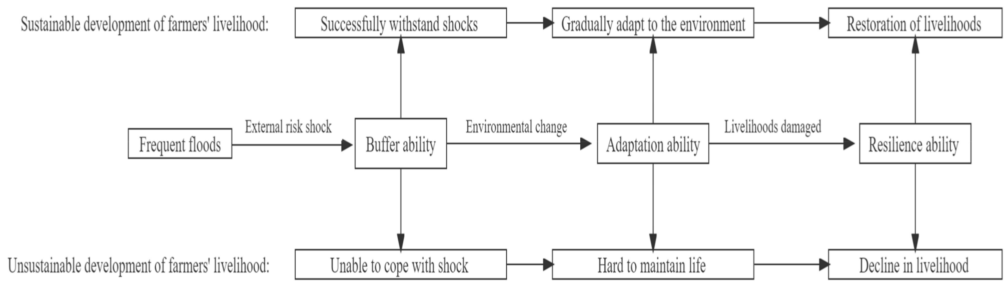

FIGURE 1 | Transmission pathways of the impact of flooding on the livelihood resilience of farm households.

livelihoods suffer from external shocks to improve their buffering capacity (Kong and Castella, 2021). Number of relatives and neighborhoods are selected to represent the social capital of farmers. Chinese villages are a typical society of acquaintances. The more complex the social relations the farmers have, the more opportunities they can seek help (Guan et al., 2018). Income per capita and liabilities are selected to characterize the financial capital of farm households. Financial capital is the most direct manifestation of farm households' buffer capacity, and the possession of financial capital directly determines whether farm households can maintain their basic livelihood status in the face of external shocks (Johanna et al., 2018).

Adaptation refers to the ability of farmers to adapt gradually to their current environment through cognition, learning, and organizational management in order to face external disturbances, and is a potential resilience (Speranza et al., 2014). When sudden external disturbances affect farmers' livelihoods, farmers can use their own buffering capacity to make an initial response, however, the impact of global warming on farmers' livelihoods is comprehensive and long-lasting, especially in the face of longer-term external shocks such as floods, which require farmers to continuously improve their livelihood capital mix to better adapt to external disturbances (Qasim et al., 2016). Agricultural insurance and subjective wellbeing are selected to characterize farmers' cognitive ability. Agricultural insurance, as a means of production risk protection purchased by farmers voluntarily, can help farmers share the losses brought by external shocks, reflecting farmers' subjective initiative in the face of flood shocks (Zeng et al., 2021); subjective wellbeing can be used as a measure of farmers' psychological Subjective wellbeing can be used as a measure of farmers' psychological tolerance, which determines the extent to which farmers can accept external disturbances. Agricultural insurance, as a means of production risk protection purchased by farmers voluntarily, can help farmers share the losses brought by external shocks, reflecting farmers' subjective initiative in the face of flood shocks (Pe'er et al., 2020); subjective wellbeing can be used as a measure of farmers' psychological tolerance, which determines the extent to which farmers can accept disturbances from outside. Information accessibility and cost of education are selected to characterize the learning ability of farmers. As an efficient and low-cost means of social interaction, the Internet can help farmers control market information in a more timely and accurate manner, and adjust their livelihood strategies to cope with the impact of environmental changes in the shortest possible time, which is in line with Milestad and Darnhofer (2003) definition of farmers' adaptation; although the cost of household investment in education and training will adversely affect the livelihood recovery ability of farmers in the short term, as a forward-looking investment with higher returns, it can reflect the learning ability of farmers, which is also related to livelihood recovery ability (Sujakhu et al., 2018). Ratio of party members and government staff were selected to characterize the organizational ability of farm households, and the increase in adaptation was also related to the extent to which farm households were linked to organizations such as government and community (Cofre-Bravo et al., 2019). Due to the specific nature of China's grassroots political system (Zhang et al., 2019), the greater the number of peasant households who are members of the Party and the greater the number of relatives in the family who work for the government, the closer the peasant households are to the grassroots organizations of the local government.

Restoration is one of the most central aspects of livelihood resilience, as farmers use both external support and internal drivers to counteract persistent external disturbances and in the process recover from low to high levels of livelihood status (Ravera et al., 2016). Government help, production support, and transferable income are selected to characterize the exogenous power of farmers. When farmers cope with natural disasters such as floods, their individual power is often too small, so government help is needed to help them recover from external shocks (Yang et al., 2021); the transfer income from the government or friends and relatives is also an important component of household income, especially in times of hardship, which can be regarded as a financial capital with obvious support (Ravera et al., 2016). Income diversity index, proportion of non-farm labor, total workforce are selected to characterize the endogenous power of farm households. With the household income diversification indicator representing the diversification of livelihood strategies adopted by farmers, implying that when farmers are affected by floods and are unable to farm, they can enrich their livelihood capital through other production methods (Zhu et al., 2018). The higher the number of farm households in off-farm employment, the more experience they have in other forms of production, which, like the level of education of the farm labor force, are both human capital accumulation. The stronger this endogenous drive is, the greater the likelihood that farmers will recover their livelihoods or even break out of the constraints of their previous livelihoods to gain greater development prospects.

CALCULATION METHODS AND DESCRIPTIVE STATISTICS FOR LIVELIHOOD RESILIENCE

Because of the diversity of external risk shocks to which farmers are exposed, the weight of each target layer that constitutes livelihood resilience is also difficult to analyze quantitatively using technical methods. Based on this, we first used the expert scoring method to determine the weights of the three attributes of buffering capacity, adaptation and restoration in the livelihood resilience of farmers. The specific process was to solicit the opinions of relevant experts by anonymously, and then to count, process, analyze, and summarize the opinions of experts, and finally determine the weight of each target layer after several rounds of opinion solicitation, feedback, and adjustment (Westerveld et al., 2021). The entropy value method was also used to measure the weights of the specific indicators that constitute the livelihood resilience (Hainmueller, 2012; Xu et al., 2019). The basic model is as follows:

$$Z = \begin{bmatrix} X_{11} & \cdots & X_{1m} \\ \vdots & & \vdots \\ X_{n1} & \cdots & X_{nm} \end{bmatrix} \tag{1}$$

In Equation (1), construct a judgment matrix Z of m assessment indicators for a sample of n.

$$s_{ij} = \frac{X_{ij} - X_{i\,\min}}{X_{i\,\max} - X_{i\,\min}} \tag{2}$$

In Equation (2), X_{ij} is the actual value of the ith evaluation object on the jth evaluation indicator, $X_{i\,\min}$ is the minimum value of the statistical data on the ith evaluation object, $X_{i\,\max}$ is the maximum value of the statistical data on the ith evaluation object and s_{ij} is the standard value of the ith evaluation object on the jth evaluation indicator.

$$S = (r_{ij})_{i\times j} \tag{3}$$

In Equation (3), the new judgment matrix $S$is obtained after dimensionless processing of the data using the extreme value method.

$$f_{ij} = \frac{r_{ij}}{\sum_{j=1}^{n} r_{ij}} \tag{4}$$

In Equation (4), f_{ij} is the characteristic weight of the ith evaluation object on the jth evaluation indicator.

$$E_j = -\frac{1}{\ln(\sum_{j=1}^{n} \ln f_{ij})} \tag{5}$$

In Equation (5), according to the definition of entropy value, the entropy value for n sample of m assessment indicators is E_j. To make sense of $\ln f_{ij}$, assume that $f_{ij} = 0$ when $f_{ij} \ln\ f_{ij}\ = 0$.

$$W_j = \frac{1 - E_j}{m - \sum_{j=1}^{m} E_j} \tag{6}$$

In Equation (6), W_j is the weighting factor of the jth evaluation indicator and satisfies $\sum_{j=1}^{m} W_j$ (see **Table 1**).

$$L_i = (B_i + A_i + R_i) \times W \tag{7}$$

Calculated by weighted average, with the ith evaluation object buffering capacity B_i; adaptation A_i; and restoration R_i. W is the weight of each target layer.

RESULTS

Livelihood Resilience Analysis of Farm Households

As can be seen from **Table 2**, the livelihood resilience index of farmers in flood-affected areas in Hubei Province is low, at 0.182, with Qichun County, a predominantly mountainous area, having a livelihood resilience index of 0.212 and Honghu City, a predominantly plain terrain, having a livelihood resilience index of 0.174. The main reason for the difference in livelihood resilience between the two areas is that farmers living in mountainous areas have more severe living conditions and are more likely to be affected by floods, so they have a stronger awareness of flood prevention in this type of farmers. In terms of each target stratum, the buffering, adaptation and resilience indices of Qichun County farmers are higher than those of Honghu City farmers, indicating that mountain farmers have a better overall ability to cope with flood impacts than those in the plain areas.

Classification of Farmers' Types and Calculation Results of Livelihood Resilience Index

As China's urbanization process continues, a large number of rural workers are choosing to leave the land to seek better employment opportunities and higher labor income in the cities, and the livelihood strategy choices of farming households in flood-affected areas of Hubei are also showing a trend toward diversification (Zhan, 2017; Lu et al., 2019). Differences in livelihood strategy choices inevitably lead to different allocations of livelihood capital, which in turn has a heterogeneous impact on the livelihood resilience of farm households. On the other hand, although the diversification of farmers' livelihood strategy choices has enriched their income channels, there is still the phenomenon of households with different livelihood strategy types being dominated by one income source due to the limited quantity and quality of labor at their disposal (Frelat et al., 2016). Therefore, using a particular source of income accounting for 60% of total household income and above as a classification criterion, farming households are divided into 5 types: (1). New agriculture-led

TABLE 1 | Livelihood resilience evaluation indicator system.

Target layer	Weight	Dimension	Index	Mean	Weight	Interpretation and assignment instructions
Buffer capacity	0.3	Human capital	A1: Educational level of the workforce	3.641	0.004	Continuous variable, average years of education of family labor force.
			A2: Health status	3.186	0.004	Continuous variable, mean of self-assessed health status of household members.
		Natural capital	A3: Cultivated land	1.533	0.056	Continuous variable, ratio of household arable land area to household size.
			A4: Convenient transportation	0.836	0.014	Whether the home is next to a motor vehicle driveway. Yes = 1; No = 0.
		Material capital	A5: Living area	52.736	0.014	Continuous variable, the ratio of household housing area to household size.
			A6: Durable goods	1.336	0.128	Continuous variable, the value of household durable goods including agricultural production machinery.
		Social capital	A7: Number of relatives	7.458	0.030	Continuous variable, the number of kin families with close ties.
			A8: Neighborhoods	1.600	0.008	Five point scale method. Evaluation of the trust relationship between neighbors.
		Finacial capital	A9: Income per capita	10.899	0.001	Continuous variable, ratio of total household income to household size.
			A10: Liabilities	2.688	0.0683	Continuous variable, logarithm of household debt amount.
Adaptation	0.3	Cognitive	B1: Agricultural insurance	1.626	0.016	Whether the farmer has agricultural insurance. Yes = 1; No = 0.
			B2: Subjective wellbeing	0.178	0.124	Continuous variable, mean of self-rated happiness of household members.
		Learning	B3: Information accessibility	0.342	0.077	Does the household use the internet to access useful agricultural information. Yes = 1; No = 0.
			B4: Cost of education	4.834	0.046	Continuous variable, logarithm of the total amount households invest in education.
		Organization	B5: Ratio of party members	0.225	0.107	Continuous variable, the ratio of the number of members of the family who joined the Chinese Communist Party to the total family population.
			B6: Government staff	0.227	0.1067	Whether the family has relatives working in government departments. Yes = 1; No = 0.
Restoration	0.4	Exogenous power	C1: Government help	1.685	0.006	Continuous variable, rating of household satisfaction with government support efforts.
			C2: Production Support	0.062	0.199	Whether the farmer can receive support from the village enterprise when conducting agricultural production. Yes = 1; No = 0
			C3: Transferable income	6.787	0.010	Continuous variable, logarithm of total income received by the household from the government or from relatives and friends.
		Endogenous power	C4: Income diversity index	2.320	0.007	Continuous variable, the number of different types of income in the total household income.
			C5: Proportion of non-farm labor	0.376	0.023	Continuous variable, the ratio of the number of household non-agricultural labor force to the total number of labor force.

type. This type of farmers take agricultural specialization as the main production method and special agricultural production as the main source of income. (2). Farming-led. A group of farmers whose main source of income is traditional rainfed dry farming or farming; (3). Labor-led. This refers to the fact that most of the labor force of farmers chooses to leave the primary industry and devote themselves to the secondary and tertiary industries with higher income, and the family income is mainly wage income; (4). Part-time balanced type. This group of farmers has a large amount of household labor at their disposal, and they earn business income from agricultural production and wage income from other sources; (5). Subsidy-dependent. This group of farmers is usually more elderly or have low working capacity due to illness or disability, and rely on state assistance or pensions for their income.

There are significant differences between farming households in terms of the number of household laborers, household income diversity index and government support. Therefore, by analyzing the internal differences of different types of farmers' livelihood resilience and their composition, we can put forward corresponding livelihood resilience-building paths for various types of farmers, so as to improve the ability of farmers to deal with the external impact caused by global warming. At the same time, in order to ensure that there are significant differences between the groups, we use the one-way variance

TABLE 2 | Livelihood resilience index.

Region	Buffer capacity	Adaptation	Restoration	Livelihood resilience
Qichun	0.233	0.261	0.160	0.212
Honghu	0.116	0.259	0.159	0.174
Total sample	0.136	0.256	0.160	0.182

TABLE 3 | Livelihood resilience index for each type of farm household and ANOVE analysis.

Farmer type	Buffer capacity	Adaptation	Restoration	Livelihood resilience	ANOVE Analysis	
New agricultural-led	0.206	0.381	0.115	0.222	*F*-value	*P*-value
Farming-led	0.185	0.293	0.106	0.186		
Labor-led	0.163	0.260	0.169	0.195	12.749	0.000
Part-time balanced	0.181	0.315	0.152	0.210		
Subsidy-dependent	0.195	0.155	0.139	0.147		

TABLE 4 | Contribution of indicators for each target tier of farm household livelihood resilience.

Farmer type		Buffer capacity			Adaptation			Restoration		
New agricultural-led	Contribution factor	A4	A10	A1	B3	B4	B1	C4	C3	C1
	Contribution	0.930	0.647	0.623	0.561	0.545	0.439	0.662	0.611	0.360
Farming-led	Contribution factor	A4	A10	A9	B3	B4	B1	C4	C1	C3
	Contribution	0.922	0.756	0.732	0.481	0.398	0.325	0.555	0.554	0.527
Labor-led	Contribution factor	A10	A8	A2	B4	B3	B2	C4	C3	C5
	Contribution	0.812	0.743	0.525	0.436	0.336	0.317	0.787	0.570	0.438
Part-time balanced	Contribution factor	A10	A9	A2	B3	B4	B2	C4	C3	C5
	Contribution	0.804	0.744	0.532	0.475	0.455	0.346	0.870	0.542	0.352

score method (ANOVE) to analyze the differences of livelihood resilience of different types of farmers. The results show that there are significant differences in livelihood restoration capacity among different types of farmers ($P = 0 < 0.05$), as shown in **Table 3**.

In terms of livelihood resilience, the farmer with the highest index of livelihood resilience is the new agriculture-led type (0.222); the lowest index is the subsidy-dependent type (0.147). The new type of agriculture-led farmers are in the lead in terms of buffering and adaptability, which may be because such farmers have accumulated rich experience in dealing with various external shocks caused by global warming during their long-term agricultural production. On the other hand, the "rural revitalization" strategy implemented by the Chinese government in recent years has greatly increased the policy support for farmers' production and livelihood, especially when the agricultural production projects they are engaged in are damaged by floods, farmers can Obtain a substantial amount of compensation from government agencies or state-run agricultural insurance companies. Therefore, farmers of this type are more likely to gain the comparative advantage of livelihood recovery from government assistance. The subsidy-dependent farmers have the lowest livelihood resilience index because they have insufficient household labor, which leads them to lack the human capital to cope with natural risk shocks including floods.

In terms of buffer capacity, the farm household type with the highest livelihood buffer capacity index was the new agriculture-led type (0.206); the lowest index was the labor-led type (0.163). The subsidy-dependent farming households that lacked labor capacity achieved a higher score (0.195) in this dimension, which may be somewhat counterintuitive. However, from the perspective of policy implementation, the Chinese government has increased its financial support to rural areas in the "poverty alleviation" implemented in 2015. In particular, farmers who are widowed, have a disabled family member or are suffering from a serious illness receive a stable monthly payment from the government, and the livelihood of these farmers is covered by the government. On the contrary, labor-led households do not have a comparative advantage in terms of policy support, resulting in a low score in this dimension.

In terms of restoration, the farm household with the highest livelihood restoration index was the labor-led type (0.169); the lowest index was the farm-led type (0.106). This may be due to the fact that the income impact of floods on labor-led households is small and they can recover quickly from the floods. On the contrary, farm-led households have a natural vulnerability as their livelihoods are mainly based on traditional farming. Therefore, they are less able to recover from the adverse environment.

Analysis of Factors Contributing to Livelihood Resilience of Farm Households

The study on the livelihood resilience of farmers not only aims to assess the livelihood status of different types of farmers, but more importantly, to clarify the dominant contributing factors affecting the livelihood resilience of farmers, so that policies and recommendations can be made in a targeted manner (Xu et al., 2018; Guo et al., 2019; Wójcik et al., 2019). Therefore, this paper applies a contribution model to calculate the contribution of each indicator to livelihood resilience by dimension, and selects the top four indicators in terms of cumulative contribution as the dominant contributors (see **Table 3**).

$$C_j = p_{ij}g_j / \sum_{j=1}^{m} p_{ij}g_j \times 100\% \tag{8}$$

In Equation (8), C_j is the degree of contribution of the jth evaluation indicator to the target, p_{ij} is the degree of affiliation of the indicator to the target, and g_i is the degree of influence role of the *j*th evaluation indicator on the target (see **Table 4**).

In terms of buffering capacity, the main contributors to the livelihood resilience of the five categories of farm households are concentrated in farm households' financial capital. The losses caused by floods to farmers are undoubtedly huge, and many farmers even sell valuable household assets to maintain the stability of household livelihood status, and the negative marginal effect of household liabilities (A10) is stronger when farmers' livelihood status is unstable.

In terms of adaptation, the main contributing factors to the livelihood resilience of the five categories of farmers were focused on cognitive and learning. Agricultural insurance (B1), as an underwriting protection for agricultural production risk, can help farmers recover agricultural losses caused by floods to a certain extent, and the stronger the willingness of farmers to purchase agricultural insurance, the stronger the subjective initiative of farmers to resist risks. At the same time, rural China is a typical "human society," and farmers have advantages in terms of information access and policy knowledge, which makes them better able to adapt to changes in the external environment. The cost of education (B4), as a long-term investment, can help farmers improve the quality of their family members and enhance their competitiveness in different environments.

In terms of resilience, the main contributing factors shared by the five types of farm households are transferable income (C3) and household income diversity index (C4). With the increase of production and livelihood subsidies by the Chinese government, transferable income (C3), as an important source of income for farm households, can be directly transformed into financial capital of farm households and improve their livelihood resilience. When the impact of flooding exceeds the capacity of farmers, they have to give up their agricultural production and earn income through other channels to maintain their livelihoods. The higher the household income diversity index (C4), the richer the income sources of farmers and the stronger the resilience of farmers.

DISCUSSION AND LIVELIHOODS RESILIENCE BUILDING PATHWAYS

Conclusion of the Study

Some scholars have systematically introduced the theoretical content and scientific value of the resilience of farmers' livelihoods, but since the concept of resilience was introduced into the field of farm livelihoods from the discipline of natural ecology, further research on the resilience of farmers' livelihoods needs to be further explored (Alam et al., 2018; Quandt, 2018; Smith and Frankenberger, 2018; Wang et al., 2021; Yang et al., 2021). Based on the research results of previous scholars, this paper constructs an evaluation system of farmers' livelihood resilience consisting of three target layers: buffering, adaptation and restoration, in the context of the further intensification of the threat to farmers' livelihoods caused by floods in Hubei Province as a result of global warming, by combining the links between external disturbances, government management and farmers' livelihood strategies. Through a combination of theoretical analysis pathways and empirical research, the following conclusions were drawn.

The overall level of livelihood recovery capacity of farming households in flood-affected areas in Hubei Province is not high. The overall livelihood restoration ability of farmers in Hubei Province is low, and the topographic factors have great differences in the livelihood resilience of farm households. Among them, the livelihood resilience index capacity of farm households in Qichun County, which is mainly mountainous area, is 0.212, and the livelihood resilience index capacity of farm households in Honghu City, which is mainly plain terrain, is 0.174.

New agriculture-led and part-time balanced households are better able to adapt to external shocks caused by floods. The analysis of the livelihood resilience indices of each type of farmers shows that the new agriculture-led and part-time balanced farmers have comparative advantages in the total index as well as several target level indices. Therefore, these two livelihood strategies should be the main direction for the livelihood development and transformation of the remaining types of farm households, especially combining with regional characteristics, giving play to the role of high-quality agricultural production areas, and gradually transforming and developing into new agriculture-oriented farm households with special industries, which has important practical significance for promoting the sustainable development of farm households' livelihoods.

The main contributing factors affecting the livelihood resilience of each type of farm households were mainly focused on household income. Looking at the three target layers separately, the main contributing factors of livelihood buffer capacity were concentrated in income per capita (A9), liabilities (A10); the main contributing factors of livelihood adaptation were concentrated in agricultural insurance (B1), cost of education (B4); the main contributing factors of livelihood restoration were concentrated in transfer income (C3), household income diversity index (C4). These factors have direct or indirect relationships with farm household income.

Optimization Strategies for Farmers' Livelihood Resilience

From the results, the livelihood resilience index of Hubei farmers is low and the livelihood sustainability of farmers is poor. Starting from each subject of regional economic development, we put forward the following three policy suggestions. First, regional governments should actively play the role of policy regulation and guidance. Before floods occur, the government should establish a sound disaster warning mechanism and encourage farmers to take pre-disaster precautions in the form of government subsidies or other incentives; second, in terms of livelihood employment, the government should focus on the development of the regional economy and strive to provide farmers with more suitable employment opportunities and financial support for agricultural production. Third, Third, farmers should also pay attention to the development of improving labor skills and their own quality. For farmers with insufficient family labor capacity, regional governments should also appropriately improve the coverage and support of rural inclusive policies according to the development of regional economy, as well as gradually improve the construction of mechanisms to consolidate the effectiveness of "poverty eradication" and rural pension mechanisms, so as to actively play the role of the government in underwriting the livelihood of vulnerable farmers.

Identifying regional resource advantages and enriching livelihood strategy options for farmers. Regional economic development agents should promote the development of new types of professional farming households based on the advantages of regional resources. As the livelihood resilience index is higher for farming-led and part-time balanced farmers among all types of farmers, the government should encourage farmers with labor conditions to take the initiative to choose livelihood strategies with higher comparative returns and provide the necessary policy support for farmers to change their livelihood strategies. For example, agricultural insurance, micro-credit for agricultural production, infrastructure development, etc. At the same time, subsidy-dependent farmers should make use of the labor force in the household that is still capable of production to develop a garden economy or develop elderly agriculture based on improved agricultural mechanization and social services in order to increase their income.

Building a livelihood restoration capacity guarantee system for farmers, mainly through industrial and financial collaboration and supplemented by policy protection. The proportion of inputs represented by capital in modern agricultural production is gradually increasing, and the financial burden of farmers in carrying out agricultural production is becoming a major source of debt for their households. The government should provide greater support to farmers who are able to repay their loans in terms of the period of use, the amount of the loan and the loan approval process. At the same time, the government should work together with insurance companies to develop a better agricultural insurance system to enhance the ability of farmers to withstand external risk shocks. On the other hand, rural grassroots organizations should also implement the various disaster prevention and relief policies formulated by higher-level organizations and actively guide local farmers to choose more appropriate livelihood strategies. By building a livelihood resilience system based on industrial and financial collaboration, supplemented by policy protection, the main problems that contribute to the low livelihood recovery capacity of farmers can be addressed.

SHORTCOMINGS OF THE RESEARCH DESIGN AND FUTURE RESEARCH DIRECTIONS

Due to the limitation of the study area and the different stages, attributes of rural development in various regions, this may lead to differences in the availability of individual livelihood indicators and the level of policy support available to farmers, resulting in differences in the selection of alternative indicators for the evaluation of the livelihood resilience of farmers in different regions. To address this shortcoming, the next research directions of the group are: firstly, to optimize the scope of application of the indicators that make up the livelihood resilience evaluation system, and secondly, to develop various livelihood resilience evaluation systems for farmers under the extreme climate impacts caused by global warming.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

XL and CZ were primarily responsible for writing the main body of the manuscript. JS provided the original data used in this manuscript. XL and ZQ provided the results of the empirical analysis for the research in this manuscript. WL provided all the tables used in this manuscript. WW made significant contributions to improve the manuscript. All authors contributed to the article and approved the submitted version.

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Built Environment Impacts on Rural Residents' Daily Travel Satisfaction

Haimei Li[1], Yuting Zhang[2,3], Yibin Ao[2], Yan Wang[4], Tong Wang[5]* and Yunfeng Chen[6]*

[1] Humanities and Law School, Chengdu University of Technology, Chengdu, China, [2] College of Environment and Civil Engineering, Chengdu University of Technology, Chengdu, China, [3] Department of Architecture and Civil Engineering, Southwest Jiaotong University Hope College, Chengdu, China, [4] Department of Engineering Management, Sichuan College of Architectural Technology, Chengdu, China, [5] Faculty of Architecture and Built Environment, Delft University of Technology, Delft, Netherlands, [6] Purdue Polytechnic Institute, Purdue University, Lafayette, LA, United States

The rapid urbanization in China urges scholars to investigate the impacts of built environment on the level of travel satisfaction of rural residents to improve their quality of life and make planning exercises more human-centric. This study samples six villages out of the 25 top rural areas in Chengdu, Sichuan, China, as the research object and constructs a structural equation model to explore the direct and indirect impacts of the built environment on daily travel satisfaction of rural residents. The research finds that building density (0.609), road density (0.569), the number of accessible markets (0.314), and private car ownership (0.02) have significant positive impacts on travel satisfaction. Public transport (−0.063) has a direct negative impact on travel satisfaction. Consequently, in order to further improve travel satisfaction, construction departments and rural planners should improve the building and road densities of new rural areas and increase the number of accessible markets. The convenience of rural public transport services also needs improvement.

Keywords: travel preference, travel satisfaction, rural China, travel mode, built environment

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Zhen Guo,
Beihang University, China
Xin Deng,
Sichuan Agricultural University, China

****Correspondence:***
Yibin Ao
aoyibin10@mail.cdut.edu.cn
Tong Wang
t.wang-12@tudelft.nl

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INTRODUCTION

Travel is an essential activity in people's daily life (Yang et al., 2022). Travel satisfaction has been defined as people's comprehensive evaluation and subjective feeling of transportation facilities and services (Gao et al., 2017a,b). Travel satisfaction reflects the quality of transportation services and can guide planners in providing good travel services for improving public health through transportation (Zhu and Fan, 2018a).

Research on travel satisfaction began in the 1960s and has been an area of research since (Diana, 2011; Abenoza et al., 2017; Gao et al., 2017b; Susilo et al., 2017; Mouratidis et al., 2019; Wang et al., 2020). In the past studies, scholars usually considered the influence of local population characteristics and travel-related variables (e.g., travel mode and travel time) on travel satisfaction (Olsson et al., 2013; St-Louis et al., 2014; De Vos et al., 2016; Ye and Titheridge, 2017; Mouratidis et al., 2019) and confirmed that various factors had a significant impact on travel satisfaction. For example, residents living in the city have a higher level of travel satisfaction when using bicycles (Mouratidis et al., 2019). Travel satisfaction will be remarkably reduced as a result of increasing population and motor vehicles, and the consequent extension in commuting time will result in low satisfaction (Meng et al., 2013). In recent years, studies have gradually incorporated the built environment (Ye and Titheridge, 2017; Zhao and Li, 2018), travel attitude (De Vos et al., 2015; Gao et al., 2017a), and travel preference (St-Louis et al., 2014; De Vos et al., 2016) into the debate. When people have a certain travel mode preference, they will use that mode as much as possible, and consequently travel satisfaction will be high (Cao and Ettema, 2014). The artificial nature of the built environment has significant impact on travel satisfaction (Ye and Titheridge, 2017). These studies, however, are based on evidence drawn from cities. Moreover, while certain studies do explore suburban residents' travel satisfaction, these are limited in scope as they only consider social attributes and travel modes (Meng et al., 2013). The study by Mouratidis et al. (2019) considers urban morphology in relation to the impact of the built environment on travel satisfaction. The results reveal that the travel satisfaction of suburban residents is lower than that of city residents. Since suburban densities are lower, distances between key points are farther and the travel durations are longer. In sum, travel satisfaction research to date is mostly centered on the city. A small number of studies do consider the suburbs, and fewer studies still are based on rural areas. Moreover, most of the research explores parameters such as travel mode, time and distance, purpose of travel, traffic conditions, and travelers' attitude (Zhu and Fan, 2018b). Scant literature, however, analyzes the impact of the built environment on travel satisfaction in rural areas (Wang et al., 2020).

The built infrastructure of rural areas is significantly different from cities and suburbs. Rural areas pivot around agricultural concerns. They are characterized by market towns, or villages, and feature a predominance of agricultural industries such as farms, commercial forests, and horticulture and vegetable production. Rural towns, too, will have a more, decentralized, scattered population in comparison with that of cities (Sougoubaike, 2021). China has made great efforts to build up rural areas in recent years, and has improved rural roads and public transport services as a means of rural revitalization and poverty alleviation (Zhao and Yu, 2020). Although in recent years, the volume of travel satisfaction studies focusing on Chinese cities has increased (Ye and Titheridge, 2017; Zhu and Fan, 2018a,c; Zhao and Li, 2019), rural areas have long been overlooked. Rural population density is relatively low, but the travel distances are relatively high. Furthermore, public transportation services are scarce in such areas (Zhao and Yu, 2020). Along with rapid urbanization, China's rural areas are fundamentally changing (Ding, 2007), and the emerging reshaped countryside is transforming traditional scattered locales into centralized communities, resulting in shortened distance between households. The rapid reconstruction of rural areas has led to dramatic change in rural built environment. The construction of infrastructure and roads around villages imposes major changes on local, rural traffic conditions, typically making it more convenient for residents to commute between towns and cities. However, it is not apparent that changes to the rural built environment necessarily guarantee an improved travel experience for rural residents. On the other hand, transport planning needs to respond to the expectation and perception of travelers as key stakeholders (Yang, 2018). Investigating the travel preferences of rural residents can improve understanding of rural residents needs and preferences, and provide a "grass-roots" traffic policy reference for future rural planning.

This study therefore takes samples out of the top 100 recognized rural areas in Sichuan Province of China as the study context to explore the influence of the rural built environment on travel satisfaction of rural residents. Subjective perceptions of the built environment are recognized as influencing factors. At the same time, travel related variables (travel preference, and travel mode choice) are also considered as objective variables. The following aspects are investigated: (1) The factors affecting rural residents' travel satisfaction under the existing rural built environment; (2) The relationship between the built environment and rural residents' travel satisfaction; (3) The influence of subjective variables of the built environment and travel preference on travel satisfaction; and (4) Path analysis of the impact of various variables on travel satisfaction.

The remainder of this paper is arranged as follows. See section "Literature Review" reviews the relevant literature. See section "Methodology" presents the main research method of this paper, including the construction of a structural equation theory model, sample village selection, data collection, and variable descriptions. See section "Results and Discussion" provides the modeling results. See section "Conclusion and Policy Implications" concludes the paper and lists policy implications.

LITERATURE REVIEW

Most existing studies classify the influencing factors of travel satisfaction into four categories: socio-demographic factors, travel-related variables, travel attitude, and the built environment (Wang et al., 2020). The following sub-sections review these determinants.

Effects of Socio-Demographic Factors on Travel Satisfaction

Scholars usually use disaggregate models to scrutinize the impact of socio-demographic factors (e.g., gender and income) on travel satisfaction. Their findings are mixed, even conflicting. Zhu and Fan (2018c) found that the satisfaction of male commuters is slightly higher than that of female counterparts, which is consistent with St-Louis et al. (2014). However, some scholars believe that travel satisfaction and gender have no statistical correlation (Carrel et al., 2016). Good health will lead to high travel satisfaction (Zhu and Fan, 2018c), and residents with poor health have low travel satisfaction (Zhu and Fan, 2018a). Personal income is adversely related to travel satisfaction, where high-income people have low travel satisfaction (Meng et al., 2013); De Vos et al. (2016) indicated that older adults have high travel satisfaction, and the number of private cars and driving licenses have significant positive impacts on travel satisfaction.

Impacts of Travel-Related Variables on Travel Satisfaction

Travel satisfaction, as a subjective experience, is evidently related to travel mode (De Vos et al., 2016; Ye and Titheridge, 2017). Travel mode affects travel satisfaction, and travel satisfaction affects the residents' choice of transportation means (Diana, 2011). Non-motorized travelers (walkers and cyclers) have the highest level of travel satisfaction (Olsson et al., 2013; St-Louis et al., 2014; De Vos et al., 2016). Motorists have a slightly lower travel satisfaction level. Public transport users (bus, subway) have the lowest travel satisfaction (Ettema et al., 2011; De Vos et al., 2015); Li et al. (2019) found that the more satisfied people are with public transportation services, the more likely they will choose public transportation. Travel time is also a factor affecting travel satisfaction. The long travel times caused by traffic congestion adversely impacts travel satisfaction (Turcotte, 2011; Olsson et al., 2013).

Impacts of the Built Environment on Travel Satisfaction

Generally, the built environment is measured by density, diversity, design, public transport accessibility, and destination accessibility for their impacts on travel behavior (Ewing and Cervero, 2010). Some of its measurement indices, such as building density and road density, can reflect the degree of infrastructure construction, to a certain extent (Ao et al., 2018). The built environment can also affect the choice of residents' travel mode. People prefer to walk more (Cervero et al., 2016) and reduce private car travel in areas with high building density or good accessibility (Ding et al., 2014; Yang et al., 2021). However, residents in the suburbs might choose to drive more because of the greater distances and reduced accessibility (Eck et al., 2005). The above research confirms that the built environment will affect the travel mode, and the travel mode will affect the travel satisfaction. Therefore, there may be a certain connection between the built environment and travel satisfaction. However, there are few studies on the impact of built environment on travel satisfaction (Wang et al., 2020). Study by Ye and Titheridge (2017) confirmed that built environment indicators indirectly affect travel satisfaction through the choice of their travel mode preference, and environmental preference. A second study by Mouratidis et al. (2019) also confirmed the indirect impact of the built environment. The greater the neighborhood density, the shorter the travel duration, with the result that people are more likely to choose to walk, leading to a higher level of travel satisfaction. Contrariwise, the farther away from major hubs or city centers, the longer the travel time, and the more inclined people are to choose to drive, resulting in lower travel satisfaction. Even though there is a direct link between the built environment and travel satisfaction, the causal relationship between them still needs further research.

Impacts of Travel Attitude and Built Environment Perception on Travel Satisfaction

Although people's attitude toward a certain mode of travel does not consistently affect travel satisfaction, their travel satisfaction will increase when choosing travel mode with a positive attitude. The positive evaluation of a certain travel mode might increase the possibility that the mode will be selected on the next trip (De Vos et al., 2016). People's perception of the built environment, such as accessibility perception, public transport perception, and positive/negative emotions toward travel, will directly or indirectly affect satisfaction (Li et al., 2012). They believed that people who have a positive attitude to travel have high travel satisfaction, and those who have a positive attitude to public transportation, walking, and driving have a higher travel satisfaction than those who prefer bicycle travel. People's different perception of accessibility will affect their choice of travel mode and travel satisfaction. Many people living in the city will still prefer a residence with good bus accessibility if they cannot afford to buy a private car (Wang and Lin, 2014). Good public transport accessibility is conducive to increasing positive emotions of those who choose to travel by public transport (Xiong and Zhang, 2014). Even the degree of greenery experienced has a positive impact on travel satisfaction and drivers' mood (Yan et al., 2007; Ye and Titheridge, 2017). We can see from the existing literature that attitude and perception can affect travel satisfaction. As a subjective factor of the built environment, the built environment perception is affected by the built environment. Therefore, when the built environment affects the travel satisfaction, it may first affect the built environment perception and then affect the travel satisfaction, but this inference needs to be confirmed by empirical studies. Therefore, studying the impacts of built environment accessibility on travel satisfaction from the subjective and objective perspectives is necessary (Zhao and Li, 2019).

Travel Research in Rural China

Most empirical travel satisfaction studies in China focus on cities, particularly large cities. With increasing new rural construction and the ongoing urbanization process, a handful of scholars have conducted travel research in rural China, while travel satisfaction research has yet to be reported. Previous studies analyzed the influencing factors of rural residents' travel mode, destination choice, and travel carbon emissions, concluding the following: Rural residents in economically developed areas make many trips of short distances and duration (Yang et al., 2014). The shorter the travel distance, the higher probability of using a private car (Feng et al., 2010). The longer the travel distance, the greater the impact of travel distance on destination choice (Yang et al., 2013). A positive correlation is found between new rural building density (and road density) and the number of vehicles in rural households, and the higher the building density, the more people will choose to travel by car or electric bicycle. The closer the destination, the more rural residents will decide to go on foot (Ao et al., 2020a,b) and the lower the average daily travel CO_2 emission (Ao et al., 2019a,b; Wang et al., 2019). The acceptable cycling distance of rural residents will be increased where special bicycle lanes are provided in rural areas. Rural residents mainly choose public transportation, electric bicycles, and walking. The level of service of buses is low, and so this needs to be improved (Zheng and Chen, 2017; Zhao and Yu, 2020). Overall, however, few studies exist on the travel satisfaction of rural residents (Meng et al., 2013).

From the existing literature, on the one hand, there is little literature on travel and travel satisfaction in rural areas. The great changes in China's rural built environment do not necessarily guarantee the improvement of rural residents' travel experience. On the other hand, although the existing literature has confirmed that there is a certain relationship between socio-demographic variables, built environment, travel mode, and travel satisfaction, there is also a mutual influence relationship between various variables. For example, sociodemographic factors and built environment affect the choice of travel mode, and travel mode affects travel satisfaction. However, there is little literature on how various variables affect travel satisfaction and the causal relationship between them.

METHODOLOGY

Model Specification

Travel satisfaction mainly refers to travelers' subjective feelings (Gao et al., 2017b) and is affected by travel mode choice, travel time, distance, and other travel-related variables. Travelers' perception of the built environment, travel attitudes, and preferences will affect their travel satisfaction (Ye and Titheridge, 2017), and the perception of the environment and their travel attitude preferences will affect the choice of travel modes to some extent. At present, Sichuan's rural areas are experiencing rapid urbanization. On the one hand, the built environment is constantly evolving, and its impact on residents' travel satisfaction requires attention. On the other hand, the perception of the environment is directly affected by the objectively measurable features of the built environment and given this is changing, so is the perception of the built environment of rural residents. The built environment perception and travel attitude vary from person to person. Different individuals have different understandings of the environment with various travel preferences, thereby resulting in different travel modes and travel satisfaction (Cao et al., 2006). The choice of travel mode and travel satisfaction will be directly affected by built environment attributes (Etminani-Ghasrodashti and Ardeshiri, 2015; Sun and Dan, 2015).

Kim et al. (2014) proposed that a general regression model is insufficient to solve the complex causality. Thus, this paper uses path analysis to analyze the direct, indirect, and total impacts among variables. The conceptual framework of this study is shown in **Figure 1**.

Sample Selection and Data Collection

Sample Selection

Sichuan Province is located in the hinterland of Southwest China, with an urbanization rate of 52.29% at the beginning of 2019. With the advancement of urbanization, its rural economy is constantly improving (Ao et al., 2021). Statistics show that the construction of transportation facilities in Sichuan Province has amounted to ¥1030 billion during the 13th Five-Year Plan period, which is 1.23 times higher than the 12th Five-Year Plan period. At present, the access rate of hardened roads in the built villages[1] has reached 100%, and the newly rebuilt rural roads have reached 97,000 km (Sichuan Provincial People's Government, 2017). At the end of 2018, the total mileage of rural roads in the province has reached 286,000 km, ranking first in the country. In 2017, the Sichuan provincial government published the list of Top 100 villages to show the development of rural areas (**Figure 2**), in which 25 villages in Chengdu are designated.

All Chengdu's Top 100 villages are selected as the study area for the following two reasons: (1) Chengdu is the capital city of Sichuan Province and has transformed into a new first-tier city in China. According to the Sichuan Bureau of Statistics, the urbanization rate of Chengdu has reached 71.85% at the beginning of 2018, and it is predicted to reach 77% (Sichuan Provincial People's Government, 2016) in 2020, which tops in the provincial list. In 2018, the regional gross domestic product reached ¥1534.277 billion (Chengdu Bureau of Statistics, 2019). The number of demonstration villages in Chengdu accounts for one-fourth of the provincial total. (2) The Top 100 villages in Chengdu are prioritized in terms of transportation infrastructure investment. Rural residents have relatively many abundant travel facilities, thereby providing a good foundation in this study. In 2019, the cumulative investment in Chengdu's transportation infrastructure will be ¥35.322 billion, including ¥210.241 million for highway construction projects (Bureau, 2019b). Among the third batch of "four good rural roads" provincial demonstration counties in Sichuan, Chengdu has added three new demonstration county-level cities. In recent years, the mileage of rural roads in Chengdu has reached 24,795 km, and the density of rural roads has reached 172 km/100 km^2. For the construction of "four good rural roads," more than 9,800 km of new rural road reconstruction projects have been completed, covering all towns, villages, and groups in the city. In addition, Chengdu has built 61 township-level passenger stations, 253 townships, and 3,747 villages (communities) to achieve bus access, and the bus accessibility rate is 98% (Bureau, 2019a). Therefore, the Top 100 villages in Chengdu are the typical representatives of new rural development in Western China.

The selection of sample villages follows three basic principles: (1) Random selection: Twelve out of the 25 villages in Chengdu are randomly selected as basic sample villages (in the list of the Top 100 villages in Sichuan Province) (Qingshuiqiao Village, Wenquan Community, Qinggangshu Village, Wuxing Village, Shibawan Village, Youqing Community, Lianghe Village, Xingfu Village, Mingyue Village, Renhe Community, Lantian Community, and Lantiansi Village). (2) All-round coverage of geographical location: The final selected sample village needs to take the center of Chengdu (Tianfu Square) as the reference point, and the Top 100 villages as research representatives in southeast, northwest, and other directions need to be around the center. ArcGIS 10.2 is used to mark the geographical location of each Top 100 place on the map, as shown in **Figure 3**. The three sample villages (Hot Spring Community, Youqing Community, and Xingfu Village) in part are relatively concentrated, and the three relatively intensive sample villages are eliminated. (3) Effectively conduct the questionnaire survey into villages and households and presurvey based on the remaining nine Top 100 villages and clarify the villagers' willingness to participate in the questionnaire survey. In accordance with the rejection degree of local residents to the questionnaire survey, three sample villages (Mingyue Village, Lianghe Village, and Renhe Community) are removed from our candidate list. Eventually, six sample villages are determined, which are located in the north of Chengdu City:

[1]The villages established with the approval of provincial and municipal state organizations are called organic villages.

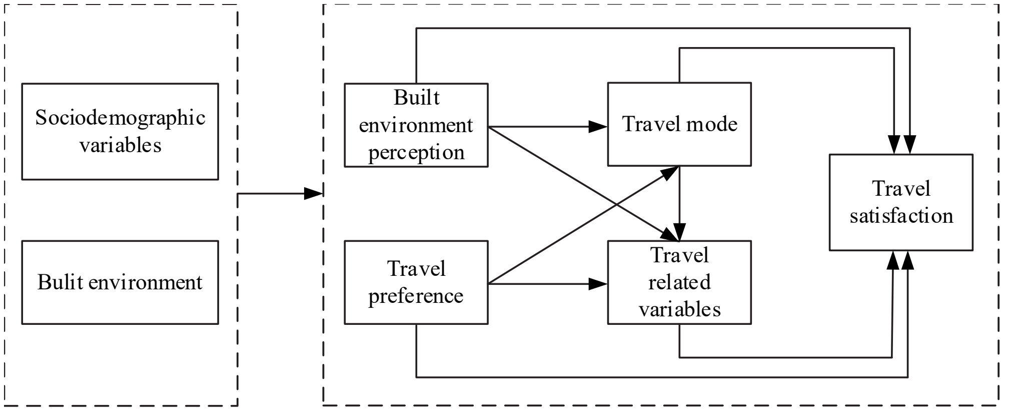

FIGURE 1 | The conceptual framework.

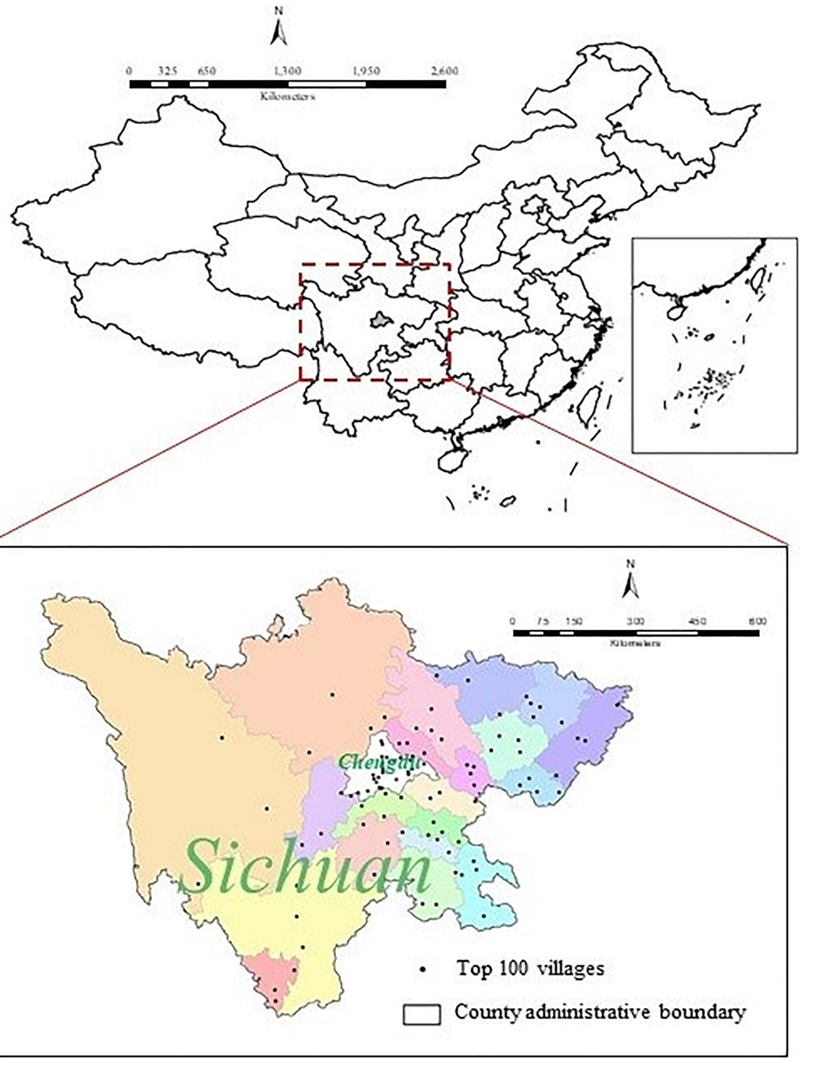

FIGURE 2 | Geographic location of top 100 villages in Sichuan Province.

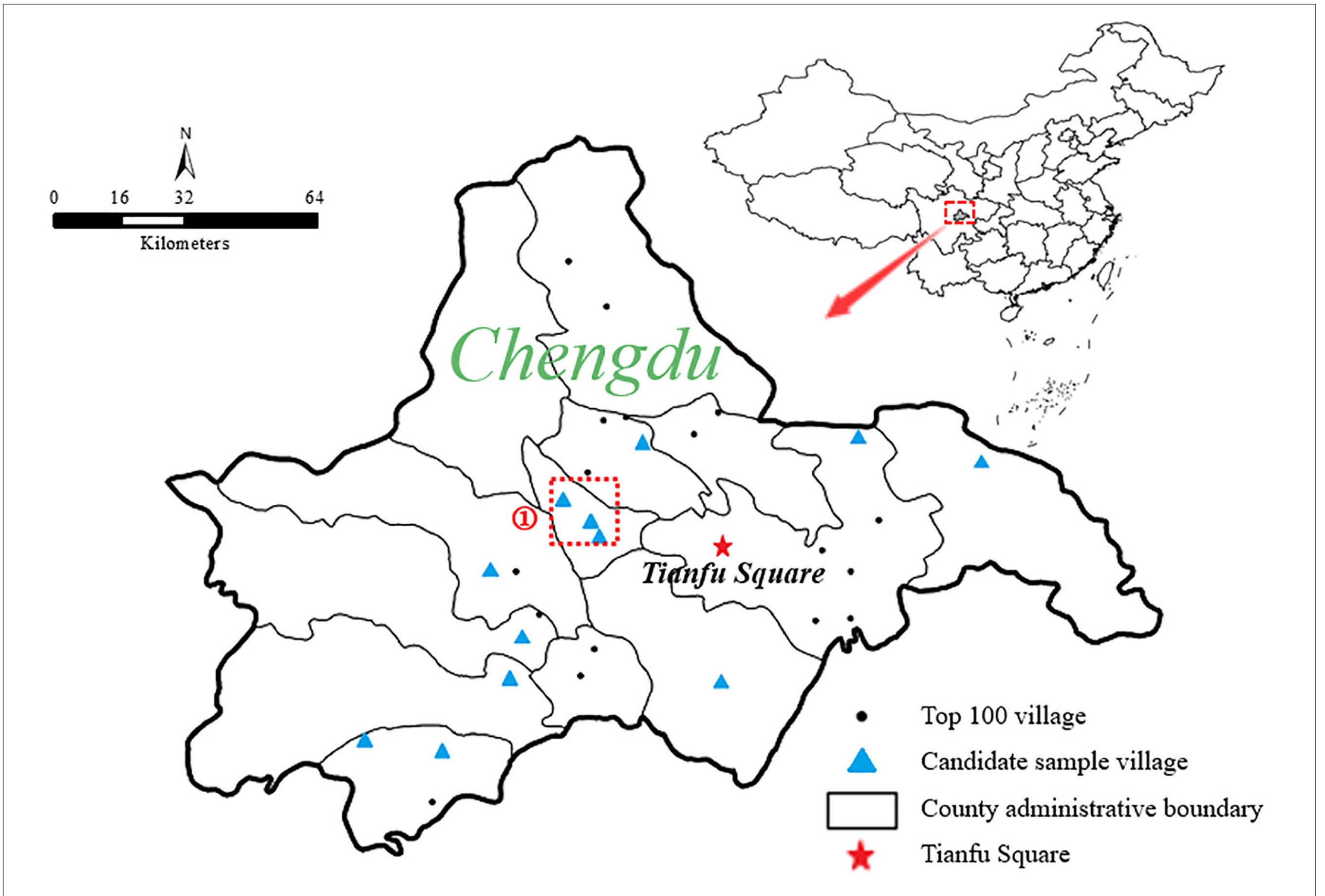

FIGURE 3 | Geographical distribution of first randomly selected sample villages.

Qinggangshu Village in Pidu District and Pingshuiqiao Village in Jintang County. The sample villages are Lantiansi Village in Shuangliu District in the south, Wuxing Village in Chongzhou City, Lantian Community in Dayi County in the west, and Shibawan Village in Qing Baijiang in the east. The geographical locations of sample villages are shown in **Figure 4**.

Data Collection

The research team recruited 12 graduate students of Chengdu University of Technology as questionnaire investigators. The research team organized questionnaire survey training and work assignment meetings to conduct an effective questionnaire survey. On the basis of the geographical location of sample villages, the researchers are divided into two teams, where each team has six people and visit three villages. During the investigation, the researchers take the village committee or the villagers' activity center as the center for conducting a divergent visit to village residents and randomly select villagers as the research objects in conducting household investigations to ensure that the respondents are evenly distributed. Stratified sampling was used, where 50 or 100 sample households were randomly visited in sample villages of less than 1,000 households or of 1,000 to 2,000 households, respectively (Zhao and Li, 2019). In the process of filling in the questionnaire, a small number of residents did not complete the form, being interrupted by chores, visitors or being called on to fulfill other activities. The final number of investigated households is listed in **Table 1**. In this survey, 591 questionnaires were collected. After eliminating invalid questionnaires, 585 valid questionnaires were retained. Effective rate of questionnaire completion was 98.98%.

Variable Specification

Scale of Satisfaction (STS) Variables

Scale of satisfaction is proposed by Ettema et al. (2011) and includes two levels of cognition and emotion. Nine questions are found in the STS, and each question scores from −3 to 3. The items of STS and the meaning of the scores are shown in **Table 2**.

On the basis of the preliminary statistical analysis, the scores of rural residents on travel satisfaction are concentrated in 0 and 1, and the proportion of negative evaluation on travel satisfaction is extremely small. The scores of each item are shown in **Figure 5**. The average score of STS scale is calculated and used in path analysis.

Socio-Demographic Variables

Socio-demographic variables have a significant impact on residents' travel satisfaction (Meng et al., 2013;

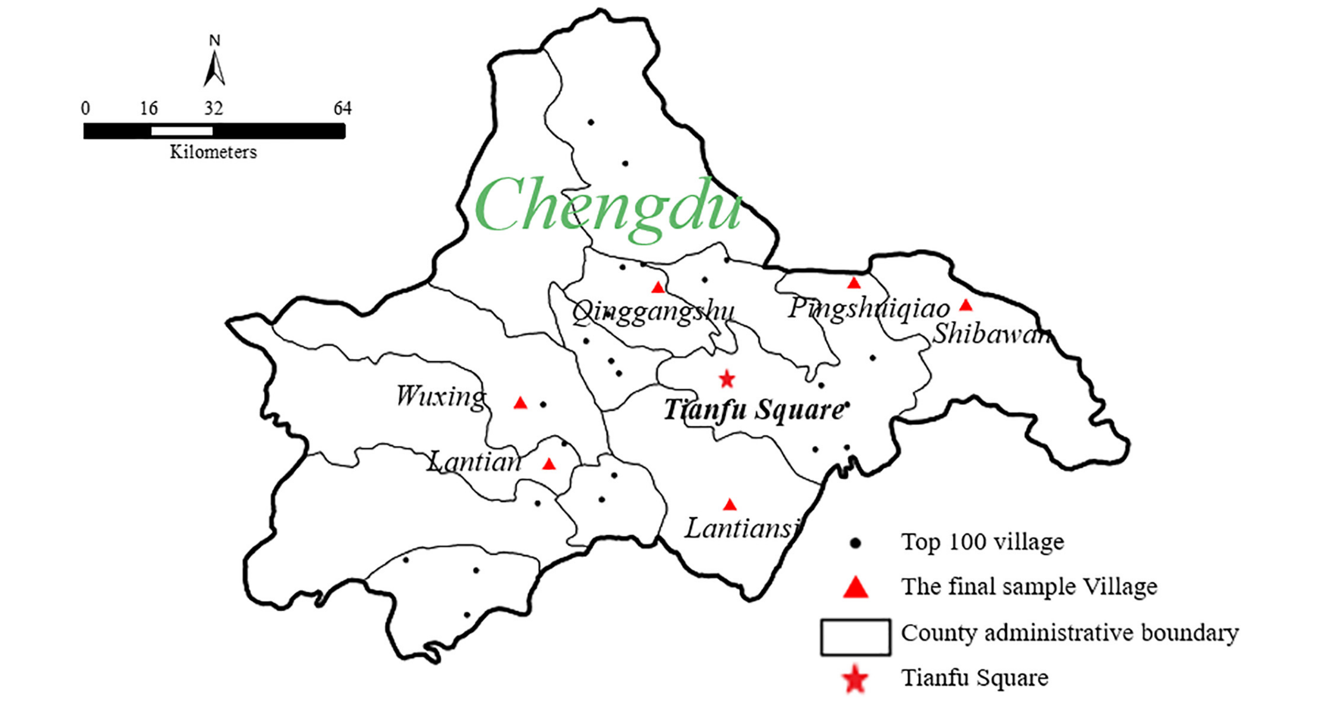

FIGURE 4 | Geographical distribution of the final selected sample villages.

TABLE 1 | Basic data of samples.

Village name	Total number of households in the village	Number of random survey households	Number of valid questionnaires	Effective sampling proportion
Wuxing	873	117	115	13.17%
Lantian	983	131	128	13.02%
Lantiansi	1,209	103	102	8.44%
Qinggangshu	932	80	80	8.58%
Shibawan	1362	80	80	5.87%
Pingshuiqiao	1,520	80	80	5.26%

St-Louis et al., 2014; Carrel et al., 2016; De Vos et al., 2016; Zhu and Fan, 2018a,c). Socio-demographic variables considered mainly include gender, age, registered residence type, annual personal income, education level, health status, and annual family income.

The preliminary statistical analysis shows that no significant difference is found in the sex ratio of the respondents, and 37.9% of the total respondents in rural areas are more than 60 years old. In China's rural areas, no higher education institutions are found, students choose to study outside, and farming is the main income source. Most of the labor force prefers to work outside the home, resulting in an extremely old rural average age. Regarding the education level, respondents with a junior high school degree and below accounts for 80.2%. In the survey sample, the average education level is low because the respondents are old, and the corresponding education level is low. The highest percentage of respondents' annual income ranges from ¥10000 to ¥50000. Among the respondents, the health condition of rural residents is good, and 96.8% of rural residents have rural registered residence. The socio-demographic variables of the respondents are consistent with the actual situation of rural areas in Chengdu. The detailed socio-demographic information of the respondents are shown in **Table 3**.

Built Environment Variables

On the basis of existing research (Ye and Titheridge, 2017; Ao et al., 2019a,b; Zhao and Li, 2019), the built environment indexes considered in this study include building density, road density, population density, the number of accessible markets, and destination accessibility. The calculation scope of the built environment measurement index is a buffer of 1 km around the center of the village (in the activities of the village committee or residents). ArcGIS 10.2 is used to extract the data of building area and road length, and the population density and the number of accessible markets are obtained from village leaders. For the destination accessibility, the researchers used OvitalMap to locate the residents and accurately obtained the distance from the residents to the market, school, health center, and town center. **Table 4** shows the built environment data of each village. The distribution of interviewees, buildings, and roads is shown in **Figure 6**.

Built Environment Perception and Travel Preference Variables

The perception of the built environment and travel preference are mainly referenced by De Vos et al. (2016),

TABLE 2 | Scale of satisfaction (STS).

Cognitive evaluation		My daily travel was worst (−3) – best I can think of (3) My daily travel was low (−3) – high standard (3) My daily travel poorly worked (−3) – worked well (3)
Emotion	Positive deactivation – negative activation	I feel my daily travel time is pressed (−3) – relaxed (3) I am worried that I would not be in time (−3) – confident I would be in time (3) I am stressed (−3) – calm (3)
	Positive activation – negative deactivation	I am tired (−3) – alert (3) Bored (−3) – enthusiastic (3) I am fed up (−3) –engaged (3)

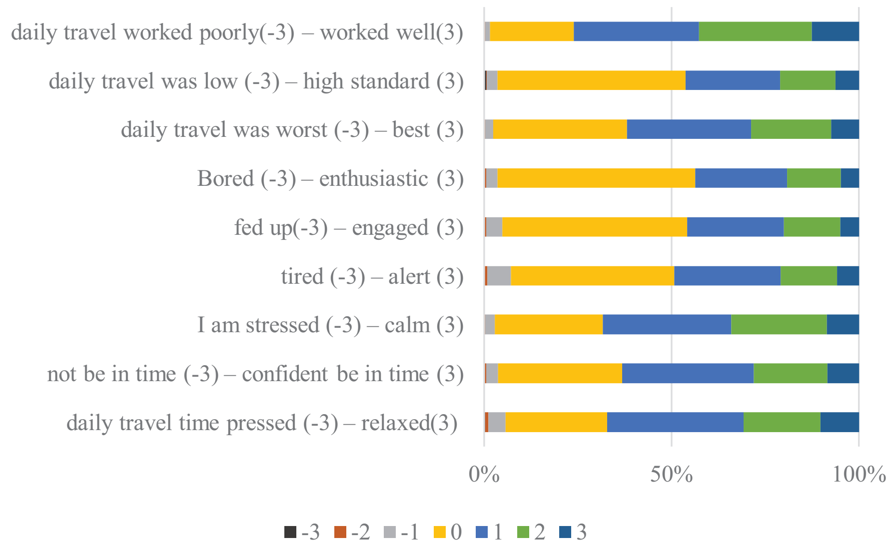

FIGURE 5 | Travel satisfaction score.

Ye and Titheridge (2017), and Ao et al. (2019b). Five variables are used in the perception of the built environment, and eight variables are applied in travel preference. In accordance with the perception of the built environment and preference for the travel mode of the respondents, they were asked to use the five-point Likert scale for determining the degree of recognition of the 13 items from 1 to 5 (Yang et al., 2020). SPSS 23.0 is used to analyze the factors of perception of the built environment and travel preference. The results show that the *p*-value is 0.000, and the KMO value is 0.840, which are suitable for factor analysis. Maximum variance rotation is used to rotate the factor matrix because the initial load structure is unclear. The cumulative interpretation variance ratio of common factors is 90.061%, and two common factors, namely, accessibility perception factor and infrastructure perception, are extracted from five variables, as shown in **Table 5**. The result of factor analysis for travel preference shows that the *p*-value is 0.000, and the KMO value is 0.788. The factor matrix is rotated through maximum variance rotation, and the cumulative interpretation variance ratio of common factors is 60.472%. Two common factors, namely, prefer own transport and prefer walking and public transport, are extracted from eight variables, as shown in **Table 6**.

Daily Travel Mode Variables

The question for recording the travel mode of respondents is "what is the most common transportation to choose for your daily travel?" The commonly used travel modes of rural residents are electric bicycles (38.8%) and walking (24.6%). Electric bicycles have a flexible body, simple operation, and low economic burden, making them preferable by rural residents. With the improvement on the living standards of rural residents, the proportion of using cars (18.5%) ranks second to electric bicycles and walking. The probability of choosing public transport[2] (6.6%), motorcycles (4.8%), tricycle (3.1%), bicycles (2.7%), and other modes (0.9%) is less than 10%.

Satisfaction With Daily Travel Mode

The respondents have been asked to use the seven-point Likert scale to express their satisfaction with daily travel mode, where 1 indicates very dissatisfied, and 7 indicates very satisfied. The results show that rural residents are fairly satisfied with their daily travel mode, with the total proportion of most satisfied

[2]Public transport here refers to rural buses and small and medium-sized buses in villages and towns.

TABLE 3 | Socio-demographic variables.

Variable		Frequency	Percentage
Gender	Male	285	48.7
	Female	300	51.3
Annual personal income	0	172	29.4
	Less than ¥10,000	88	15.0
	¥10,000–50,000	270	46.2
	¥50,000–100,000	43	7.4
	¥100,000–150,000	9	1.5
	More than ¥150,000	3	0.5
Education level	Primary school and below	301	51.4
	Junior middle school	168	28.7
	High school (technical secondary school)	66	11.3
	Junior college	34	5.8
	Undergraduate	15	2.6
	Postgraduate and above	1	0.2
Health condition	Very bad	3	0.5
	Bad	61	10.4
	Common	146	25.0
	Healthy	254	43.4
	Very healthy	121	20.7
Registered residence type	Rural registered residence	566	96.8
	Urban registered residence	19	3.2
Annual family income	Less than 10,000	22	3.7
	10,000–50,000	311	53.2
	50,000–100,000	197	33.7
	100,000–150,000	33	5.6
	150,000–200,000	12	2.1
	More than 200,000	10	1.7
Age	Under 20 years old	11	1.9
	20–29 years old	33	5.7
	30–39 years old	52	8.9
	40–49 years old	110	18.8
	50–59 years old	157	26.8
	60–69 years old	120	20.5
	Over 70 years old	102	17.4

(9.7%), very satisfied (34.4%), and relatively satisfied (26.0%) accounting for 70.1%, and 23.8% of them are generally satisfied with travel mode. The total proportion of dissatisfied (5.30%), very dissatisfied (0.5%), and very dissatisfied (0.3%) is only 6.1%, in which 0.3% is very dissatisfied.

Multicollinearity Test

Before path analysis modeling, the author have tested all the variables for collinearity. In this paper, variance expansion factor (VIF) is used to test the collinearity. VIF > 10 indicates serious multicollinearity between variables (Wu, 2014), thereby affecting the model fitting (Yang et al., 2019). The VIF value of the variable in this study is less than 10, as shown in **Table 7**. No multicollinearity is found between the variables. Thus, the path analysis in the next step can be conducted.

TABLE 4 | Built environment data.

Village variables	Building density	Road density	Population density	Number of accessible markets	Average destination accessibility
Wuxing	0.108	3.958	0.651	1	1.097
Lantian	0.253	2.041	0.702	1	1.455
Lantiansi	0.037	3.050	0.835	3	0.856
Qinggangshu	0.079	2.646	0.478	1	2.056
Shibawan	0.088	2.857	0.757	1	1.699
Pingshuiqiao	0.047	3.404	0.992	1	1.819

Building density = area of construction land/total area of the research area (total area of research land: take the village committee as the center and 1 km as the radius to draw a circle for determining the scope); Road density = total length of road/total area of the study area; Population density = population/total area of the study area; Number of accessible markets: obtain the actual value of the sample village; Destination accessibility = $\Sigma_k\{1/(d_k + 1)\}$, k = 1, 2, 3, 4 (distance from home of respondents to market d_1, school d_2, health center d_3, and town center d_4) (Anowar et al., 2014; Ao et al., 2019b).

RESULTS AND DISCUSSION

In this paper, Amos21.0 has been used to build a path analysis model of influencing factors of travel satisfaction. The path relationship between the variables has been constructed and fitted in accordance with the theoretical hypothesis model in 3.1. After removing the non-significant path ($p > 0.1$) from the model fitting results, fitting has been conducted until all the paths are significant, and the model has been modified in accordance with the modified index (MI).

Analysis of Model Results

The p-value of the model is 0.001, which is significantly less than the test value of 0.05. Thus, the model is established. The chi-square is 275.588, and the degree of freedom (DF) is 203. The root mean square error of approximation (RMSEA) (0.025) is less than 0.05, indicating that the model has good suitability, and the comparative fit index (CFI) (0.984) is greater than 0.9, indicating that the model has a good acceptability. Chi-square statistics (CMIN)/DF, normed fit index (NFI), and increment fit index (IFI) values are all in line with the standard, and the model fitting parameters are shown in **Table 8**. The direct, indirect, and total Impact results of path analysis are shown in **Table 9**.

Impacts of Socio-Demographic Factors on Travel Satisfaction

As shown in **Table 9**, education level, annual family income, and annual personal income have a significant impact on travel satisfaction. The total impact of education on travel satisfaction is 0.005, indicating that the higher the education level, the higher the travel satisfaction. The path map of education level to travel satisfaction is shown in **Figure 7A**.

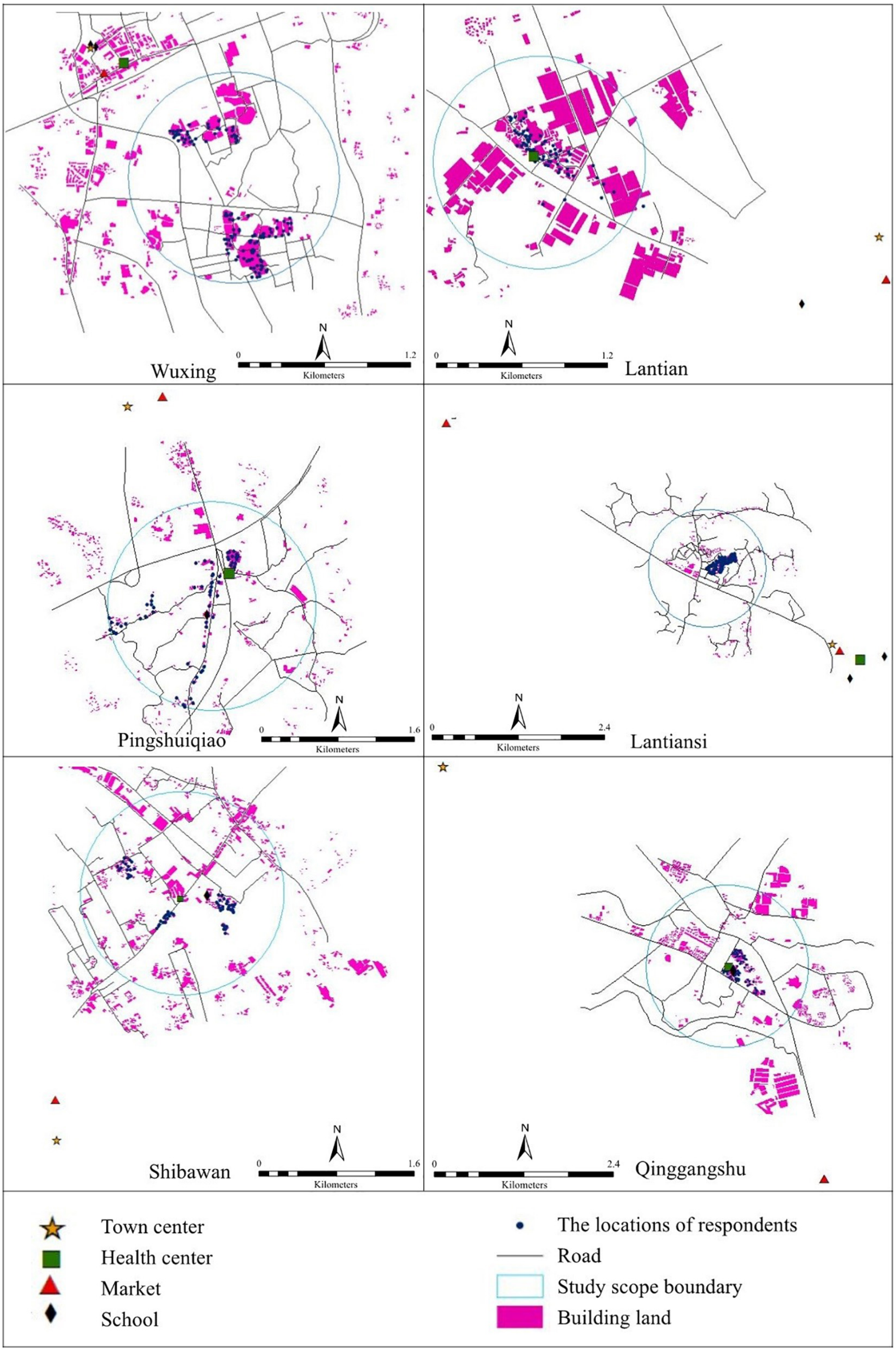

FIGURE 6 | Distribution of respondents, buildings, and roads.

TABLE 5 | Built environment perception: composition matrix after rotation.

Items	Component	
	Infrastructure perception	**Accessibility perception**
Good sidewalk for travel	**0.876**	0.41
Good bicycle lane for travel	**0.895**	0.384
Good motorway for travel	**0.814**	0.454
Convenient to reach the public transport station	0.359	**0.876**
The destination is accessible	0.468	**0.797**
Characteristic value	4.042	0.461
Variance percentage (%)	51.563	38.498
Cumulative variance percentage (%)	51.563	90.061

TABLE 6 | Travel mode preference: component matrix after rotation.

Items	Component	
	Prefer own transport	**Prefer walking and public transport**
I like driving	**0.692**	−0.223
I like to ride electric bicycle	**0.521**	0.283
I like riding motorcycles	**0.861**	−0.025
I like cycling	**0.658**	0.37
I like to drive a tricycle	**0.79**	0.06
I like other modes to travel	**0.802**	0.262
I like to take public transport	0.104	**0.777**
I like walking	0.014	**0.832**
Characteristic value	3.384	1.454
Variance percentage (%)	40.032	20.441
Cumulative variance percentage (%)	40.032	60.472

TABLE 7 | Multicollinearity test.

	Variable	VIF
socio-demographic factors	Gender	1.237
	Age	2.192
	Education level	2.211
	Registered residence type	1.172
	Annual personal income	2.091
	Annual family income	1.795
	Health condition	1.332
Built environment	Building density	7.425
	Road density	5.360
	Population density	1.446
	Number of accessible markets	6.168
	Destination accessibility	3.921
Travel mode satisfaction	Travel mode satisfaction	1.478
Daily travel mode	Car	2.609
	Motorcycle	1.380
	Electric bicycle	1.926
	Cycling	1.180
	tricycle	1.239
	Public transport	1.445
	Other travel modes	1.105
Built environment perception and travel mode preference	Accessibility perception	1.417
	Infrastructure perception	1.883
	Prefer own transport	1.533
	Prefer walking and public transport	1.676

TABLE 8 | Fitting results of SEM.

Model fitting index	Model fitting value	Standard value	Test result
CMIN/DF	1.358	<2.0	Satisfactory
P	0.001	<0.05	Satisfactory
RMSEA	0.025	<0.05	Satisfactory
NFI	0.945	>0.9	Satisfactory
CFI	0.984	>0.9	Satisfactory
IFI	0.985	>0.9	Satisfactory

Regarding gender variables, the model analysis takes women as the reference group. The results show that travel satisfaction is lower for females than for males, which is consistent with previous research (St-Louis et al., 2014; Zhu and Fan, 2018c), as shown in **Table 9**. Chinese rural women focus more on housework, resulting in less experience in travel activities (Zhao and Yu, 2020). Less travel experience combined with low satisfaction in public transport are the reasons for their overall low travel satisfaction (Gender – Travel mode satisfaction – Travel satisfaction and Gender – Public transport – Travel satisfaction negatively affect travel satisfaction), **Figure 7B**.

Age has a negative indirect impact on travel satisfaction (−0.015). **Table 9** shows that older adults' satisfaction with travel is lower than that of young people, which is contrary to the conclusion of existing scholars on cities (Cao and Ettema, 2014; Gao et al., 2017a). This finding is because many older adults are found in rural areas, and the elderly have more experience in transportation facilities than do young people. Old age limits the travel options of the elderly, resulting in low satisfaction. The main negative influence path is Age – Car – Travel mode satisfaction – Travel satisfaction, as shown in **Figure 7B**. This path shows that the older you are, the less likely you will choose to travel by car, thereby weakening the impact on travel satisfaction.

The influence of annual family income (0.128) on travel satisfaction is positive, as shown in **Table 9**. The influence of annual family income on travel satisfaction is positive, as shown in **Figure 7C**. The higher the annual household income, the higher the satisfaction of rural residents, which is consistent with Zhao and Li (2019) conclusion. Families with good economic circumstances can afford private cars (in **Figure 7C**), and the impact of annual family income on private car travel is 0.138.

TABLE 9 | Direct, indirect, and total impacts among variables.

		Socio-demographic factors						Built environment					Perception of built environment and travel preference				Travel mode		Travel mode satisfaction
		Education level	**Annual family income**	**Age**	**Gender**	**Health condition**	**annual personal income**	**Number of accessible markets**	**Road density**	**Building density**	**Population density**	**Number of accessible markets**	**Prefer walking and public transport**	**Infrastructure perception**	**Accessibility perception**	**Prefer own transport**	**Car**	**Public transport**	**Travel mode satisfaction**
Prefer walking and public transport	Total	/	/	/	/	/	/	0.571***	0.568***	0.701***	−0.118***	0.17**	/	/	/	/	/	/	/
	Direct	/	/	/	/	/	/	0.571***	0.568***	0.701***	−0.118***	0.17**	/	/	/	/	/	/	/
	Indirect	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
Infrastructure perception	Total	0.096***	/	/	/	/	/	0.665***	0.63***	0.801***	−0.21***	0.136***	/	/	/	/	/	/	/
	Direct	0.096***	/	/	/	/	/	0.665***	0.63***	0.801***	−0.21***	0.136***	/	/	/	/	/	/	/
	Indirect	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
Accessibility perception	Total	0.101**	/	/	/	0.092**	−0.084**	/	/	/	−0.305***	−0.152***	/	/	/	/	/	/	/
	Direct	0.101**	/	/	/	0.092**	−0.084**	/	/	/	−0.305***	−0.152***	/	/	/	/	/	/	/
	Indirect	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
Prefer own transport	Total	0.178***	/	−0.174***	−0.069*	/	0.234***	/	/	0.262***	0.093**	0.072**	/	/	/	/	/	/	/
	Direct	0.178***	/	−0.174***	−0.069*	/	0.234***	/	/	0.262***	0.093**	0.072**	/	/	/	/	/	/	/
	Indirect	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
Car	Total	0.204**	0.138***	−0.156***	−0.1***	0.057*	0.191**	−0.029	−0.032	−0.037	/	−0.014	−0.146***	0.081**	/	/	/	/	/
	Direct	0.196**	0.138***	−0.156***	−0.1***	0.057*	0.191**	/	/	/	/	/	−0.146***	0.081**	/	/	/	/	/
	Indirect	0.008**	/	/	/	/	/	−0.029*	−0.032	−0.037	/	−0.014	/	/	/	/	/	/	/
Public transport	Total	/	/	/	0.081**	0.119***	−0.143***	/	−0.422***	−0.502***	/	−0.301***	/	/	/	/	/	/	/
	Direct	/	/	/	0.081**	0.119***	−0.143***	/	−0.422***	−0.502***	/	−0.301***	/	/	/	/	/	/	/
	Indirect	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
Other	Total	0.088**	/	/	/	/	/	/	/	/	/	/	/			/	/	/	/
	Direct	0.088**	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
	Indirect	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
cycling	Total	/	/	/	/	/	−0.125***	0.048	0.048	0.219***	−0.01	0.014	0.084**	/	/	/	/	/	/
	Direct	/	/	/	/	/	−0.125***	/	/	0.159***	/	/	0.084**	/	/	/	/	/	/
	Indirect	/	/	/	/	/	/	0.048	0.048	0.059***	−0.01	0.014	/	/	/	/	/	/	/
tricycle	Total	/	/	/	/	/	/	−0.06	−0.06	0.173***	0.012	−0.11***	−0.105***	/	/	/	/	/	/
	Direct	/	/	/	/	/	/	/	/	0.247***	/	−0.092***	−0.105***	/	/	/	/	/	/
	Indirect	/	/	/	/	/	/	−0.06	−0.06	−0.074***	0.012	−0.018***	/	/	/	/	/	/	/
Electric bicycle	Total	−0.131***	/	−0.025	−0.01	/	0.033	/	0.109**	0.145**	0.013	0.109***	/	/	/	0.142***	/	/	/
	Direct	−0.157***	/	/	/	/	/	/	0.109**	0.108**	/	0.099***	/	/	/	0.142***	/	/	/
	Indirect	0.025***	/	−0.025	−0.01	/	0.033	/	/	0.037**	0.013	0.01***	/	/	/	/	/	/	/

(Continued)

TABLE 9 | (Continued)

		Socio-demographic factors						Built environment					Perception of built environment and travel preference				Travel mode		Travel mode satisfaction
		Education level	Annual family income	Age	Gender	Health condition	annual personal income	Number of accessible markets	Road density	Building density	Population density	Number of accessible markets	Prefer walking and public transport	Infrastructure perception	Accessibility perception	Prefer own transport	Car	Public transport	Travel mode satisfaction
Motorcycle	Total	0.004	/	−0.017	−0.095**	/	0.022	−0.148	−0.143	−0.155	0.049	−0.029	−0.103**	−0.134***	/	0.095**	/	/	/
	Direct	/	/	/	−0.089**	/	/	/	/	/	/	/	−0.103**	−0.134***	/	0.095**	/	/	/
	Indirect	0.004	/	−0.017	−0.007**	/	0.022	−0.148	−0.143	−0.155	0.049	−0.029	/	/	/	/	/	/	/
Travel mode satisfaction	Total	0.067	0.01	−0.011	−0.081**	0.028	−0.141***	0.061***	0.23	0.29	−0.243**	−0.143***	0.09**	0.284***	0.256***	/	0.072*	/	/
	Direct	/	/	/	−0.073**	/	−0.133***	−0.179***	/	/	−0.095**	−0.158***	0.1**	0.278***	0.256***	/	0.072*	/	/
	Indirect	0.067	0.01	−0.011	−0.007**	0.028	−0.008***	0.24***	0.23	0.29	−0.148**	0.015***	−0.01**	0.006***	/	/	/	/	/
Travel satisfaction	Total	0.005*	0.128***	−0.015	−0.033	0.019	−0.112**	0.314***	0.569***	0.609***	−0.171	−0.018	0.025	0.298***	0.278***	0.07*	0.02	−0.063*	0.281***
	Direct	−0.069*	0.125***	/	/	/	−0.081**	0.152***	0.34***	0.303***	/	/	/	0.218***	0.207***	0.07*	/	−0.063*	0.281***
	Indirect	0.073*	0.003***	−0.015	−0.033	0.019	−0.031**	0.162***	0.229***	0.306***	−0.171	−0.018	0.025	0.08***	0.072***	/	0.02	/	/

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Rural areas are far away from markets and urban areas. Thus, private car travel is convenient and fast, thereby increasing travel satisfaction.

Rural residents in good health (0.019) have high travel satisfaction, as shown in **Table 9**. The route map (**Figure 7D**) shows that residents with a better physical condition have high accessibility awareness, and the probability of choosing to drive or using public transport is high. Annual personal income has a negative impact on travel satisfaction (−0.112), as shown in **Table 9**. In accordance with the path map (**Figure 7E**), annual personal income has a negative impact through the path annual personal income – Travel mode satisfaction – Travel satisfaction, and the direct negative impact of annual personal income on travel satisfaction (−0.081) increases.

In general, the impact of social demographic attributes on travel satisfaction is small, with education notably so (0.005).

Impact of Built Environment Variables on Travel Satisfaction

Among the built environment variables, building density, road density, and the number of accessible markets have significant impacts on rural residents' travel satisfaction (**Table 9**). In this study, building density has a significant positive impact on people's travel satisfaction, and the total impact is 0.609. Rural building density represents the degree of new construction manifest in the countryside, where the increase in building density can immensely improve residents' perception of infrastructure (0.801) and pedestrian bus preference (0.701) (**Figure 8A**). Change in rural urbanization and an increase in construction will improve the travel satisfaction of residents. In the study of Ye and Titheridge (2017), the built environment index has an indirect impact on travel satisfaction through travel mode and other travel variables, which is basically consistent with the conclusion of this paper.

The total impact of road density on travel satisfaction is 0.569, as shown in **Table 9**. The impact of road density on infrastructure perception is positive, with a value of 0.63 (**Figure 8B**). This finding shows that the greater the number of rural roads, the better people's perception of infrastructure, and the higher satisfaction with travel. Similarly, many roads provide rural residents with greater travel convenience, where the range of travel options is greater, which can effectively improve residents' travel satisfaction. In **Figure 8B**, the path Road density – Prefer walking and public transport – Travel mode satisfaction – Travel satisfaction shows that the increase in the number of roads makes greater road network density better meet people's walking preference to improve the satisfaction of rural residents' travel mode and travel satisfaction.

Destination accessibility does not directly affect rural residents' travel satisfaction but indirectly affects travel satisfaction through other variables. The total impact is −0.018 (**Table 9**), which is contrary to the conclusion of certain scholars studying the city (Woldeamanuel and Cyganski, 2011). This condition may be explained by the following: Although the new rural built environment has objectively created better travel conditions for rural residents or has achieved the goal of

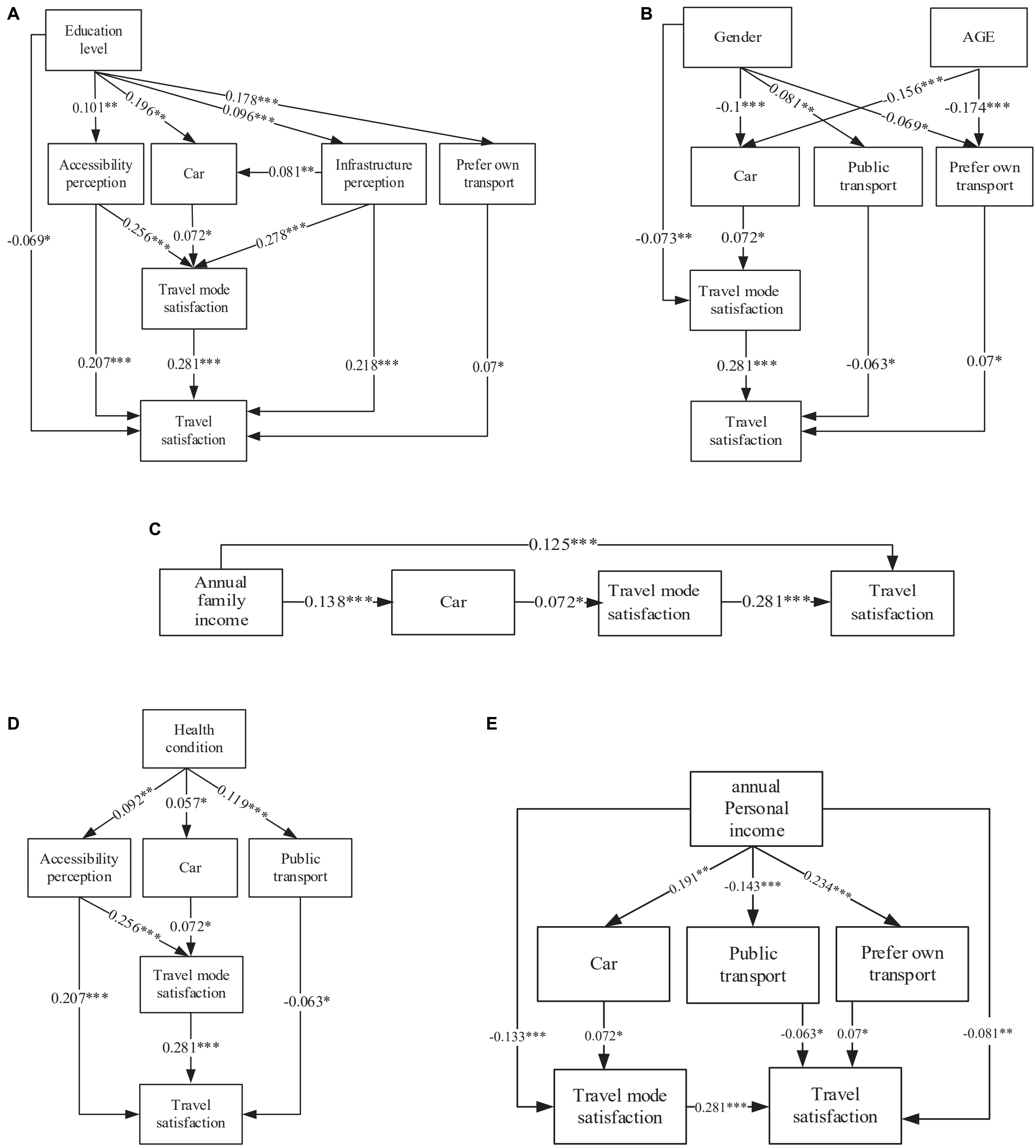

FIGURE 7 | (A) Education level. **(B)** Gender and age. **(C)** Annual family income. **(D)** Health condition. **(E)** Annual personal income. ***Represents *p* value < 0.01, **Represents *p* value < 0.05, and *Represents *p* value < 0.1.

destination accessibility in theory, a deviation is found from the actual accessibility perception of residents (path Destination accessibility – Accessibility perception – Travel satisfaction) (**Figure 8C**). Although the rural areas are still far away from the urban areas or some limitations are found in the choice of travel modes, the actual accessibility will weaken the satisfaction of rural residents to the travel modes they use, thereby causing a negative impact on travel satisfaction (path Destination accessibility – Travel mode satisfaction – Travel satisfaction) (**Figure 8C**).

The total impact of population density on travel satisfaction is −0.018 (**Table 9**). In Mouratidis et al.'s (2019) study, the impact of population density on travel satisfaction is −0.034. The impact of

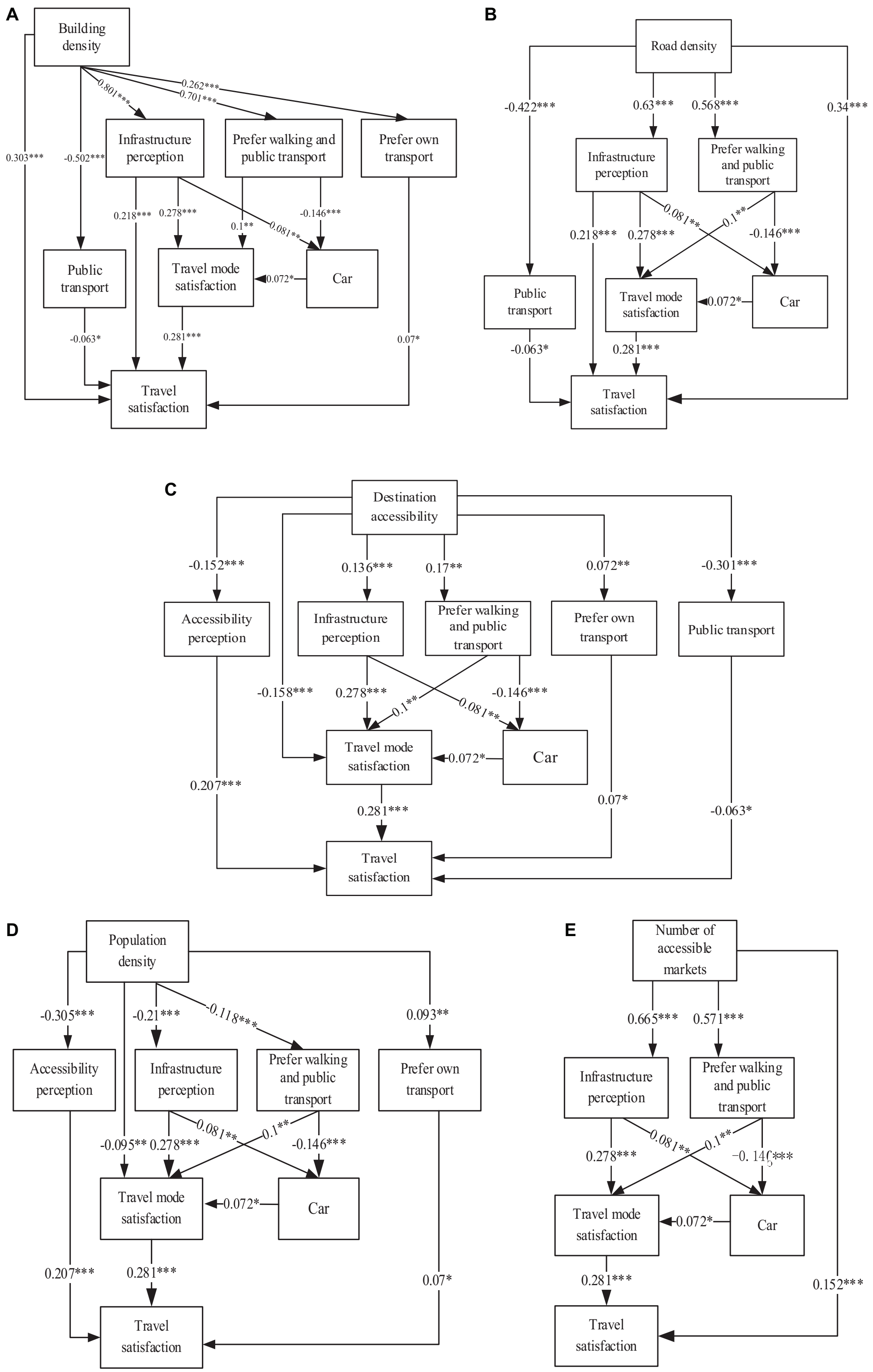

FIGURE 8 | (A) Building density. **(B)** Road density. **(C)** Destination accessibility. **(D)** Population density. **(E)** Number of accessible markets. ***Represents *p* value < 0.01, **Represents *p* value < 0.05, and *Represents *p* value < 0.1.

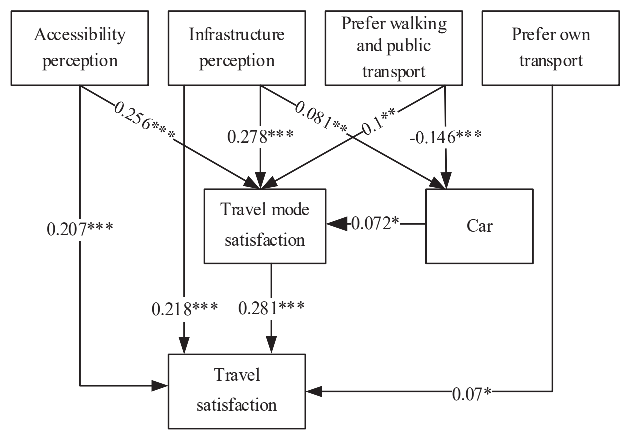

FIGURE 9 | Built environment perception and travel mode preference. ***Represents *p* value < 0.01, **Represents *p* value < 0.05, and *Represents *p* value < 0.1.

population density on travel satisfaction in this study is slightly smaller than that in Mouratidis et al.'s (2019) study. Travel satisfaction decreases with an increase in population density. In the path of Population density – Accessibility perception – Travel satisfaction (**Figure 8D**), the impact of population density on accessibility (−0.305) is negative. Although the overall travel facilities in rural areas have been improved compared with the past, the per capita ownership is very small, and many people will cause a shortage of resources and a feeling of poor accessibility (Meng et al., 2013). The number of accessible markets can reflect the convenience experienced in residents' daily life. In this study, the number of accessible markets has a significant positive impact on rural residents' travel satisfaction, with a value of 0.314 (**Table 9**). At the same time, the number of accessible markets has a positive impact on residents' perception of infrastructure (0.665) and pedestrian bus preference (0.571), as shown in the path (**Figure 8E**).

Impact of Built Environment Perception and Travel Mode Preference on Travel Satisfaction

In the built environment perception and travel mode preference, in addition to the preference for walking public transport variables, accessibility perception, infrastructure perception, and prefer own transport, have a direct positive impact on travel satisfaction, as shown in **Table 9**. The total effect of accessibility perception on travel satisfaction is 0.278 (**Table 9**). The path Accessibility perception – Travel mode satisfaction – Travel satisfaction reflects that people's perceived accessibility will bring better travel mode satisfaction and enhance a positive impact on travel satisfaction, as shown in **Figure 9**. The perception of infrastructure has a positive impact on travel satisfaction, where people think that the better the sidewalks, bicycle lanes, and motorways around the living environment, the more conducive these amenities are to their daily walking, riding electric cars, and driving needs, thereby enhancing their satisfaction with daily travel mode and the impact on travel satisfaction (path Infrastructure perception – Travel mode satisfaction – Travel satisfaction) (**Figure 9**). Wang et al. (2020) believed that residents' relocation to communities with good infrastructure services would improve their travel satisfaction. The preference on own transport has a direct positive impact on travel satisfaction (0.07). People who like driving tend to choose private cars and have high satisfaction (Ye and Titheridge, 2017); St-Louis et al. (2014) indicated that choosing one's preferred mode of travel will have a positive impact on travel satisfaction, which is consistent with the conclusion of this study. Preference for walking and public transport has an indirect negative impact on travel satisfaction, where residents' who prefer walking and public transport will reduce their driving probability. Preferring own transport has a direct positive impact on travel satisfaction (0.07) (**Table 9**). For example, people who prefer driving will choose private cars and have high satisfaction (Ye and Titheridge, 2017); St-Louis et al. (2014) indicated that choosing a preferred travel mode will have a positive impact on travel satisfaction, which is consistent with the conclusion of this study.

Impact of Travel Mode and Travel Mode Satisfaction on Travel Satisfaction

As shown in **Figure 10**, public transport (−0.063) has a direct negative impact on travel satisfaction, whereas driving mode has an indirect positive impact on travel satisfaction (0.020), **Table 9**. In this study, the five remaining travel modes, namely, electric bicycles, motorcycle, bicycle, tricycle, and other travel modes, have no significant impact on travel satisfaction (walking as reference). In the existing research on cities, walking, bicycle, private car, and other travel modes have a significant impact on travel satisfaction (Chng et al., 2016; Mao et al., 2016; Lancée et al., 2017; Zhu and Fan, 2018c).

The differences between rural and urban areas may be because rural residents seldom change their travel modes in daily life

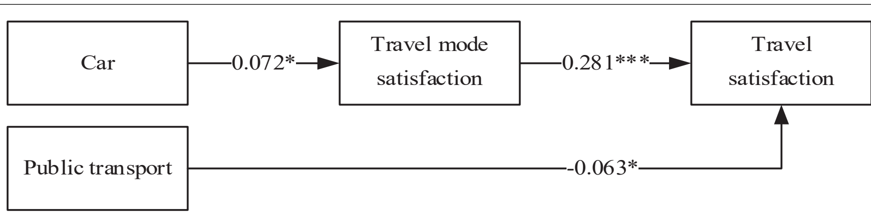

FIGURE 10 | Travel mode and travel mode satisfaction. *Represents *p* value < 0.1 and ***Represents *p* value < 0.01.

and are fixed in a certain manner. In previous studies, scholars found that suburban residents are likely to choose to drive (Chen et al., 2008). For rural residents, private car travel is less time consuming and flexible, resulting in high travel satisfaction. However, the travel satisfaction of public transport is negative, which is consistent with the existing research (De Vos et al., 2016; Zhu and Fan, 2018c). China's rural public transport is characterized by having only few modes where the service level is low (Zhao and Yu, 2020). During this research, rural residents commented that the number of rural public transport options, including small and medium-sized buses, was limited, the waiting time long, and the experience of taking public transport poor. These conditions lead to the residents' low satisfaction in choosing public transport travel.

CONCLUSION AND POLICY IMPLICATIONS

Given China's rapid development and urbanization, this paper investigates the current situation of China's rural transportation services from the perspective of rural residents, and offers recommendations to improve travel satisfaction. This study takes the six out of the Top 100 villages of Sichuan Province in Chengdu with strong rural economic development as the research object, establishes an SEM, and studies the direct and indirect impacts of socio-demographic variables, built environment, built environment perception, travel mode preference, daily travel mode, and daily travel mode satisfaction on travel satisfaction through path analysis. The research is conducted under the special development background of China's rural areas. The conclusions of this study are different from those of many western countries and several cities in China. The unique conclusions are summarized as follows: (1) Among the variables impacting travel satisfaction, the impact of built environment variables is the largest: the total impact of building density is 0.609; the total impact of road density is 0.569; and the total impact of the number of accessible markets is 0.314. The impact of population density and destination accessibility on travel satisfaction is indirectly negative. (2) The more satisfied the rural residents are with their travel modes, the higher their travel satisfaction. (3) In the built environment attitude and travel mode preference, infrastructure perception (0.298), accessibility perception (0.278), and the number of accessible markets (0.314) have a significant positive impact on residents' travel satisfaction. Residents believe that the better transportation facilities around a residential area, the stronger the accessibility will be; and the greater the number of nearby markets, the higher the travel satisfaction will be. (4) The influence of socio-demographic variables on travel satisfaction is relatively low. Age (−0.015), gender (−0.033), and annual personal income (−0.112) have negative impacts on travel satisfaction, whereas education level (0.005), physical quality (0.019), and annual family income (0.128) have significant positive Impacts on travel satisfaction. (5) Among the travel mode variables, motorcycles, electric bicycles, bicycles, tricycle, and other travel modes (walking as a reference) do not affect the travel satisfaction of rural residents, which is different from many urban-based research conclusions. Rural residents' choice of public transport as daily travel mode has a significant negative impact on their daily travel satisfaction (−0.063), whereas private car travel (0.02) has a significant indirect positive impact on their travel satisfaction.

On the basis of the above research conclusions, this paper proposes the following policy recommendations, with the aim of alleviating problems in China's rural areas: (1) An increase in building and road densities can, to a certain extent, be expected to improve the travel satisfaction of rural residents. The construction of rural roads and transportation infrastructure should be continued, and the accessibility of destinations and amenities for residents must be improved. (2) Increase the number of convenient markets for rural residents, and the village government can open more markets near the village. (3) Rural residents' satisfaction with public transport travel is shown to be negative, which indicates that rural public transport services must be improved. Government ought to consider appropriately increasing the frequency of rural buses services – especially small and medium-sized buses – while also adding more bus stops and in so doing shortening the distance between bus stops, augmenting existing bus routes, and increasing investment of quality of rural buses. (4) Rural built environment perception and travel preferences have a positive impact on the improvement of travel satisfaction. In considering the subjective feelings of rural residents when planning rural transportation, resident's positive travel experience can be expected to improve.

To conclude, this study contributes in the following aspects: (1) Enrich the study of travel satisfaction in rural areas; (2) Consider the influence of subjective and objective built environment variables on travel satisfaction; (3) Identify directly the influence path of variables on travel satisfactions using a Structural equation model; (4) Generate unique insights based on the analysis; and (5) Provide targeting policy recommendations following the analysis. Our study also has some limitations. The sample villages selected in the study are the top 100 villages with good economic conditions. These villages belong to concentrated living rural areas, so they can only reflect part of the situation of concentrated living rural areas. Although rural areas are in the stage of rapid development, there is still a gap with cities, and the measurement indicators of rural built environment need to be further improved.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because they are face to face interviews in Chinese. Requests to access the datasets should be directed to the corresponding authors where the data shall be released upon reasonable request.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the Local Legislation and

Institutional Requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

HL and YA: conceptualization. HL and YZ: methodology, software, data curation, and data collection. YA, YW, and TW: resources. HL, YA, and TW: writing – original draft preparation. YA, TW, and YC: writing, review, and editing. All authors have read and agreed to the published version of the manuscript.

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Climate Change and Farmers' Household Financial Vulnerability: Evidence From China

Sen Yang[1], Kai Zou[2], Tianyi Lei[2], Zehua Ni[3] and Jingyi Yang[3]*

[1]College of Business, Huanggang Normal University, Huanggang, China, [2]School of Finance, Zhongnan University of Economics and Law, Wuhan, China, [3]Beijing Institute of Technology, Beijing, China

Climate change is one of the most severe threats to human survival and a significant factor influencing financial stability. Different from previous studies, this paper investigates the economic impact of climate change at the micro level based on data from China Meteorological Administration database, and China Household Finance Survey (CHFS) 2017 released in 2019. The empirical findings indicate that climate change contributes to the financial vulnerability of farmers' households, which is confirmed following robustness tests. The mechanism analysis reveals that climate change has effects on rural households' financial vulnerability via farmers' health, credit availability, and agricultural output. Furthermore, the effect of climate change on farmers' household financial vulnerability (HFV) is more pronounced in farmers with lower education levels. The changes in temperature and precipitation show different intensity effects in different areas, but all of them provide reasonable heterogeneity mechanisms. This paper's policy value is demonstrated by the fact that it uncovers the effects of climate change on farmers' HFV, information that may be useful for addressing climate change and rural financial stability.

Keywords: climate change, farmers' household financial vulnerability, livelihood capitals, credit constraints, health, agricultural output

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University of Energy and Natural Resources, Ghana

****Correspondence:***
Tianyi Lei
tyray1992@163.com

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1 INTRODUCTION

Climate change is one of the most severe threats to human survival and a significant factor influencing financial stability. At the World Economic Forum 2022 video conference, the United Nations (UN) emphasized that the world urgently needs to address three major challenges—inequitable vaccine distribution, a revitalized financial system, and climate change—to emerge from the ongoing economic and health crisis and achieve the UN's Sustainable Development Goals. According to the Intergovernmental Panel on Climate Change (IPCC)'s latest report, 'Climate Change 2022: Impacts, Adaptation, and Vulnerability', China will be one of the most affected regions if greenhouse gas emissions are not reduced[1]. In addition, future climate change will continue to alter the spatial and temporal distributions of temperature and precipitation, increasing the frequency and intensity of extreme events such as heavy rainfalls, floods, droughts, and pest outbreaks. Furthermore, a report by the Financial Stability Oversight Council

[1]The report "Climate Change 2022: Impacts, Adaptation and Vulnerability" (IPCC), available at https://report.ipcc.ch/ar6wg2/pdf/IPCC_AR6_WGII_FinalDraft_FullReport.pdf.

(FSOC) on Climate-Related Financial Risk2021[2] emphasizes climate change as a "new threat to United States financial stability", and thus, it is necessary to regulate and supervise climate-related financial risks. The possible economic and financial risks caused by climate change have become a hot issue in academia.

Climate change have seriously effects on the ecological environment and the normal operation of the social economy (Li et al., 2022a; Li and Wang, 2022). According to some studies, increasing average temperature, which is a type of climate change, negatively affects economic variables such as agriculture (Mendelsohn et al., 1994; Reilly et al., 2003; Schlenker et al., 2005; Fisher et al., 2012; Chen and Gong, 2021), industrial output (Chen and Yang, 2017), and yield or production efficiency growth (Colacito et al., 2019; Kumar and Khanna, 2019; Li et al., 2015). Moreover, the fluctuation in the amount of precipitation is another measure of climate change. Xie et al. (2020) consider the temperature, precipitation, and standard deviations in China's agricultural policy simulation and projection model (CAPSiM) and find that climate change negatively affects agricultural output, which is similar to the previous conclusion. Lanzafame (2014) investigates the effect of the relationship between temperature and rainfall on economic development in Africa based on the annual data of 36 African countries from 1962 to 2000. Temperature is found to negatively affect every capita income in both short and long term, but there is little support for the assertion that rainfall affects the economy. Unlike the above results, Villavicencio et al. (2013) investigate the impacts of climate change on agricultural total factor productivity (TFP) in the United States, the findings of which show that annual precipitation has a significant positive effect on agricultural TFP but that precipitation intensity has a significant opposite effect, and temperature changes have no effect on agricultural TFP in most areas. These findings shows that the unique characteristics of agriculture and rural areas place them at the center of global climate change adaptation efforts. However, the majority of scholars are concerned with the effects of climate change on a larger scale.

Regarding household financial vulnerability (HFV), the related research is still in its infancy. Early concepts of financial vulnerability evolved from lifecycle theory (Campbell, 2006; Lin and Grace, 2007), which shows the likelihood that a family will be in financial distress in the future (O'Connor et al., 2018) and can be used to measure household financial stability. Mian and Sufi (2009) and Leika and Marchettini (2017) confirm the significant interrelationship between HFV and the stability of financial system. The Financial Stability Review (FSR) of the Bank of Indonesia regards HFV as an assessment of the resilience of macro-financial stability (Noerhidajati et al., 2020). Moreover, some factors affect HFV, including the socioeconomic characteristics of individuals and family-level characteristics. In addition, individual characteristics include age, gender, marital status, education level, and income level, while the characteristics at the family level include indicators of household assets and liabilities, household size, social capital, etc. Using an ordered probit model based on 902 individual respondents in Malaysia, Daud et al. (2019) find that income level, marital status, age, level of education, and financial behavior in money management all strongly influence HFV. They also point out that improving education positively contributes to HFV. In terms of income level, families with low income find it more difficult to deal with emergencies and afford expenditures, which leads to deep HFV among these families. Abdullah Yusof et al. (2015) hold the same view based on data from Malaysia. Moreover, based on data from Indonesia, Noerhidajati et al. (2020) find that middle- and upper-income groups have more debt, resulting in higher HFV compared to lower-income households. Moreover, financial literacy plays a vital role in HFV (Abdullah Yusof et al., 2015; French and McKillop, 2016), attracting much attention among scholars. According to Daud et al. (2019), owning a house helps a household survive severe financial insecurity. Similarly, Lusardi and Mitchelli (2007) emphasize the importance of financial literacy in the improvement of financial fragility and find that the larger scale of the family brings about higher expenditure and consumption levels, which exacerbates HFV. In addition, HFV is also affected by institutional factors, including information sharing arrangements and individual bankruptcy regulation (Jappelli et al., 2010). By reviewing the literature, existing studies have explored mainly the factors influencing HFV at the micro level, neglecting the impact of macroeconomic shocks, especially climate change, as a macro variable on HFV.

This paper aims to determine whether climate change increases the financial vulnerability of rural households. If so, what are the mechanisms of this influence? The major contributions of this paper are as follows. First, this paper fills the research gap regarding climate change and farmers' HFV. Although the current literature provides theoretical support and methodological inspiration for this paper, a complete analytical framework and empirical results are lacking. The climate change issue is becoming increasingly urgent and is shifting from a future challenge to an ongoing crisis. As the largest developing country all over the world, China has progressed in participating in global climate governance and addressing climate change. This development indicates that this study is highly relevant and may provide empirical inspiration for future research. Second, this paper extends the study of farmers' HFV. The empirical results show that climate change creates a microeconomic shock and exacerbates HFV. Besides, to ensure the scientific and rigorous findings of this study, different scenarios and measurement methods are considered. In addition, other robustness tests are applied. After a series of tests, the findings of this paper remain significant. Third, how to prevent and respond to climate change and improve the financial vulnerability of households have become critical topics. Yin et al. (2021) point out the perception of flood disaster risk positively contributes to the flood disaster preparedness behaviors of households, and this work regards climate change as a kind of macro risk, provides recommendations for climate change and rural financial stability. Besides, it also confirms the effect of the mechanism of climate change on household financial fragility in rural areas.

[2]The report "Climate-Related Financial Risk 2021" (FSOC), available at https://www.federalregister.gov/documents/2021/05/25/2021-11168/climate-related-financial-risk.

The remainder of the paper is organized as follows. **Section 2** presents the theoretical analysis and hypothesis development; **Section 3** presents the data, variable selection, and methodology; **Section 4** presents the empirical results; and **Section 5** presents the conclusions and policy recommendations.

2 THEORETICAL ANALYSIS AND HYPOTHESIS DEVELOPMENT

2.1 Climate Change and HFV

Researchers define "vulnerability" in terms of the resilience of humans to natural disasters. For example, Kreimer and Arnold (2000) regard vulnerability as the ability of an individual, household, or community to prevent, mitigate, and rebuild in the face of natural hazards, with poor or near-poor households being more vulnerable to natural hazards. The greater vulnerability of poor or near-poor households to natural disasters stems primarily from the fact that vulnerable households have relatively few assets and lack access to necessary capital (Alwang, 2000). Community disaster resilience closely relates to the risk perception in earthquake-stricken areas. The community with better resource endowment, disaster management, information communication, less vulnerability the residents face with (Ma et al., 2021; Ma et al., 2022). Based on obtained primary household data from Akwa Ibom State, Nigeria, Amos et al. (2015) develop a livelihood vulnerability index (LVI) to assess vulnerability and find that households are vulnerable to climate change and that a shortage of adequate finance is the most important challenge. Albert et al. (2021) point out that empirical evidence suggests that higher temperatures and extreme weather can have a negative impact on economic activity. According to Paavola (2008), climate change in Tanzania limits livelihood options for women, children, and those vulnerable groups without adequate access to employment and public services, increasing their insecurity and making their livelihood even worse. In addition, farmers have always found ways to adapt to the impact of climate change, and based on data from Nigeria, Abraham and Fonta (2018) find that the exposure of farmers to climate change significantly relates to their need for financial access as an adaptation strategy. Moreover, according to a survey of 380 resource-poor riverbank erosion-prone households in Bangladesh, Alam et al. (2017) explore the local knowledge of adaptation in response to the perceived impacts of climate change and climatic hazards. The results indicate that changes in the climate and extreme climatic events have an effect on the households' livelihood and resources, increasing their perceptions of vulnerability. Furthermore, climate change caused by air pollution, natural disasters like earthquake, lead to higher expenditures for insurance purchases (Xu et al., 2018), especially for health insurance (Zhao, 2020), and extreme climate events significantly decrease the expenditure of households heavily dependent on agriculture for their income (Urama et al., 2019). In general, higher household expenditure contributes to HFV when income remains the same.

Therefore, we believe that climate change exacerbates HFV and propose the following hypothesis:

Hypothesis 1. Climate change exacerbates farmers' HFV.

2.2 Mechanisms of Livelihood Capitals

Human, physical and financial capital are important factors that affect the livelihoods of farm households (Vemuri and Costanza, 2006; Xu et al., 2019; Yang et al., 2021) and are also the main areas of vulnerability to the adverse effects of climate change (Handmer et al., 2012). Physical capital consists of the infrastructure and materials needed to support livelihoods. Human capital refers to individuals' knowledge, health status, etc., for earning a living. Financial capital refers to the financial resources, which typically include cash, savings, credit, remittances, and transfer income, used by households or individuals to achieve their life goals. First, the high dependence of agricultural production on the natural environment makes agriculture often affected by windstorms, rainstorms, hailstorms, persistent drought, and pests and diseases caused by climate change. These factors affect the physical capital of farm households. Second, disease risk affects farm households' human capital, which leads to the increased financial vulnerability of rural households. Finally, climate change can impair the operations of rural financial institutions, thereby affecting the financial capital of rural households. It is unclear how climate change affects the financial stability of rural households by influencing the cost of livelihoods and thus the financial stability of rural households.

Burgess et al. (2014) uses Indian data to explore whether hot weather shocks affect mortality differently in rural and urban areas and finds a 7.3% increase in annual mortality in rural areas for a per °C increase in average daily temperature. However, there is no evidence of such effects in urban areas, and it is predicted that global warming between 2015 and 2019 will reduce life expectancy in rural areas. According to Bosello et al. (2012), climate shocks affect crop production and people's health, and the effects on different areas vary. These effects are weaker at higher latitudes and stronger at lower latitudes. Moreover, it is generally agreed that health risk factors significantly worsen the financial vulnerability of farm households and that the higher the health risk is, the higher the probability of expected financial deterioration of farm households. Uddin et al. (2017) provide evidence that climate change has been perceived by most farmers, with increased temperatures and decreased precipitation over the past 20 years, negatively impacting farmers' health and livelihoods. In addition, concern of health risk plays as the mechanism of the public attention to environment and air pollution (Li et al., 2022b).

On the one hand, the presence of health problems in farm households reduces their income. Casasnovas et al. (2005), Narayan et al. (2010), and Chetty et al. (2016) argue that health affects economic productivity and thus reduces rural household income. On the other hand, health shocks can also affect household financial exposure and household financial decisions through household medical expenditures (Merton, 1969). Christiaensen and Subbarao (2005) find that reducing the incidence of malaria and increasing adult literacy and market openness significantly reduce household economic vulnerability based on data from rural Kenya. One study finds no significant effect of disease shocks on household nonmedical consumption expenditures (Townsend, 1994). The differences in the above findings may be due to the heterogeneous effects of health shocks on the financial risk of households with different incomes or different mechanisms of influencing household risk, both direct (Rosen and Wu, 2004; Wang et al., 2021) and indirect (Berkowitz and Qiu, 2006). In addition, in rural areas, the return to poverty due to illness is still one of the main factors negatively affecting the financial vulnerability of rural households.

Therefore, we believe that climate change worsens farmers' health, which positively contributes to HFV in rural areas. Therefore, we propose the following hypothesis:

Hypothesis 2. Climate change worsens farmers' health, and then exacerbates farmers' HFV.

Household financial disincentives and underdeveloped credit markets are common in rural areas of many developing countries, resulting in widespread credit constraints for farm households. Hornbeck (2009) believes that financial system overspecialization in sectors such as agriculture may lead to increased vulnerability to climate shocks. The natural disasters caused by climate change undermine the value of collateral for bank loans and inhibit market liquidity through bank financing channels, causing negative shocks to the financial system's stability. Physical asset damage caused by sudden climate disasters such as floods, hurricanes, high temperatures, or long-term climate problems such as a rise in sea level, precipitation changes, and seawater acidification can directly lead to a decline in the value of collateral in the household and business sectors. This decline in collateral value increases the risk of loan default for households and businesses (Klomp, 2014; Yannis et al., 2018). Furthermore, climate catastrophic shocks can lead to bank lending shyness, making banks more cautious in lending and thus reducing credit supply and market liquidity (Berg and Schrader, 2012; Hosono et al., 2016). Bank lending shyness causes rural households hit by such disaster to face more severe financing constraints and also further increases bank credit default rates, undermining banks' ability to operate and thus creating a vicious cycle. This bank lending shyness is caused mainly by postdisaster losses, especially the loss of uninsured assets. Bank lending reluctance is more pronounced in developing countries following climate disasters than in developed countries (David, 2011). In turn, natural disasters caused by climate change also affect the rural financial system. Some natural disasters have the potential to damage rural finance offices, equipment, information systems, and records. Disaster losses faced by rural finance clients can also have indirect effects on the microfinance institutions (MFIs) themselves (Pantoja, 2002). In addition, some macroeconomic fluctuations triggered by natural disasters, such as inflation or recession triggered by large-scale disasters, may also indirectly have a significant negative impact on microfinance. For example, after Bangladesh suffered a severe flood disaster in 1998, 25% of Grameen Bank borrowers defaulted on their debts, which led to the cessation of loan repayments and the decline in mandatory savings, which depleted the bank's liquidity (David, 1998).

Therefore, we believe that climate change can increase financing constraints, which can promote HFV. Thus, we propose the following hypothesis:

Hypothesis 3. Climate change exacerbates credit constraints, and then exacerbates farmers' HFV.

Villavicencio et al. (2013) show that precipitation and its intensity significantly affect agricultural TFP growth in the United States, while the effect of temperature is not significant. Jin et al. (2002) estimate the change in the TFP of rice in China from 1980 to 1995 with the Tornqvist-Theil index and conclude that climatic factors have significant effects on the TFP growth of rice. Yoji et al. (2016) use spatial geography to investigate the role of climate change in the process of influencing rice TFP and find that there is spatial autocorrelation in rice TFP and that climate change, like socioeconomic factors, has a persistent effect on rice TFP, but the extent of this impact varies across regions. In a general scenario, higher temperatures decrease yields, while more precipitation increases yields (Dell et al., 2014). Dinar (1998) studies how climate change affects Indian agriculture using cross-sectional data from Indian agricultural zones; he uses a general circulation model (GCM) to predict future changes in CO_2 levels, affecting temperature and rainfall values in the region. Moreover, with the Ricardian model, he investigates the sensitivity of Indian agriculture to climate change. Based on the livelihoods of coastal farming households in Mozambique and Tanzania, Bunce et al. (2010) argue that if coastal Africa continues to attract migrants and the services of land and marine ecosystems continue to deteriorate, the risks to rural livelihoods from climate change will be amplified in western Africa. In addition, agriculture is the primary source of livelihood for most people in the region. Rising temperatures or changes in rainfall lead to lower river levels, crop failures, delayed planting seasons, lower incomes and reduced crop yields, with significant impacts on the natural resources on which agriculture depends. In addition, this can lead to the increased vulnerability of agriculture-based livelihoods for farmers. Furthermore, there is a significant risk of exacerbating and hastening the current 'downward spiral' of underdevelopment, poverty, and environmental degradation (Sissoko et al., 2011).

Therefore, we believe that climate change can influence the output of agriculture, which can intensify HFV. Thus, we propose the following hypothesis:

Hypothesis 4. Climate change lowers agricultural output, and then exacerbates farmers' HFV (**Figure 1**).

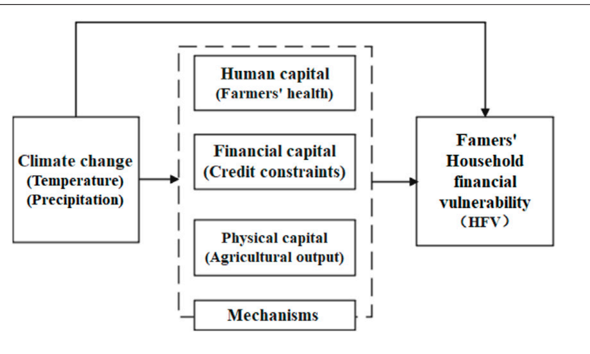

FIGURE 1 | The mechanisms of climate change's effects on HFV.

TABLE 1 | Descriptive analysis.

Variables	Explanation	Mean	Std. Dev	Min	Max
HFV	0 = no over-indebtedness and having emergency savings 1 = over-indebtedness but having emergency savings or no over-indebtedness and having no emergency savings 2 = both over-indebtedness and having no emergency savings	0.3432	0.4757	0	2
Tc	Changes in temperature	0.1992	0.1798	0.0104	2.2704
Pc	Changes in precipitation	1.4520	0.4698	0.6945	4.9049
Gender	1 = male 2 = female	1.1039	0.3051	1	2
Age		61.7197	11.9394	18	97
Education	1 = no schooling at all 2 = primary school 3 = junior high 4 = high school 5 = technical high school 6 = college/vocational school 7 = bachelor's degree 8 = master's degree 9 = doctorate degree	2.4721	0.9439	1	8
Marriage	0 = no spouse 1 = having a spouse	0.8845	0.3196	0	1
Family members	Numbers	3.5558	1.7386	1	15
Family income	Ln (family total income)	10.0442	1.2913	6.9088	15.4250
Number of houses		1.1541	0.4071	0	6
Whether operates a business	0 = no 1 = yes	0.0964	0.2951	0	1
Farmers' health	1 = very bad 2 = bad 3 = ordinary 4 = good 5 = very good	3.0936	1.0430	1	5
Credit constraints	0 = no 1 = yes	0.0857	0.2799	0	1
Agricultural output	Ln (agricultural GDP)	26.3289	13.5825	2.3462	60.0550

3 DATA AND METHODOLOGY

3.1 Model

The independent variable HFV is a dummy variable, so this paper mainly uses the ologit model to verify the impact of climate change on the financial vulnerability of rural households. The regression model is as follows:

$$HFV_i = \theta_0 + \theta_1 CM_i + \theta_2 Controls_i + \theta_3 \delta_i + \varepsilon_i \tag{1}$$

where HFV_i is the explained variable; CM_i is the core explanatory variable representing climate change (including the changes in temperature and precipitation); i denotes the city; $Controls_i$ represent other control variables; δ_i represents the province fixed effect, and ε_i is the error disturbance term.

Furthermore, we explore the underlying mechanisms as well as test the mechanisms of hypotheses 2 to 4. The specific model is set as follows:

$$I_i = \alpha_0 + \alpha_1 CM_i + \alpha_2 Controls_i + \alpha_3 \delta_i + \varphi_i \tag{2}$$

$$HFV_i = b_0 + b_1 I_i + b_2 Controls_i + b_3 \delta_i + \tau_i \tag{3}$$

where I_i represents underlying mechanism variables including farmers' health, credit accessibility and agricultural output. Models (2) and (3) together aim to find the underlying mechanisms. If the coefficients α_1 and b_1 are significant, then it may be underlying mechanism.

3.2 Variables

3.2.1 HFV

Following O'Connor et al. (2018) and Loke (2017), this paper uses over-indebtedness and consumer arrears to estimate HFV. The household debt level is used to estimate the over-indebtedness, while emergency saving is the indicator of consumer arrears reflecting household capacity to buffer income shocks. This paper defines household over-indebtedness as a greater than 30% household debt-to-income ratio, which we assign a value of 1. If the household debt-to-income ratio is lower than 30%, the household is defined as non-overindebted and is assigned a value of 0.

Moreover, referring to Loke (2017), a household with savings of less than 3 months of living expenses is regarded as having no emergency savings and is assigned a value of 1, while having emergency savings is assigned a value of 0. Therefore, this paper assigns a value of 0 to households with no over-indebtedness and emergency savings, representing lower financial vulnerability. A value of 1 refers to the households with

TABLE 2 | Baseline regression results.

Variables	(1)	(2)	(3)	(4)
Tc	1.1561***	0.5253*		
	(0.1300)	(0.2905)		
Pc			0.3601***	0.5048***
			(0.0449)	(0.0625)
Gender		−0.0582		−0.0503
		(0.0876)		(0.0878)
Marriage		0.0648		0.0749
		(0.0866)		(0.0868)
Age		−0.0464***		−0.0461***
		(0.0024)		(0.0024)
Education		−0.0224		−0.0252
		(0.0286)		(0.0286)
Farmers' health		−0.2347***		−0.2316***
		(0.0286)		(0.0248)
Family members		0.1602***		0.1661***
		(0.0163)		(0.0163)
Family income		−0.2816***		−0.2886***
		(0.0222)		(0.0224)
Number of houses		0.5159***		0.5030***
		(0.0606)		(0.0609)
Whether operates a business		0.4794***		0.4732***
		(0.0823)		(0.0830)
Province FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.0077	0.1051	0.0051	0.1094
N	9,059	9,059	9,059	9,059

*Note: Standard errors are in parentheses; *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.*

TABLE 3 | Robustness test results: changing models.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Oprobit	**Ologit**	**OLS**	**Oprobit**	**Ologit**	**OLS**
Tc	0.3263*	0.5172*	0.1191*			
	(0.1671)	(0.2914)	(0.0619)			
Pc				0.2966***	0.5042***	0.0985***
				(0.0365)	(0.0623)	(0.0109)
Gender	−0.0364	−0.0559	−0.0102	−0.0329	−0.0477	−0.0088
	(0.0518)	(0.0876)	(0.0165)	(0.0518)	(0.0878)	(0.0164)
Age	0.0290	0.0668	−0.0091***	0.0343	0.0768	−0.0090***
	(0.0513)	(0.0864)	(0.0004)	(0.0515)	(0.0867)	(0.0004)
Education	−0.0276***	−0.0464***	−0.0049	−0.0274***	−0.0460***	−0.0052
	(0.0014)	(0.0024)	(0.0056)	(0.0014)	(0.0024)	(0.0056)
Marriage	−0.0130	−0.0214	0.0063	−0.0148	−0.0242	0.0077
	(0.0170)	(0.0286)	(0.0158)	(0.0170)	(0.0287)	(0.0158)
Farmers' health	−0.1394***	−0.2351***	−0.0444***	−0.1373***	−0.2321***	−0.0435***
	(0.0146)	(0.0248)	(0.0048)	(0.0147)	(0.0248)	(0.0047)
Family members	0.0965***	0.1600***	0.0329***	0.0997***	0.1659***	0.0340***
	(0.0097)	(0.0163)	(0.0033)	(0.0097)	(0.0163)	(0.0033)
Family income	−0.1668***	−0.2815***	−0.0573***	−0.1701***	−0.2884***	−0.0582***
	(0.0132)	(0.0223)	(0.0043)	(0.0133)	(0.0224)	(0.0043)
Number of houses	0.3073***	0.5147***	0.1050***	0.2984***	0.5025***	0.1010***
	(0.0357)	(0.0606)	(0.0126)	(0.0358)	(0.0610)	(0.0126)
Whether operates a business	0.2884***	0.4809***	0.0985***	0.2842***	0.4748***	0.0962***
	(0.0491)	(0.0824)	(0.0175)	(0.0493)	(0.0832)	(0.0175)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.1048	0.1054		0.1090	0.1098	
Adjusted R^2			0.1255			0.1307
N	9,059	9,059	9,059	9,059	9,059	9,059

*Note: Standard errors are in parentheses; *, ** and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.*

TABLE 4 | Robustness test results: Oster's method.

Variables	(1) β^{R1}	(2) β^{R2}	(3) β^{F1}	(4) β^{F2}	(5) β^{R1}	(6) β^{R2}	(7) β^{F1}	(8) β^{F2}
Tc	1.1561***	0.8428***	1.0003***	0.5257*				
	(0.1300)	(0.1331)	(0.1395)	(0.2907)				
Pc					0.3601***	0.3846***	0.4184***	0.5010***
					(0.0449)	(0.0463)	(0.0473)	(0.0625)
σ	7.42	1.66			7.18	4.3		
Province FE				Yes				Yes
Pseudo R^2	0.0077	0.0610	0.0901	0.1056	0.0051	0.0625	0.0905	0.1098
N	9,059	9,059		9,059	9,059	9,059	9,059	9,059

*Note: Standard errors are in parentheses; *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.*

TABLE 5 | Mechanism of farmers' health.

Variables	I_1 (Farmers' Health) (1)	(2)	HFV (3)
Tc	−0.4156***		
	(0.1156)		
Pc		−0.1278***	
		(0.0395)	
Farmers' health			−0.2361***
			(0.0247)
Gender	−0.2080***	−0.2111***	−0.0560
	(0.0717)	(0.0718)	(0.0874)
Marriage	−0.0631	−0.0675	0.0635
	(0.0696)	(0.0697)	(0.0865)
Age	−0.0244***	−0.0235***	−0.0466***
	(0.0019)	(0.0018)	(0.0024)
Education	0.1774***	0.1848***	−0.0235
	(0.0221)	(0.0221)	(0.0286)
Family members	−0.0886***	−0.0879***	0.1593***
	(0.0127)	(0.0126)	(0.0163)
Family income	0.2672***	0.2684***	−0.2814***
	(0.0176)	(0.0176)	(0.0223)
Number of houses	0.1577***	0.1670***	0.5179***
	(0.0461)	(0.0463)	(0.0606)
Whether operates a business	0.3058***	0.3186***	0.4766***
	(0.0641)	(0.0641)	(0.0822)
Province FE	Yes	Yes	Yes
Pseudo R^2	0.0359	0.0357	0.1047
N	9,059	9,059	9,059

*Note: Standard errors are in parentheses; *, **, and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.*

over-indebtedness but emergency savings, or no over-indebtedness and no emergency savings, representing medium financial vulnerability. A value of 2 indicates that households have both over-indebtedness and no emergency savings, indicating a high level of financial vulnerability. The scale of HFV ranges from 0 to 2, with a higher value indicating a higher level of financial vulnerability and a lower ability to withstand economic risks. In addition, emergency savings and over-indebtedness are dichotomous variables.

3.2.2 Climate Change

Climate change is a long-term process with small fluctuations in adjacent years. Because of the availability of data with a relatively short observation period, the average value of variable changes each year is very small, affecting the representativeness of the indicators. This paper uses the changes in temperature and precipitation to estimate climate change during the observation period. Therefore, following the measurement of risk and change (Christiano et al., 2014; Shimojo et al., 1991), it refers to the high-low method of volatility as the proportion of value (maximum-minimum) to the minimum value to estimate the changes in temperature *(Tc)* and precipitation (*Pc*).

3.2.3 Other Variables

Following the literature, this paper controls for individual and household characteristic variables. Individual-level variables include gender, age, education, marital status, and physical

TABLE 6 | Mechanism of credit constraints.

Variables	I_2 (Credit Constraints)		HFV
	(1)	(2)	(3)
Tc	0.5758***		
	(0.1507)		
Pc		0.1492*	
		(0.0837)	
Credit constraints			0.9395***
			(0.0835)
Gender	−0.2735*	−0.2638*	−0.0327
	(0.1484)	(0.1475)	(0.0883)
Marriage	−0.0448	−0.0374	0.0742
	(0.1350)	(0.1348)	(0.0872)
Age	−0.0226***	−0.0240***	−0.0460***
	(0.0035)	(0.0034)	(0.0024)
Education	−0.1086**	−0.1224***	−0.0157
	(0.0439)	(0.0442)	(0.0288)
Farmers' health	−0.1982***	−0.2005***	−0.2250***
	(0.0401)	(0.0402)	(0.0249)
Family members	0.0425*	0.0409*	0.1604***
	(0.0240)	(0.0240)	(0.0163)
Family income	0.0089	0.0082	−0.2902***
	(0.0335)	(0.0335)	(0.0225)
Number of houses	−0.0179	−0.0307	0.5252***
	(0.0962)	(0.0963)	(0.0612)
Whether operates a business	0.1982	0.1811	0.4624***
	(0.1244)	(0.1240)	(0.0827)
Province FE	Yes	Yes	Yes
Pseudo R^2	0.0186	0.0176	0.1159
N	9,059	9,059	9,059

*Note: Standard errors are in parentheses; *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.*

condition. Household-level variables include household size, family income, housing status, and whether the household operates a business. The intermediate variables include farmers' health, credit constraints and agricultural output. Based on the questions of China Household Finance Survey (CHFS) 2017, the explanations are shown in **Table 1**.

3.3 Data Source and Descriptive Statistics

This article uses data from the CHFS 2017, which was released in 2019 by the Southwestern University of Finance and Economics. The database was obtained from the fourth round of the national survey, covering 29 provinces, autonomous regions and municipalities. In addition, the climate change data, including those on temperature and precipitation from 1991 to 2017, come from the China Meteorological Administration database.

Combining the purpose of the study and data accessibility, this work processes the data as follows. First, we match the climate change data of the 2017 prefecture-level cities with the data of CHFS 2017 and exclude the index data of Tibet and Xinjiang. Second, the samples of nonagricultural households and other forms of households are also excluded. Third, we exclude households whose heads are less than 18 years old. Fourth, missing values and outliers are also excluded from the data. After the above data processing, there are 9,059 valid observations as farmers left in the sample in 2017. **Table 1** shows the descriptive statistics of the major variables.

4 EMPIRICAL RESULTS

4.1 Baseline Regression Based on the Ologit Model

Table 2 reports the baseline regression results of climate change on farmers' HFV in terms of temperature and precipitation. According to the results, both changes in temperature and precipitation positively contribute to the farmers' HFV during the observation period, which supports Hypothesis 1. In terms of risk, climate change implies higher fluctuations and risks, which increase the complexity of household finance and then lead to financial vulnerability. Age has a negative effect on HFV. Compared to young farmers, older farmers may have more experience and skills to deal with financial problems and less HFV. The more family members there are, the easier it is for them to get into financial trouble, which supports the views of Lusardi and Mitchelli (2007). The higher income and wealth are, the easier it is for farmers to overcome financial vulnerability, which is similar to the conclusion of Noerhidajati et al. (2020). In addition, according to the negative coefficients of education and health, if farmers have more knowledge and are in better physical condition, their household finances are more stable.

4.2 Robustness Tests

The possible endogeneity problems in this paper are problems about measurement error and omitted variables in models. This

TABLE 7 | Mechanism of agricultural output.

Variables	I_3 (Agricultural Output)		HFV
	(1)	(2)	(3)
Tc	−0.5379***		
	(0.0460)		
Pc		−0.1195***	
		(0.0148)	
Agricultural output			−0.1002*
			(0.0575)
Gender	−0.0658**	−0.0609**	−0.0766
	(0.0262)	(0.0267)	(0.0956)
Marriage	0.0507**	0.0407	0.0337
	(0.0248)	(0.0252)	(0.0939)
Age	0.0013*	0.0022***	−0.0464***
	(0.0007)	(0.0007)	(0.0026)
Education	−0.0145*	−0.0118	−0.0260
	(0.0081)	(0.0081)	(0.0303)
Farmers' health	−0.0241***	−0.0228***	−0.2437***
	(0.0071)	(0.0072)	(0.0267)
Family members	−0.0165***	−0.0124***	0.1656***
	(0.0046)	(0.0046)	(0.0176)
Family income	0.0293***	0.0285***	−0.2958***
	(0.0066)	(0.0067)	(0.0242)
Number of houses	−0.0092	−0.0032	0.5013***
	(0.0169)	(0.0170)	(0.0638)
Whether operates a business	0.0271	0.0432*	0.4981***
	(0.0234)	(0.0234)	(0.0867)
Province FE	Yes	Yes	Yes
Adjusted R^2	0.0248	0.0121	
Pseudo R^2			0.1103
N	8,047	8,047	8,047

*Note: Standard errors are in parentheses; *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.*

paper provides three methods with which to test the robustness in **Tables 3**, **4**. The first method is to change the models. From ologit to oprobit, columns (1) and 4) show the results. Regarding the ordered variables as continuous variables, the model is changed from ologit to ordinary least squares (OLS), the results of which are shown in columns (3) and (6). The second method is to replace the measurement of HFV, the results of which are provided in columns (2) and (5) in **Table 3**.

Furthermore, farmers' HFV is caused by complex factors, and climate change also faces unobservable effects. Therefore, the analysis of the relationship between climate change and farmers' household vulnerability also faces the problem of endogeneity due to the omission of unobservable variables. Referring to Altonji et al. (2005) and Oster (2017), this paper introduces different observable variables to estimate the bias in parameter estimates due to unobservable variables by observing the change in parameter estimates in a direct way. σ reflects the changes in estimated parameters, and $\sigma = |\beta^F/(\beta^R-\beta^F)|$, where β^R denotes the parameter estimates of the core explanatory variables when the constrained control variables are introduced, and β^F denotes the parameter estimates of the core explanatory variables when all observable variables are introduced as control variables. A larger σ value implies that the omitted variables are less likely to affect the parameter estimates of the core explanatory variables. The first constrained model introduces only the core explanatory variable climate change, while the second constrained model introduces climate change and household head characteristics variables, including gender, marriage, age, education and physical condition. Based on the two constrained models described above, the two full models take the household characteristics variables, the use of the internet and province fixed effects. **Table 4** shows that the results and the coefficients of the parameter estimates of the constrained and full models are all more than 1 in columns (1) to (8), which means that the parameter estimates are less influenced by the omitted variables (Altonji et al., 2005).

In summary, after several robustness tests, the direction of the regression coefficients of the explanatory variables as well as their significance remain consistent with the baseline regression results, which indicates that the results of the empirical analysis are robust.

4.3 Underlying Mechanisms of Household Capital

4.3.1 Mechanism of Farmers' Health in the Relationship Between Climate Change and Farmers' HFV

To test the mechanism of farmers' health in hypothesis 2, climate change influences farmers' HFV via farmers' health. According to Zeng et al. (2021), it uses farmers' health to represent human capital. Farmers' health is estimated on the basis of answers in the CHFS 2017 results. **Table 5** shows the results. It can be seen that

TABLE 8 | Heterogeneity of areas.

Variables	(1) East	(2) Middle	(3) West	(4) Northeast
a				
Tc	0.1056	2.1766***	0.2943	1.1347***
	(0.8166)	(0.6522)	(0.2481)	(0.2711)
Gender	0.0836	−0.1907	0.0282	−0.1802
	(0.1568)	(0.1712)	(0.1425)	(0.2558)
Marriage	0.0763	0.2967*	0.0632	−0.1499
	(0.1608)	(0.1617)	(0.1474)	(0.2387)
Age	−0.0388***	−0.0498***	−0.0445***	−0.0490***
	(0.0043)	(0.0043)	(0.0040)	(0.0068)
Education	0.0342	−0.1156**	−0.0029	−0.1952**
	(0.0493)	(0.0479)	(0.0491)	(0.0907)
Farmers' health	−0.2393***	−0.2054***	−0.3153***	−0.2571***
	(0.0443)	(0.0431)	(0.0431)	(0.0653)
Family members	0.1105***	0.1403***	0.1815***	0.2834***
	(0.0291)	(0.0277)	(0.0273)	(0.0532)
Family income	−0.1909***	−0.3432***	−0.3220***	−0.3277***
	(0.0377)	(0.0415)	(0.0381)	(0.0619)
Number of houses	0.5969***	0.4958***	0.4606***	0.3451**
	(0.0892)	(0.1161)	(0.1115)	(0.1742)
Whether operates a business	0.4649***	0.6868***	0.4011***	0.1192
	(0.1189)	(0.1514)	(0.1557)	(0.2857)
Province FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.0755	0.0809	0.0927	0.1007
N	2,722	2,680	2,523	1,134
b				
Pc	0.7055***	0.2776**	0.5862***	0.3513***
	(0.1061)	(0.1081)	(0.0848)	(0.0929)
Gender	0.1090	−0.1522	−0.0163	−0.3075
	(0.1654)	(0.1715)	(0.1475)	(0.2632)
Marriage	0.0535	0.2769*	−0.0138	−0.1714
	(0.1672)	(0.1615)	(0.1525)	(0.2502)
Age	−0.0428***	−0.0493***	−0.0484***	−0.0528***
	(0.0047)	(0.0044)	(0.0042)	(0.0070)
Education	0.0444	−0.1021**	−0.0350	−0.1591*
	(0.0549)	(0.0484)	(0.0507)	(0.0907)
Farmers' health	−0.2005***	−0.2110***	−0.3167***	−0.2307***
	(0.0498)	(0.0444)	(0.0446)	(0.0670)
Family members	0.1282***	0.1308***	0.1957***	0.2522***
	(0.0304)	(0.0282)	(0.0284)	(0.0544)
Family income	−0.1999***	−0.3360***	−0.3101***	−0.3053***
	(0.0407)	(0.0428)	(0.0400)	(0.0640)
Number of houses	0.5932***	0.4958***	0.4163***	0.3472*
	(0.0965)	(0.1194)	(0.1165)	(0.1803)
Whether operates a business	0.4640***	0.6599***	0.4159**	0.0294
	(0.1320)	(0.1552)	(0.1638)	(0.2793)
Province FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.0874	0.0775	0.1015	0.0941
N	2,722	2,680	2,523	1,134

*Note: Standard errors are in parentheses; *, **, and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.*

temperature changes have a negative effect on farmers' health at the 1% confidence level in column (1). The effects of precipitation changes also have a negative effect on farmers' health at the 1% confidence level in column (2). Perhaps the changes in temperature and precipitation increase the possibilities for farmers to suffer from disease, especially respiratory problems, which is pointed out by Bartholy and Pongrácz (2018). Xue et al. (2019) also find that increased temperature change is associated with a higher probability of decreased mental health. Moreover, the coefficient of farmers' health and HFV is negative, reflecting that the better a farmer's physical condition is, the lower his or her HFV at the 1% confidence level in column (3). If farmers have trouble in terms of their physical condition, then they find it more difficult to earn money, and such expenditure may be focused on helping them become healthier. Therefore, they are more likely to face financial problems. In other words, climate change negatively

TABLE 9 | Heterogeneity of education.

Variables	(1) Low Education	(2) High Education	(3) Low Education	(4) High Education
Tc	1.0394***	−0.6244		
	(0.1401)	(1.1432)		
Pc			0.4141***	1.5825
			(0.0472)	(1.0900)
Gender	−0.0323	−0.9650	−0.0074	−1.3983
	(0.0865)	(1.1652)	(0.0859)	(1.0693)
Marriage	0.0678	0.3750	0.0748	0.3890
	(0.0857)	(0.9438)	(0.0856)	(1.0042)
Age	−0.0482***	−0.0106	−0.0502***	−0.0087
	(0.0023)	(0.0226)	(0.0023)	(0.0235)
Farmers' health	−0.2517***	−0.3309	−0.2548***	−0.4394
	(0.0243)	(0.3002)	(0.0244)	(0.2913)
Family members	0.1671***	0.1985	0.1681***	0.2045
	(0.0156)	(0.1578)	(0.0156)	(0.1622)
Family income	0.2968***	−0.4395	−0.3036***	−0.4361
	(0.0215)	(0.2821)	(0.0217)	(0.2758)
Number of houses	0.5257***	0.2466	0.4966***	−0.4219
	(0.0596)	(0.4149)	(0.0596)	(0.6232)
Whether operates a business	0.4640***	0.3019	0.4342***	0.2003
	(0.0822)	(0.6147)	(0.0820)	(0.6606)
Province FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.0908	0.0793	0.0911	0.1095
N	8,973	86	8,973	86

*Note: Standard errors are in parentheses; *, **, and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.*

affects farmers' health and then increases their financial vulnerability. These results support hypothesis 2.

4.3.2 Mechanism of Credit Constraint Between Climate Change and Farmers' HFV

According to Zeng et al. (2021), the shortage of funds reflects the financial risk of farmers' livelihood risks, it takes use of credit constraint to assess financial risk. The mechanism of credit constraint in hypothesis 3, that is, that climate change influences credit constraint and then has an effect on farmers' HFV, is tested. When credit constraint has a value of 1, it means that farmers face financing difficulties. In addition, the value of the credit constraint of 0 reflects farmers' easy access to credit. The values come from the results of the CHFS 2017 questionnaire. **Table 6** shows that changes in temperature positively contribute to credit constraints at the 1% confidence level in column (1), while changes in precipitation positively contribute to credit constraints at the 10% confidence level in column (2). Climate change increases risks, which makes it more difficult for farmers to obtain credit. Moreover, the coefficient of credit constraints and HFV is positive, reflecting that the higher the credit constraint is, the higher the HFV at the 1% confidence level in column (3). In other words, when farmers have less access to credit, they will face higher HFV. These results support Hypothesis 3.

4.3.3 Mechanism of Agricultural Output Between Climate Change and Farmers' HFV

To test the mechanism of credit constraint in hypothesis 4, climate change affects agricultural output and then influences farmers' HFV. Agricultural output is measured by the logarithm of agricultural gross domestic product, referring to some literature, such as Temple (2006) and Skuras et al. (2010). **Table 7** shows that temperature changes have a negative effect on agricultural output at the 1% confidence level in column (1), consistent with the findings of Dell et al. (2012). Precipitation also has a negative effect on agricultural output in column (2) during the observation period. Moreover, the coefficient of agricultural output and HFV is negative at the 10% confidence level in column (3), which shows that higher agricultural output alleviates HFV. This finding validates Hypothesis 4.

4.4 Heterogeneity Analysis

4.4.1 Different Areas

Because of China's vast territory and diverse climate, the impacts of climate change on each region vary (Both and Visser, 2001). It is worth investigating the different effects of climate change on farmers' HFV in different areas. According to the classification for the middle, east, west and northeast by the National Bureau of Statistics, the empirical results show that farmers in middle and northeastern areas are more likely to suffer from increasing HFV from changes in temperature, which can be seen in **Table 8**. Perhaps the central and northeastern plains are vast and have a high proportion of subsistence agricultural production. The increased vulnerability is more pronounced when farmers' agriculture is subject to temperature change shocks. Moreover, from **Table 8**, the role of increasing precipitation in exacerbating HFV is shown to be significantly higher in the east than in the rest of the areas in China. In addition, unstable precipitation is the main reason for the frequent occurrence of drought. The eastern region is heavily influenced by monsoons and is a concentrated area in terms of the population and economy, and the greater the fluctuation in precipitation is, the more obvious the increase in household vulnerability in the eastern region is than in the rest in China.

4.4.2 Education

Whether different educational backgrounds have different impacts on the effects of climate change on farmers' HFV remains to be seen. To determine the value of education, this heterogeneity analysis was performed. Therefore, education is classified by whether the national entrance examination should be taken. High education includes college or vocational school and above. **Table 9** shows the results. Against different education backgrounds, the changes in temperature and precipitation have the same effects. Specifically, farmers with lower education levels and household financial vulnerabilities are more likely to be influenced by climate change. This finding implies that education is important in improving farmers' HFV caused by climate change. Therefore, farmers should learn more to overcome the negative effects of climate change.

5 CONCLUSION AND IMPLICATIONS

This paper investigates the economic impact of climate change at the micro level using data from the CHFS 2017 and China Meteorological Administration database. The empirical findings indicate that temperature and precipitation changes positively contribute to the financial vulnerability of farmers' households. After some robustness tests, this conclusion is confirmed. The mechanism analysis reveals that climate change has an impact on rural households' financial vulnerability via farmers' health, credit availability, and agricultural output. Furthermore, the effect of climate change on farmers' HFV is more evident in farmers with low education. The farmers in the middle and northeastern areas are more likely to suffer from increasing HFV from temperature changes, while the aggravating effects on HFV of precipitation changes in the east are stronger than those in the west, middle and northeastern regions.

According to our findings, it is critical to consider how to prevent and respond to climate change and reduce HFV. Specific policy recommendations are as follows. First, it is urgent to establish a climate change risk management system. Climate change leads to frequent natural disasters, which requires relevant policy departments to strengthen climate observation. Furthermore, early warning mechanisms should be deployed to increase the speed and breadth of climate information dissemination among macroregions and microhomes. Additionally, it is pertinent to develop emergency preparedness plans for climate change, improve households' ability to cope with climate change through various means, like skills training, and reduce the harm of climate change on household health. Second, the government should promote education, especially financial literacy, which is su–ggested to enhance the practical ability of financial participation. Among the required actors, the government, community committees, and financial public welfare organizations should conduct a variety of financial literacy activities to increase resident households' financial participation and the effectiveness of their behavioral decisions. Educational efforts to promote financial risk knowledge should also be stepped up to improve rural households' ability to handle risks and enhance their self-protection awareness. They can be more rational and scientific in their decision making and less risky in their participation in acquiring financial resources. Third, the government should improve scientific guidance for rural households' agricultural production and operation and assist them in various areas, such as agricultural insurance and agricultural response to climate change. These efforts will improve rural households' agricultural production ability to combat severe natural disasters.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: CHFS 2017, China Meteorological Administration database.

AUTHOR CONTRIBUTIONS

SY reviews literature, KZ writes the conclusion and helps empirical study. TL write the introduction and with the rest two students collect the relative literature and data, analyze results and translate and revise the whole paper.

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Impact of Natural Disaster Shocks on Farm Household Poverty Vulnerability—A Threshold Effect Based on Livelihood Resilience

Honggang Lu[1], Jiaxi Zheng[2], Hanyun Ou[2], Yinong Liu[2] and Xijian Li[2]*

[1] *Agriculture and Forestry Economics and Management, School of Economics and Management, Zhejiang Agriculture and Forestry University, Hangzhou, China,* [2] *Agricultural Economics, School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China*

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Anyang Institute of Technology, China

***Correspondence:**
Jiaxi Zheng
470507355@qq.com

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Poverty caused by disasters poses a great challenge to consolidate the achievements of poverty alleviation. Livelihood resilience is the key factor for farmers to resist risks and get rid of poverty. Therefore, this study used the China Family Panel Studies (CFPS) database. Firstly, we examined the impact of natural disasters on the poverty vulnerability of farmers. Secondly, taking livelihood resilience and its decomposition dimensions as threshold variables, we examined the mechanism of livelihood resilience between natural disasters and poverty. The results show that natural disaster shocks, natural disaster intensity, and natural disaster frequency all had a significant positive effect on farm households' vulnerability to poverty. The threshold test shows that natural disasters had larger effects on the poverty vulnerability of the farmers with lower buffer capacity, self-organizing capacity, and learning capacity. When the livelihood resilience value exceeded the third threshold, the impact of natural disasters on the poverty vulnerability of farmers turned from positive to negative. When the buffer capacity exceeded the third threshold, the impact of natural disasters on poverty vulnerability turned from positive to negative; when the self-organizing capacity exceeded the first threshold, the impact of natural disasters on poverty vulnerability turned from positive to negative; when the learning capacity exceeded the third threshold, the impact of natural disasters on poverty vulnerability turned from positive to negative. Therefore, it is suggested that appropriate policies should be needed to support farmers' livelihood resilience and address disaster-induced poverty by improving farmers' buffer capacity, self-organizing capacity, and learning capacity. Focusing on farmers' livelihood resilience, government should establish a policy support system aimed at improving farmers' buffer capacity, self-organizing capacity, and learning capacity, that will help farmers to escape from disaster-induced poverty.

Keywords: livelihood resilience, threshold effect, poverty vulnerability, natural disaster, farm household

INTRODUCTION

Poverty caused by disasters has always been a huge challenge to consolidate poverty alleviation. Natural disasters directly affect crop production and farmers' livelihoods, threaten farmers' sources of income and living conditions, and easily lead non-poor farmers into poverty and those who have been lifted out of poverty back into poverty. According to the World Meteorological Organization's (WMO) Statement on the State of the Global Climate in 2019, the decade 2010–2019 has been the hottest on record (Kappelle, 2020). Global warming has increased water circulation and caused more catastrophic climate disasters such as floods, droughts, heatwaves, tropical cyclones, and wildfires (Donat et al., 2016; Johnson et al., 2018), with tens of millions of the population to become "climate refugees." China is a country severely affected by natural disasters. In 2020, various natural disasters in China affected 138 million people, caused 5.891 million people to evacuate, damaged 1.807 million houses, and destroyed 19.958 million hectares of crops. Currently, although China has comprehensively addressed absolute poverty, large population who have escaped from poverty still lack endogenous development incentives and sustainable livelihoods. Some studies show that 15% of people who have escaped from poverty have a high risk of returning to poverty after 3–5 years (Chen et al., 2020), and nearly 2 million people in China are at risk of returning to poverty (Li, 2021). Livelihood resilience plays an important role in helping farm households to resist risks and escape from poverty. Adequate buffer capacity, learning capacity, and self-organizing capacity provide strong support for transforming farm households' livelihood strategies and stabilizing basic returns when coping with disasters. Therefore, in order to improve farmers' capacity to resist disasters and consolidate the achievements of poverty alleviation, it is of great significance to explore the impact of natural disasters on farmers' poverty vulnerability from the perspective of livelihood resilience.

LITERATURE REVIEW

Many studies have focused on disasters and farm household poverty. Hallegatte et al. (2015) argued that natural disaster shocks to agricultural production and health prevented households from escaping poverty. Yang et al. (2016) found that meteorological disasters significantly reduced farmers' incomes in specific areas and negatively affected farmers' agricultural and non-agricultural incomes. Walsh and Hallegatte (2019) incorporated socio-economic resilience into the risk assessment framework and found that floods would immediately lead Sri Lankans into poverty, especially for low-income groups. However, some scholars argued that disasters have a boosting effect on income. Banerjee (2007) analyzed the rise in demand for agricultural labor in Bangladesh after floods, which instead led to an increasing income of rural workers dependent on agricultural wages for their livelihoods. Gignoux and Menéndez (2016) found that individuals affected by the earthquake experienced short-term economic losses, but recovered to their original levels in the medium term (2–5 years) and even achieved long-term gains after 6–12 years.

The concept of resilience first appeared in the study of ecosystems to denote the ability to recover physical characteristics under ecological changes (Holling, 1973). Adger (2000) first introduced the concept of resilience into social science research. Then, resilience has gradually been applied into study the ability of human and social systems to recover livelihoods (Davidson, 2010). In studies of uncertainty and human wellbeing, the concept of resilience has been further expanded. Nowadays, livelihood resilience indicates an ability of a system to maintain its original characteristics after a shock (Tambo, 2016), which is widely used in economic organizational behavior, social-ecological systems and disaster management. In measurement of livelihood resilience, Speranza et al. (2014) built a framework of buffer capacity, self-organizing capacity, and learning capacity. Smith and Frankenberger (2018) classified livelihood resilience into absorptive capacity, adaptive capacity, and transformational capacity. Zhou et al. (2021a) considered livelihood resilience as an important means of addressing disaster shocks, included farmers' disaster prevention and mitigation capacity into the research framework of livelihood resilience and measured livelihood resilience in four dimensions: buffer capacity, self-organizing capacity, learning capacity, and disaster resilience.

The impact of livelihood resilience on poverty can be discussed in terms of buffer capacity, self-organizing capacity, and learning capacity. Firstly, buffer capacity represents the degree of change or disturbance that a system can withstand to maintain its structure, function, and feedback. In the farmers' livelihood system, farmers can use existing accessible assets to cope with shocks and capture opportunities for better livelihood outcomes. For example, Wang W. et al. (2021) argued that the initial livelihood capital endowment was critical for farm households to escape from poverty. Some studies show that physical capital such as agricultural means of production, housing and durable goods are effective in reducing poverty occurrence among farm households (Shinn and Gillespie, 1994; Amendola and Vecchi, 2014; Oni and Oyelade, 2014). Secondly, self-organizing capacity describes the impact of institutions, rights and social organizational structures on livelihood resilience. Its impact on poverty can alleviate poverty through institutional systems, social organizations and groups as well as social networks (Jung, 2007; Yan, 2018). Thirdly, learning capacity emphasizes the adaptive management of systems to transform knowledge into productivity. Farmers with higher learning capacity can better participate in the urbanization and industrialization process. Thus, they can achieve a shift in livelihood strategy to escape from poverty by working away from home or starting a business (Yang, 2012; Jia et al., 2017).

In general, a wide variety of research has been conducted on the relationship between disasters and poverty as well as the relationship between livelihood resilience and poverty. However, there are still some shortcomings in existing studies. Firstly, the definition of poverty focuses more on static absolute poverty, which can only reflect the poverty status of rural households in the current period instead of dynamical future trends of poverty (Chaudhuri et al., 2002; Ligon and Schechter, 2003). The poverty vulnerability index measures the likelihood of falling into poverty for rural households in future periods, which is forward-looking for measuring the impact of disaster shocks on farm households' poverty. Secondly, the impact of natural disasters on farm household poverty has been rarely studied from the perspective of livelihood resilience. Thus, based on the definition of poverty vulnerability and livelihood resilience, livelihood resilience was divided into buffer capacity, self-organizing capacity, and learning capacity in this paper.

Furthermore, the threshold role of the three capacities between disaster and poverty was explored. This will provide a theoretical implication and decision-making insight for reducing disaster poverty risk and improving the livelihood sustainability of farm households.

HYPOTHESIS

Disasters directly cause poverty, mainly by disaster-causing factors, disaster risks and bearers. Poverty caused by disaster-causing factors and disaster risks involves direct links between disaster and poverty. Poverty caused by disaster factors is manifested as economic losses and casualties of farmers due to natural disasters. Such impacts hit farmers' income and consumption in the short term, causing them to be vulnerable to poverty. Poverty by disaster risks involves the hidden poverty driven by different disasters. There are differences in the impact of low-frequency and high-loss intensive disasters and high-frequency and low-loss widespread disasters on poverty of farmers. The former type mainly causes economic losses and deaths, while the latter has more cumulative indirect impacts. For example, frequent rainstorms and droughts are major causes of the continuous reduction of farmers' agricultural income and precarious livelihoods.

The impoverishment of bearing bodies is manifested in that different hazard bearing bodies in the same intensity of disasters magnify the losses of disasters due to higher cost value and lower livelihood resilience in the face of disasters. That is, the difference in the livelihood resilience of the carrier may lead to changes in the direction or intensity of the effect of disasters on poverty (Wilhite et al., 2007). Livelihood resilience can be further divided into buffer capacity, self-organizing capacity, and learning capacity according to its roles and functions in anti-poverty. Firstly, as the households' ability to resist risks, buffer capacity is responsible for smoothing households' production and consumption, by which the household's primary welfare is maintained. Low buffer capacity will exacerbate the risk of disaster shocks and prevent farmers from adjusting production and livelihoods in time to adapt to environmental changes. Consequently, farmers will fall into poverty trap. In contrast, for those with sufficient buffer capacity, this short-term impact is too limited to change their livelihood sources. Secondly, self-organizing capacity represents the farmers' ability to integrate into the local economy, society and institutional environment. When farmers are affected by disasters, components including environmental and institutional factors are critical to helping farmers effectively get rid of the predicament. For example, factors such as convenient transportation and organizational participation are conducive to farmers adopting non-agricultural employment to respond to disaster shocks and mitigate the negative impact of disasters. Thus, these will help farmers get rid of poverty. Farmers with low self-organizing capacity cannot integrate into neighboring systems and organizations when dealing with disasters. It is difficult to avoid disaster risks and thus farmers may fall into poverty. Thirdly, learning capacity represents the farmers' ability to adapt to disturbances. When the livelihood development of farmers is exposed to short-term disaster shocks, it can help farmers cope with the impact of short-term disasters. However, with the increase of external disturbances and their duration, farmers need to constantly adapt to external disturbances while improving their abilities. In the changing environment, farmers with strong learning capacity can change their livelihood strategies in real time and take adaptive measures such as labor transfer and non-agricultural employment to alleviate the sharp fall in income caused by disaster shocks. Farmers with weak learning ability are unable to cope with disaster shocks by changing their livelihood strategies and can only engage in agricultural production, which aggravates their poverty vulnerability.

> **Hypothesis 1**: Shocks, intensity and frequency of natural disasters lead to poverty vulnerability of farm households.

> **Hypothesis 2**: Natural disaster shocks have non-linear effects on the poverty vulnerability of farm households with a threshold of livelihood resilience.

METHODOLOGY AND DATA

Explained Variable: Poverty Vulnerability Indicator

The adjustment to poverty involves eradicating specific poverty and eliminating sudden poverty vulnerability. Silber and Wan (2016) argued that it is necessary to adjust poverty thresholds according to vulnerability, and the adjusted poverty line can represent the minimum living standard in a vulnerable environment. There are three definitions of poverty vulnerability measures, i.e., poverty vulnerability (VEP), low expected utility vulnerability (VEU), and risk exposure vulnerability (VER). Most scholars adopt the VEP approach (Peng J. et al., 2019; Yang et al., 2021). The main reason is that with $\alpha = 0$, VEP can be simplified as the probability that consumption is lower than poverty. Therefore, the VEP measure is used in this paper to measure the poverty vulnerability of farm households:

$$V_{it} = \Pr(Y_{i,t+1} \leq pl) \tag{1}$$

where V_{it} represents the poverty vulnerability of the farm household i in period t. It refers to the probability that the farm household's future net consumption ($Y_{i,t+1}$) per capita is below the poverty line (pl). In the empirical study, the specific calculation method of V_{it} refers to the three-stage feasible generalized least squares (FGLS) used by Chaudhuri et al. (2002). The regression process is mainly divided into three steps:

Step 1: the model of consumption average and consumption fluctuation is established. The consumption average model is estimated with the OLS method. The square of the residual obtained after regression is used to represent the consumption fluctuation. Then, the OLS method is used to regress the consumption variance model to obtain the heteroscedasticity structure:

$$\ln Y_{i,t} = \beta_i X_{i,t} + \mu_i \tag{2}$$

where $Y_{i,t}$ denotes the consumption of the household i in period t; $X_{i,t}$ denotes the household's observable characteristic variables, including individual characteristic variables such as age, gender, and education of the household head and characteristic variables such as the number of household laborers and health status; β_i denotes the vector of household's characteristic coefficients; μ_i denotes the disturbance term.

Step 2: by using the heteroscedasticity structure calculated in the first step as the weight, weighted regression (WLS) was performed on the consumption mean and consumption variance model to obtain the required parameter estimates. The future consumption level and its variance according to the parameter estimates can be predicted:

$$\hat{E}\left[\ln y_i \,|X_i\right] = \hat{\beta} X_i \tag{3}$$

$$\hat{V}\left[\ln y_i \,|X_i\right] = \sigma^2 = \hat{\delta} X_i \tag{4}$$

Step 3: The poverty line is selected when the logarithmic variance of consumption and logarithmic expectation of consumption are known, and the vulnerability of households to poverty in the current period is calculated according to the normal distribution function, which can be expressed as:

$$VEP_i = \Pr\left\{\ln(pl)\,|X_i\right\} = \Delta\left[\frac{\ln(pl) - X_i\hat{\beta}}{(\hat{\delta}X_i)^{1/2}}\right] \tag{5}$$

A household i is vulnerable to poverty if the probability that the household will fall into poverty in the future is larger than the poverty vulnerability threshold. The international poverty criteria adopted by the World Bank for low- and middle-income countries are US$1.9 and US$3.2 per capita per day. Considering that the actual currency purchasing power varies across countries, this paper selected US$3.2 per capita per day as the poverty standard line according to Wang J. et al. (2021) and used the annual purchasing power parity (PPP) index to convert the US dollar indicator into the corresponding RMB measure.[1] Poverty vulnerability is usually set in three forms, i.e., poverty incidence (Peng J. et al., 2019), 50% probability value (Sheng and Guo, 2018), and 29% probability value (Günther and Harttgen, 2009). Since using 50% as the vulnerability line will cause the omission of temporarily poor families, in recent years, some scholars began to use the 29% as the vulnerability line, i.e., a household is considered poor and vulnerable if its probability of falling into or remaining poverty in the future is not less than 29%. Therefore, the 29% probability value was selected as the poverty vulnerability line criterion in this paper.

Core Explanatory Variables: Natural Disaster Shocks

Three core explanatory variables were designed in this paper. (1) Natural disaster shocks. According to the China Family Panel Studies (CFPS) community questionnaire ("During the period from January 1, 2010 to December 31, 2013, has your village suffered from the following natural disasters?") including nine types of natural disasters in detail such as droughts, floods, and typhoons, if the village suffers a natural disaster, the value of these variables is taken as 1; otherwise, the value is taken as 0. (2) Natural disaster shock intensity. According to the number of types of natural disasters occurring in the area, the natural disaster impact intensity variable was constructed and set as the integer "1–9." (3) Frequent disasters. According to questionnaire ("Is the area a natural disaster-prone area?"), If the answer is "yes," the village is considered to be affected by a long-term natural disaster and the value is 1; otherwise, the value is 0.

Threshold Variable: Livelihood Resilience and Its Decomposition Term

Referring to the livelihood resilience measurement framework proposed by Speranza et al. (2014), relevant literature and data (Cao et al., 2016; Gerlitz et al., 2017; Peng L. et al., 2019; Sina et al., 2019; Zhou et al., 2021a) were combined to construct a three-dimensional—livelihood resilience evaluation system of buffer capacity, self-organizing capacity, and learning capacity. Buffer capacity refers to the farmers' ability to use available assets when coping with shocks. In combination with the sustainable livelihood analysis framework, the indicators reflecting the buffer capacity of farmers were selected, including natural capital (Arable land area), financial capital (per capita income), human capital (dependency ratio and amount of labor force), material capital (housing capital, durable goods value, and production capital), and social capital (social spending). Self-organizing capacity reflects the impact of system, rights and social organization structures on livelihood resilience. The variables including traffic accessibility (Distance to the nearest township and county), social organization participation and economic assistance were selected. Learning capacity emphasizes the adaptive management ability of the system, which refers to the ability of farmers to transform knowledge into productivity. This paper selects variables such as years of education of the head of household, the income of immigrants, the degree of participation in training, and the use of Internet for learning.

Proposed by Wu et al. (2019), the entropy weighting method was used to measure the weights. As an objective assignment method, the entropy method can reduce the interference of artificial elements on the evaluation results and yield more scientific evaluation results (Xu et al., 2018, 2019; Guo et al., 2019; Zhou et al., 2021b). Specific indicators and weights are shown in **Table 1**.

Control Variables

In addition to disaster shocks, the poverty vulnerability of rural households is also affected by many other factors. In order to ensure the scientific validity and integrity of the model, variables such as household head characteristics, family characteristics and external support were included based on previous research and data availability. Household head characteristics included age, gender (1 = male; 0 = female) and marital status (1 = married; 0 = otherwise). Family characteristics include the proportion of unhealthy people, social services (logarithm of agricultural machinery rental), whether the land was transferred

[1]According to data published by the World Bank, the PPP conversion factor for household consumption in China in 2014 was 3.945, and thus the $3.2 poverty criterion was converted to RMB 4607.76 per capita per year.

TABLE 1 | Indexes of the livelihood resilience of rural households for analysis.

Livelihood resilience	Variables	Explanation	Nature of indicator	Weights	Mean	*SD*
Buffer capacity	Income per capita	Ratio of annual household income to the total number of persons (10,000 yuan)	+	0.0643	1.3502	1.6552
	Dependency ratio	Household elderly and children as a proportion of the total number of people (%)	–	0.0644	32.71%	27.15%
	Labor	Number of laborers in the farming household (number)	+	0.0676	2.6459	1.3104
	Saving	The total value of cash and deposits (10,000 yuan)	+	0.0555	1.6909	4.3249
	Housing capital	Housing value (million yuan)	+	0.0612	12.3040	23.9664
	Durable goods value	Value of household durable goods (10,000 yuan)	+	0.0599	1.4401	3.2032
	Production capital	Value of farm machinery (10,000 yuan)	+	0.0555	0.2326	0.6677
	Natural capital	Arable land area (mu)	+	0.0612	9.7690	24.7202
	Social capital	Social spending (10,000 yuan)	+	0.0618	0.2821	0.4323
Self-organizing capacity	Township distance	Distance to the nearest township (km)	–	0.0621	10.4153	22.8291
	County distance	Distance to the nearest county (km)	–	0.0655	52.4116	41.8754
	Social organization participation	Whether to participate in village committee voting (0, did not participate; 1, participated)	+	0.0598	0.3652	0.4815
	Financial assistance	Financial assistance from relatives and friends (10,000 yuan)	+	0.0471	0.0841	0.5018
Learning capacity	Education	Educational years of the head of household (years)	+	0.0652	6.2528	4.1752
	Outworking	Share of income from outworking in total household income (%)	+	0.0649	56.93%	40.32%
	Whether to participate in training	Number of non-academic education (times)	+	0.0387	0.1191	1.1142
	Use the Internet to learn	Do you use the Internet to learn? (0 = Never; 1 = every few months; 2 = once a month; 3 = 2–3 times per month; 4 = once or twice a week; 5 = 3–4 times a week; 6 = almost every day)	+	0.0454	0.2666	1.0868

out (1 = land was transferred out; 0 = land was not transferred out) and government subsidies were selected for external support (1 = received government subsidies; 0 = did not receive government subsidies) and social donations (1 = received social donations; 0 = did not receive social donations). In addition, whether the included area was a mine was used as a regional control variable. **Table 2** presents the descriptive statistics of the main variables.

Basic Regression

The master model is specified as:

$$Poverty = \beta_0 + \beta_1 \mathrm{X} + \beta_2 \mathrm{control} + \varepsilon \tag{6}$$

where Y represents the poverty vulnerability; X indicates natural disaster impact, natural disaster intensity and natural disaster frequency; β_0 is a constant; ε is the error term; β_1 and β_2 are coefficients to be determined.

Threshold Effect Model

When examining the factors that cause heterogeneous effects of explanatory variables on the explained variables, grouping tests or interaction terms are commonly used, but it is difficult to determine the grouping criteria for grouping tests (Xu et al., 2021). Therefore, within the traditional linear model framework, it is impossible to clarify the differential relationship between natural disaster shocks and farmers' poverty vulnerability at different livelihood resilience levels. In order to overcome the limitations of current research methods, Hansen (1999) established a grouping regression model on the basis of grouping approach in threshold regression:

$$\begin{cases} y_i = \theta_1 x_i + \varepsilon_i, q_i \le \gamma \\ y_i = \theta_2 x_i + \varepsilon_i, q_i > \gamma \end{cases} \tag{7}$$

where q_i represents livelihood resilience and its decomposition term, γ represents the critical point of the threshold variable.

TABLE 2 | Descriptive statistics.

Variable	Mean	*SD*	Min	Max
Poverty vulnerability	0.5546	0.4970	0	1
Livelihood resilience	0.2767	0.0537	0.0998	0.5115
Buffer capacity	0.0757	0.0273	0.0001	0.1949
Self-organizing ability	0.1411	0.0307	0.0536	0.2017
Learning ability	0.0600	0.0330	0	0.1740
Natural disaster shocks	0.7674	0.4225	0	1
Frequency of natural disasters	0.8058	0.3956	0	1
Natural disaster shock intensity	2.0386	1.7546	0	9
Gender	0..5740	0.4945	0	1
Age	49.2121	12.893	16	88
Square term of age	2588.027	1277.16	256	7,744
Marriage	0.8906	0.3123	0	1
Proportion of unhealthy people	0.0127	0.1119	0	1
Social donation	0.0127	0.1119	0	1
Government subsidies	0.7108	0.4534	0	1
Agricultural socialization services	2.2545	3.1461	0	9.9988
Land transfer	0.0990	0.2986	0	1
Mining area	0.0633	0.2436	0	1

According to n critical values, the total sample can be divided into $n + 1$ sample intervals, θ_1 and θ_2 represents the estimation coefficients of different sample intervals, respectively.

Data Source

This study used data from the CFPS, a large-scale micro-household survey implemented by the China Social Science Survey Center of Peking University. CFPS is nationally representative and aims to reflect the changes in China from the perspective of society, economy, population, education, and health. It tracks and collects data from individuals, households and communities, covering household microdata from most provinces (municipalities and autonomous regions) across China.

EMPIRICAL RESULTS

Model Regression Results

Table 3 shows the regression results of the effects of natural disasters on poverty vulnerability of farm households. Models (1), (2), and (3) are the effects of natural disaster shocks, natural disaster frequency, and natural disaster intensity on the poverty vulnerability of farm households, respectively. Column (1) shows that natural disaster shocks had a positive effect on the poverty vulnerability of farm households and were highly significant at the 5% level; Columns (2) and (3) show that natural disaster frequency and intensity both had a significant positive effect on the poverty vulnerability of farm households and was highly significant at the 10% level, respectively. Thus, Hypothesis 1 was verified. The reason is that intensive disasters (e.g., catastrophes) directly hit farm households and lead to death and asset loss, which in turn leads to poverty vulnerability. The risk of extensive disasters (e.g., recurrent floods and agricultural droughts) is responsible for asset damage and economic losses, and their continuous cumulative indirect effects (e.g., welfare damage, health deterioration, and income decline) contribute to chronic and deep poverty.

TABLE 3 | Impact of natural disasters on the vulnerability of farm households to poverty.

	(1)	(2)	(3)
Natural disaster shocks	0.0354**		
	(2.37)		
Frequency of natural disasters		0.0305*	
		(1.93)	
Natural disaster shock intensity			0.0066*
			(1.76)
Gender	0.0442***	0.0440***	0.0431***
	(3.51)	(3.49)	(3.41)
Age	−0.0157***	−0.0157***	−0.0156***
	(−5.40)	(−5.38)	(−5.35)
Square term of age	0.0003***	0.0003***	0.0003***
	(11.03)	(11.03)	(11.01)
Marriage	−0.0668***	−0.0669***	−0.0667***
	(−3.43)	(−3.43)	(−3.43)
Proportion of unhealthy people	0.0557**	0.0569**	0.0555**
	(2.48)	(2.53)	(2.47)
Social donation	0.1181**	0.1160**	0.1167**
	(2.44)	(2.39)	(2.41)
Government subsidies	0.1321***	0.1320***	0.1325***
	(9.16)	(9.13)	(9.18)
Agricultural socialization services	0.0025	0.0023	0.0026
	(1.24)	(1.16)	(1.28)
Land transfer	−0.1831***	−0.1837***	−0.1828***
	(−9.50)	(−9.53)	(−9.52)
Mining area	0.0590**	0.0594**	0.0518**
	(2.36)	(2.37)	(2.08)
Central region[2]	0.0146	0.0164	0.0198
	(0.94)	(1.06)	(1.29)
Western region	0.1133***	0.1156***	0.1140***
	(7.41)	(7.60)	(7.27)
Cons	0.3908***	0.3911***	0.3992***
	(5.58)	(5.57)	(5.71)
N	5,366	5,366	5,366
R^2	0.2244	0.2241	0.2240

, **, and * represent 1%, 5%, and 10% significance levels, respectively. The values in brackets are t-values.*

[2]Eastern Region: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; Central region: Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; Western region: Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Guangxi.

Among the control variables, age, marriage, and land transfer had significant negative effects on poverty vulnerability, while gender, the square term of age, social donations, government subsidies, the proportion of unhealthy people, and being in a mining area all have significant positive impacts on the poverty vulnerability of farmers. It can be seen that there was an inverted U-shaped relationship between age and poverty vulnerability. When the household head was in their young and middle age, the farming household had stronger workability and learning capacity, which is more advantageous in making a living and earning income. When the age exceeded the threshold point, problems such as deteriorating health, work difficulty and mobility constraints restrict the income growth and consumption desire of the farming household. Married households can effectively alleviate poverty vulnerability since the income growth brought by marriage facilitates the escape from poverty. Farmers can reasonably allocate labor resources to achieve diversified income growth by farming and working away from home. The increase in the proportion of unhealthy families not only reduces the labor force, but also increases the burden on the existing labor force, thus increasing the possibility of farmers' poverty vulnerability. The change in livelihood strategy caused by the land transfer effectively contributes to income growth and poverty alleviation. Both social donation and government subsidies have a positive effect on poverty vulnerability, because short-term support policies can help farmers overcome their difficulties, while they may also lead to the attitude of "waiting for, relying on and requesting" aid. This makes it difficult for farmers to escape from poverty in the long term, thus increasing their poverty vulnerability. Farmers in mining areas are more likely to fall into poverty vulnerability. The possible reason may be that the "resource dependence trap" leads to a lack of human capital investment and technological progress for farmers, and thus they fall into poverty.

Endogeneity Test

Endogeneity problems may exist as survey data were susceptible to respondent bias and recall during collection, and there may also be omitted variables that affect livelihood resilience. In this paper, the instrumental variable measurement by Dell et al. (2014) was used and the disaster incidence in other regions in the same province was selected as the instrumental variable of the IV model to estimate the disaster impact. The natural disaster occurrence recorded in the CFPS 2014 questionnaire spanned from 2010 to 2013, and the probability of natural disaster occurrence in districts and counties within the same province was similar over a longer period, which can reflect the natural disaster occurrence in the village. In addition, the natural disaster occurrence in areas except for one specific village was not directly related to the relative poverty level of local farm households. Therefore, the condition of exogeneity is met.

From the 2SLS estimation results in **Table 4**, the results of the IV under-identification test indicate that the LM statistic (*p*-value) of the model significantly rejected the original hypothesis, indicating that the model did not show under-identification of instrumental variables. The Cragg-Donald Wald F-statistic was significantly larger than the threshold value of StockYogo weak instrumental variables, indicating that the model did not have the problem of weak instrumental variables. The first-stage regression results present a positive relationship between the occurrence of natural disasters in the neighboring areas and the occurrence of natural disasters in the area. The coefficient from the second-stage regression was 0.2507 and reached statistical significance at the 1% level, which was a significant increase compared to the coefficient in baseline regression. This shows that ignoring the endogeneity problem will lead to the underestimation of the estimated coefficients.

Threshold Effect Test

According to the principle of the threshold effect model, the F statistic and the corresponding *p*-values at 1%, 5%, and 10% significance levels were compared, as shown in **Table 5**. Under livelihood resilience, all triple threshold estimates (0.263, 0.329, and 0.371) passed the test at the 1% significance level, with significant differences between these three values. Similarly, the estimates of buffer capacity all passed the test at the 1% significance level, and the three thresholds were 0.021, 0.046, and 0.095, respectively. The double threshold of self-organizing capacity passed the test at the 1% significance level, while the triple threshold did not. Thus, there was a double threshold estimate of self-organizing capacity, and the actual values corresponding to the double threshold were 0.189 and 0.190. The estimated values of learning capacity all passed the test at a 1% significance level, and the three thresholds were 0.031, 0.078, and 0.108, respectively (see **Table 6** for details).

From **Table 7** we can see that the extent of the impact of natural disaster shocks on farm household poverty vulnerability varied with different livelihood resilience. When the livelihood resilience was below the first threshold, the impact of natural disaster shocks on the poverty vulnerability of farm households was highly significant at the 1% level, with an estimated coefficient of 0.1110; when the livelihood resilience was between the first and second thresholds, the impact was

TABLE 4 | Instrumental variable estimation.

Variable	(1)	First stage	Second stage
Natural disaster shocks	0.0354**		0.2507***
	(2.37)		(7.02)
Instrumental variable		0.9667***	
		(30.30)	
IV underidentification test: Kleibergen.LM value (*P*-value)		580.108 (0.0000)	
Weak instrumental variable test: Cragg-Donald Wald *F*-value		1051.516	
N	5,366	5,366	5,366

, **, and * represent 1%, 5%, and 10% significance levels, respectively. The values in brackets are t-values.*

TABLE 5 | Threshold effect test.

	Number of thresholds	*F*-value	*P*-value	10% threshold	5% threshold	1% threshold
Livelihood resilience	Single threshold	47.369***	0.000	4.920	3.280	2.580
	Double threshold	15.238***	0.000	−9.417	−17.151	−20.373
	Triple threshold	12.211***	0.000	4.972	3.255	2.634
Buffer capacity	Single threshold	106.550***	0.000	6.630	3.943	3.024
	Double threshold	40.069***	0.000	7.817	4.086	3.245
	Triple threshold	11.806***	0.000	7.720	4.230	2.874
Self-organizing capacity	Single threshold	11.468***	0.000	5.827	3.334	2.429
	Double threshold	7.575***	0.000	6.296	3.700	2.659
Learning capacity	Single threshold	3.330	0.130	6.829	5.120	4.200
	Double threshold	73.021***	0.000	7.942	4.722	2.997
	Triple threshold	22.680***	0.000	−5.131	−11.197	−14.810

, **, and * represent 1%, 5%, and 10% significance levels, respectively.*

highly significant at the 1% level, with an estimated coefficient of 0.0547; when the livelihood resilience was between the second and third thresholds, the impact of natural disaster shocks on the poverty vulnerability of farmers was not significant; when the livelihood resilience was larger than the third threshold, the impact was highly significant at the 1% level, with an estimated coefficient of −0.1961, and the sign of the impact coefficient changed from positive to negative. In general, it shows that when the livelihood resilience of farmers was at a low level, the natural disaster shock positively affected the poverty vulnerability of farmers; when the livelihood resilience of farmers exceeded 0.371, the natural disaster shock alleviated the poverty vulnerability of farmers instead. Based on our hypotheses, there are two main reasons. Firstly, farmers with high livelihood resilience tend to adopt livelihood transitions in response to reduced agricultural production and income caused by disasters. Secondly, for farmers with high mechanization and disaster resilience, the imbalance between supply and demand of agricultural products after disasters is instead beneficial to the income growth of such farmers.

When the buffer level was below the first threshold, the impact of natural disaster shocks on farm household poverty vulnerability was highly significant at the 1% level, with an estimated coefficient of 0.4291; when the buffer capacity was between the first and second thresholds, the impact was highly significant at the 1% level, with an estimated coefficient of 0.1572; when the buffer capacity was between the second threshold and the third threshold, the impact of natural disaster shocks on the poverty vulnerability of farmers was highly significant

TABLE 6 | Estimated threshold values.

	Number of thresholds	Threshold estimates	95% confidence interval
Livelihood resilience	Single threshold	0.263	[0.210, 0.392]
	Double threshold	0.329	[0.306, 0.345]
	Triple threshold	0.371	[0.326, 0.379]
Buffer capacity	Single threshold	0.021	[0.014, 0.025]
	Double threshold	0.046	[0.043, 0.134]
	Triple threshold	0.095	[0.093, 0.102]
Self-organizing capacity	Single threshold	0.189	[0.189, 0.189]
	Double threshold	0.190	[0.189, 0.192]
Learning capacity	Single threshold	0.031	[0.002, 0.116]
	Double threshold	0.078	[0.064, 0.085]
	Triple threshold	0.108	[0.005, 0.151]

TABLE 7 | Parameter estimation results of the model.

	(1)	(2)	(3)	(4)
Livelihood resilience (1)	0.1110***			
Livelihood resilience ≤ 0.263	(6.63)			
Livelihood resilience (2)	0.0547***			
0.263 < Livelihood resilience ≤ 0.329	(3.41)			
Livelihood resilience (3)	−0.0272			
0.329 < Livelihood resilience ≤ 0.371	(−1.10)			
Livelihood resilience (4)	−0.1961***			
0.371 < Livelihood resilience	(−4.53)			
Buffer capacity (1)		0.4291***		
Buffer capacity ≤ 0.021		(11.23)		
Buffer capacity (2)		0.1572***		
0.021 < Buffer capacity ≤ 0.046		(5.50)		
Buffer capacity (3)		0.0654***		
0.046 < Buffer capacity ≤ 0.095		(3.98)		
Buffer capacity (4)		−0.0381*		
0.095 < Buffer capacity		(−1.82)		
Self-organizing capacity			0.0652***	
Self-organizing capacity ≤ 0.189			(4.51)	
Self-organizing capacity (2)			−0.2412***	
0.189 < Self-organizing capacity ≤ 0.190			(−3.14)	
Self-organizing capacity (3)			−0.0057	
0.190 < Self-organizing capacity			(−0.14)	
Learning capacity				0.1632***
Learning capacity ≤ 0.031				(8.71)
Learning capacity (2)				0.0675***
0.031 < Learning capacity ≤ 0.078				(4.11)
Learning capacity (3)				−0.0072
0.078 < Learning capacity ≤ 0.108				(−0.40)
Learning capacity (4)				−0.1312***
0.108 < Learning capacity				(−3.54)

, **, and * represent 1%, 5%, and 10% significance levels, respectively. The values in brackets are t-values.*

at the 1% level, with an estimated coefficient of 0.0654; when the buffer capacity was greater than the third threshold, the impact of natural disaster shocks on the poverty vulnerability of farmers was highly significant at the 10% level, with an estimated coefficient of −0.0381. Overall, when the buffer capacity exceeded the third threshold (0.095), it can effectively alleviate the positive impact of natural disasters on farmers' poverty. The reason is that buffer capacity can help to withstand disaster shocks and reduce disaster losses. In addition, farmers with higher human and social capital can change their livelihood strategies more rapidly in the face of disaster shocks, thus reducing disaster risks.

When the self-organizing capacity was below the first threshold, the impact of natural disaster shocks on the poverty vulnerability of farm households was highly significant at the 1% level with an estimated coefficient of 0.0652; when the self-organizing capacity was between the first and second thresholds, the impact was highly significant at the 1% level with an estimated coefficient of −0.2412; when the self-organizing capacity was larger than the third threshold, the impact was insignificant. Overall, when the self-organizing capacity reached the threshold value (0.189), the impact of natural disaster shocks on the farmers' poverty vulnerability turned from negative to positive. Stronger self-organizing capacity of farmers represents a more stable relationship network and higher social quality, which enables farmers to exchange materials, capabilities and information with various subjects of the network in the face of disaster impacts, thus reducing the negative impact of disaster impact.

When learning capacity was below the first threshold, the impact of natural disaster shocks on farmers' poverty vulnerability was highly significant at the 1% level, with an estimated coefficient of 0.1632; when learning capacity was between the first and second thresholds, the impact was highly significant at the 1% level, with an estimated coefficient of 0.0675; when the learning capacity was between the second threshold and the third threshold, the impact of natural disaster on farmers' poverty vulnerability was not significant; when the learning capacity was greater than the third threshold, the impact of natural disaster impact on farmers' poverty vulnerability was highly significant at the level of 1%, and the estimated coefficient was 0.1312. In conclusion, when the learning capacity exceeded the threshold of 0.108, it can effectively alleviate the negative impact of natural disasters on farmers. A stronger learning capacity indicates the stronger transformation ability of farmers' livelihood. When dealing with the disaster impact, farmers with a strong learning capacity can immediately change their livelihood strategies and transfer resources to production departments with higher utilization efficiency, thus reducing the negative impact of natural disasters.

CONCLUSION AND DISCUSSION

Based on data from China Family Panel Survey, the impact of natural disasters on poverty vulnerability was first analyzed. It is found that natural disaster shocks, intensity, and frequency all exhibited significant positive effects on farm household poverty vulnerability. Secondly, there was a threshold effect of livelihood resilience in the impact of natural disasters on farm households' poverty vulnerability, and the impact turned from positive to negative when livelihood resilience exceeded the third threshold. Finally, as is shown in the threshold effect of buffer capacity, self-organizing capacity, and learning capacity, when the buffer capacity exceeded the third threshold, the impact of natural disasters on poverty vulnerability changed from positive to negative; when the self-organizing capacity exceeded the first threshold, the impact of natural disasters on poverty vulnerability changed from positive to negative; when the learning capacity exceeded the third threshold, the impact of natural disasters on poverty vulnerability changed from positive to negative.

Based on the above research conclusions, implications can be drawn as follows: firstly, to improve the rural natural disaster prevention and control system, local governments should prepare and implement plans to prevent, mitigate and relieve disasters in villages. It is recommended to combine technologies such as the 5G network and socialized services to improve the support system of science and technology, especially early warning capabilities. The second is to improve farmers' buffer capacity and the government's assistance system for low-income farmers and to cultivate the livelihood capacity of such farmers in a targeted manner, such as promoting the transformation of small-scale farmers into family farms and assisting farmers to engage in non-agricultural employment, so as to improve their buffer capacity. The third is to improve the farmers' self-organizing capacity by giving full play to the main role of farmers, organizing farmers according to the voluntary principles based on organizations such as farmers' cooperatives, village collectives, village committees, and other organizations, and guiding scattered farmers to the rural community. Simultaneously, improvement of infrastructure construction is necessary to reduce inter-regional mobility costs and transform farmers' livelihood strategies. The fourth is to improve farmers' learning capacity, focus on cultivating the independent learning capacity of farmers and promote small-scale farmers to actively learn various knowledge of agricultural production and operational activities out of their subjective and objective needs. These will help to develop their cognitive structure system for the promotion of agricultural science and technology and production informatization. In addition, it is necessary to enhance the ability of small-scale farmers to practice and learn and strive to improve their ability to recognize, analyze, and solve problems, so as to help solve various problems in agricultural production and operation.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://opendata.pku.edu.cn/dataverse/CFPS?q=&types=files&sort=dateSort&order==desc&page=1.

AUTHOR CONTRIBUTIONS

JZ and HL: conceptualization, formal analysis, and investigation. HL: methodology and software. HL, HO, YL, and XL: validation. JZ: resources, writing—original draft preparation, review and editing, and project funding acquisition. HO, YL, and XL: data curation. JZ: supervision. All authors read and agreed to the published version of the manuscript.

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