Research Topics

Climate change information for regional impact and risk assessment

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Climate change information for regional impact and risk assessment

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Editorial: Climate change information for Regional impact and risk assessment

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Editorial on the Research Topic
Climate Change Information for Regional Impact and Risk Assessment

Introduction

Regional information about climate risks and the impacts of climate change is vital in decision-making in a wide range of contexts. In distilling such information from multiple lines of evidence, the values and contextual knowledge of the stakeholders are vital for appropriate interpretation and an appreciation of the relevance of the information. Additionally, the knowledge of how the fitness for purpose guides the selection of the sources facilitates decision-making. This Research Topic of Frontiers in Environmental Science with the theme “Climate Change Information for Regional Impact and Risk Assessment” includes nine articles by authors from various parts of the world.

The articles describe the relationship between microclimate and cow behavior and milk yield (Song et al.), methods for the assessment of impacts and risks (Estrada et al.), climate change impact on different sectors and how to alleviate them in some cases (Wu et al., Chai et al., Okeke-Ogbuafor et al., Chen et al.), different aspects of risks (Estrada et al., Sun and Wang), and ways of obtaining different information (Estrada et al., Huang and Li, Agyekum et al.). In relation to greenhouse emissions, there is a study on the impact of climate change and population urbanization in China (Chai et al.). A study on the impact of extreme weather on the poverty vulnerability of farming households in China (Chen et al.) is in the right direction as extreme weather events are projected to increase in intensity and frequency over different geographical areas under a changing climate. Manuscripts on the contribution of weather forecast information to specific sectors (Agyekum et al.) and crop insurance and re-insurance under systemic risk bring to the fore the Research Topic of early warning and insurance. It is about time further research is done to ascertain the role of early warning coupled with early action vis-à-vis the payment of insurance premiums. A cost-benefit analysis study is recommended in this regard.

The diversity in the manuscripts submitted under this research topic illustrates the different sources of information, the different contexts that could be relevant, the different ways of obtaining information, the different human and ecological systems and the different geographical areas covered. The distillation process become very important when all these different issues pertain for instance, to say a given geographical area. With the growing sources of data and the need to obtain regional information at a relatively high resolution or scale, different tools and different ways of generating information need to be employed in decision making at a much faster rate than is currently being practiced. The distillation process might call for expert systems to handle the increasing range of data sources in addition to decision support systems. These manuscripts only highlight the need for new methods such as Machine Learning and Artificial intelligence, convection permitting models, multi-model ensembles, among others, in generating regional weather and climate information. The manuscripts have illustrated the fact that, in the context of climate change, risks can arise from impacts of climate change as well as from the potential human responses to climate change. This takes cognizance of the IPCC definition of risk as the potential for adverse consequences for human or ecological systems, recognizing the diversity of values and objectives associated with such systems.

Author contributions

BL—guest editor RK—associate editor MA-B—associate editor.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The Implication of Copula-Based Models for Crop Insurance and Reinsurance Under Systemic Risk

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The purpose of this paper is to estimate county-level aggregate crop insurance and reinsurance losses under systematic risk. The effect of dependence risk on losses assessment and insurance pricing is quantified by establishing joint distribution functions between county-level yields using different forms of multivariate copulas. The research also stresses the importance of selecting the appropriate copula form for estimating losses. This article highlights several significant findings. The estimated aggregate losses for related counties are not significantly different between the model assuming dependence (copula-based) and the model assuming independence (individual) that adheres to the equivalence principle. On the other hand, the copula-based model has a discernible effect on the estimated Value-at-Risk and Expected Shortfall for related counties. Additionally, for the different layers of the Standard Reinsurance Agreement policy, the copula-based model can measure the aggregate losses more accurately than the individual models. Furthermore, when there is obvious tail dependence in the related counties' yields, the vine copula function form, which provides a more flexible description of the dependence, is more suitable for quantifying tail risk. As a result, insurers and governments should conduct a more comprehensive risk assessment of yield dependence when rate-making and allocating subsidies.

Keywords: copula function, crop insurance, reinsurance, actuarial fair pricing, effective analysis

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1 INTRODUCTION

The federal crop insurance program in the United States, which currently provides yield-based coverage and revenue insurance to help agricultural producers avoid losses due to low crop yields or lower-than-expected crop prices, is one of the most extensive support programs for agricultural producers.

Under the federal crop insurance program, producers can purchase insurance policies at a subsidized rate. These insurance policies compensate producers for current losses caused by either below-average yields (yield-based coverage) or below-average revenue (revenue-based coverage) (revenue insurance). Under a Standard Reinsurance Agreement (SRA), policies are sold through private insurance companies. USDA's Risk Management Agency (RMA) subsidized the policy premium and a portion of the companies' administrative and operating expenses and shares in the companies' underwriting gains and losses. Premium subsidy rates have increased in recent decades for a variety of policy types so that producers typically pay only about 40% of their premiums. It cost the federal government \$5 billion in 2016 and nearly \$9 billion on an annual average basis over the last 5 years.

Many studies cast doubt on the government's support for crop insurance schemes, claiming that the substantial subsidies offered to farmers and insurance corporations would result in a variety of inefficiencies in the aggregate economy (Smith and Goodwin, 1996; Goodwin and Vado, 2007; Goodwin and Smith, 2013; Smith, 2011). Otherwise, proponents of such schemes argue that agricultural damage from possible systemic risks such as droughts and floods is too great for commercial insurers and reinsurers to cover adequately (Miranda and Glauber, 1997; Coble et al., 2003).

Crop insurance policies are designed to protect against income losses caused by fluctuations in crop prices and yields. Premium pricing for such contracts is an actuarial issue that involves describing the joint distribution of prices and yields (Coble et al., 2010). A density function of crop yields under proper information circumstances must be determined as part of the actuarial fair pricing procedure. Unlike most other types of insurance, crop insurance lacks the necessary information to accurately estimate the likelihood and magnitude of losses. One of the most significant issues is a lack of relevant data. Today's standard method regresses historical yield time series data and then uses the predicted and adjusted residuals to estimate a crop yield conditional density function. Numerous studies have been conducted to determine the marginal distribution of yields. For example, Atwood, Shaik, and Watts (2003) argue that calculating trends with short-term panel data biases the analysis in a Type II direction, failing to reject normality when the underlying distribution is nonnormal. This research reveals that yield parameterization can influence crop insurance payouts. Unchecked yield distribution specifications may result in economic inaccuracies in crop insurance rating and expected payouts (Sherrick et al., 2004). Goodwin et al. (2000) compared price risk estimation and insurance rates and used specification tests to analyze distributional assumptions. The reality that the best-fitting distribution in-sample is not necessarily the best choice out-of-sample is critical for determining crop yield distributions. Woodard and Sherrick (2011) present a method for estimating flexible and efficient mixed models using cross-validation that alleviates many of these model selection difficulties. Nelson and Preckel (1989) proposed the conditional beta distribution as a parameterized model for the probability distribution of agricultural output by a two-stage maximum likelihood estimation method.

In addition, inaccurate predictions and inferences of a parametric may result from incorrect distributional choices. Due to these restrictions, nonparametric approaches for estimating yield distributions have been developed (Goodwin and Ker, 1998). Tolhurst and Ker (2015) propose estimating crop yields using mixtures with embedded trend functions to account for potentially different technical development rates. When distinct trend functions are incorporated into mixture components, projected conditional yield densities differ from those derived from detrended data. The focus of these researches has been on estimating the marginal distribution of crop yields and determining whether an optimal marginal distribution can be established. Even though years of research have failed to determine which distribution provides the most accurate yield estimate, the current trend is toward employing more flexible parameter distributions that accommodate for skewness and excess kurtosis (Ramsey and Goodwin, 2019).

For the discussion of utilizing the copula function to measure the dependence of variables in contract design and pricing for government revenue insurance, Ramsey et al. (2019) conclude that the economic impact of copula choice on pricing for individual policies was minor, and changes in marginal distributions significantly influence rates. At the moment, the revenue insurance pricing model makes two assumptions regarding the structure of the dependence. The first assumption is that the Gaussian copula accurately captures the relationship between price and yield, and the second is that the Gaussian copula function is deterministic for each state (Ramsey et al., 2019). The second implication is that crop insurance rate determination ignores the county-level yield dependence, which may result in some mistakes or omissions of systemic risk.

Because yield risk is spatially correlated, a measure of the spatial dependence of yield is required. The empirical investigation has indicated that the systemic risk tends to be much greater when extreme weather circumstances such as drought occur (e.g., Goodwin, 2001). Quantifying the degree of systemic risk is critical for addressing public policy issues regarding the need for large crop insurance subsidies, especially relevant given the reliance on county-level yield hazards. For example, Wang and Zhang (2003) use spatial statistics to investigate the efficiency of risk pooling for crop insurance in the presence of correlation. When modeling the insured losses dependence structure, the size of the buffer load is determined by the value-at-risk (VaR) of aggregate losses between states (Xu et al., 2010, Okhrin et al., 2012). Goodwin and Hungerford (2015) use a variety of copula models to assess the degree to which weather and natural disaster risks in agriculture are systemic and state-dependent. Their findings indicate that the approach taken to quantify multiple, correlated sources of risk may have significant implications for the accurate measurement of portfolio risks. Studies have also argued for improved pricing accuracy based on yield data from surrounding counties and that the dependent yield information can make insurance pricing more accurate when the dependency structure is known (Racine and Ker, 2006; Zhu, Goodwin, and Ghosh, 2014).

The critical challenge of estimating and pricing the loss risk of a portfolio of crop insurance policies has attracted significant attention. The same component that creates dependencies between yields in different locations in crop yield modeling can also lead to systematic risk in a crop insurance portfolio. To model a portfolio of county-level contracts, we must consider the inter-dependencies between the portfolio's county-level yields. A copula can be used in the yield model to estimate the dependence's losses, and then the contract can be priced actuarially based on the mean of the loss distribution. The copula function that represents the dependence of random variables and generates the distribution of random variables must be estimated in modeling this yield structure. Goodwin and Hungerford (2015) propose that RMA may use the deterministic Gaussian copula assumption to fit the dependent structure of price and yield when the data sample is small and the effects of different copula function forms on rate-making are negligible.

So far as we know, no objective criterion exists to compare the accuracy of copula-based approaches to those that do not account for yield dependence. Moreover, no research has been undertaken to ascertain the efficacy of the copula-based approach for crop insurance indemnity in the presence of systemic risk. This research aims to determine the extent to which systematic risk directly or indirectly affects indemnification by developing aggregate losses models for county-level yields using various copula forms. We are particularly interested in the tail risk of the losses distribution, as the possibility of experiencing large losses is critical for getting reinsurance funds and subsidies. We also measure the tail risk here by simulating the aggregate losses' VaR and Expected Shortfall (ES). Stochastic simulation approaches can calculate the aggregate losses, ES, and VaR using the estimated copula functions and marginal distributions of county-level yields. By comparing the simulation results, we could determine whether the pricing model with a dependence assumption is more effective than the individual model with no dependence assumption.

This research conducts an empirical study of the efficacy of risk measurement in two particular areas. We test the effectiveness of the estimation approach for crop insurance indemnity of risk portfolio based on copula-based and individual models. Then, we examine the accuracy of those two models for the aggregate losses assessment at various layers of SRA policy. We conclude that, compared to the individual models, the copula-based models have a negligible effect on estimating aggregate losses under the equivalence principle while beating the individual models in estimating VaR and ES values. Otherwise, the copula-based models have significant consequences for appropriately estimating portfolio risk at various layers of SRA policy at various layers of SRA policy. The Vine copula function approach, which allows for a more flexible definition of dependence risk, is more suitable for loss measurement in crop insurance when the tail dependence can be captured.

The rest of the paper is structured in the following. **Section 2** provides an overview of the data sources. **Section 3** discusses using copula functions as the Vine copula in modeling county-level dependent risk, the model-building procedure, and the effectiveness assessment. In **Section 4**, this approach is used to county-level data sets of the United States to conduct empirical analysis, and the findings are reported. The paper is ended by exploring the effectiveness of copula-based models for estimating dependent risk in crop insurance.

2 DATA SOURCES

We obtain the average county-level corn yield per acre from the US Department of Agriculture's National Agricultural Statistics Service (NASS) (USDA). SRA established three state-based reinsurance pools[1]. Because our objective is to quantify yield dependence under systemic risk for each group, we restrict our analysis to the rainfed region of the United States (east of the 100th meridian) from 1977 to 2007. Our model consists of three states (Illinois (IL), Indiana (IN), and Iowa (IA) in Group 1, Alabama (AL), Arkansas (AR), and Florida (FL) in Group 2, and Pennsylvania (PA), New Jersey (NJ), and Maryland (MD) in Group 3) each with three related counties. As a result, the data sets include the aggregated yields of 27 counties (**Figure 1**). Notably, we randomly select the counties in each state, which either contain adjoining or nonadjacent counties, to test the effectiveness of the copula-based model for losses estimation in different situations.

Each county's raw yields were detrended using robust regression procedures similar to those used in RMA. The regression method we use, M-estimation, is a more generalization of MM-estimation (Huber, 1973). Finger (2010) notes that the errors associated with this detrending method are likely to be small or moderate in magnitude.

3 METHODOLOGY

3.1 The Methods for Measuring Aggregate Losses

The SRA decides the government's losses/gain split with Approved Insurance Providers (AIPs, the RMA's designation for insurance companies), which means that the government will bear all unaffordable underwriting losses. The FCIC provides both proportional and non-proportional reinsurance under the present SRA. Insurance companies are permitted to commercially reinsure any portion of their liability that has not been ceded to the FCIC, as long as they disclose all facts in their operations plan. The SRA's non-proportional reinsurance provision reduces insurers' liability exposure on their retained book of business. The FCIC's share of losses on an insurer's retained book of business varies with each fund and is contingent on the insurer's losses ratio. The state losses ratio of an individual AIP determines the AIP's gain/losses share. Each state fund's losses ratio is determined separately[2]. The FCIC employs a graded structure in which insurers are held accountable for diminishing percentages of eventual net losses as their losses ratio improve.

Under the SRA, a company's retention levels and potential gain/losses are greatest when policies are placed in the Commercial Fund and lowest in the Assigned Risk Fund.

[1]"State Group 1" means Illinois, Indiana, Iowa, Minnesota, and Nebraska. "State Group 2" means Alabama, Arizona, Arkansas, California, Colorado, Florida, Georgia, Idaho, Kansas, Kentucky, Louisiana, Michigan, Missouri, Mississippi, Montana, North Carolina, North Dakota, New Mexico, Ohio, Oklahoma, Oregon, South Carolina, South Dakota, Tennessee, Texas, Virginia, Washington, and Wisconsin. "State Group 3" means Alaska, Connecticut, Delaware, Hawaii, Maine, Massachusetts, Maryland, Nevada, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Utah, Vermont, West Virginia, and Wyoming.
[2]The losses ratio that determines the AIP percent share of the underwriting results is based on their entire state book of insurance, i.e. it is the combined losses ratio for all crops and all contracts for the state.

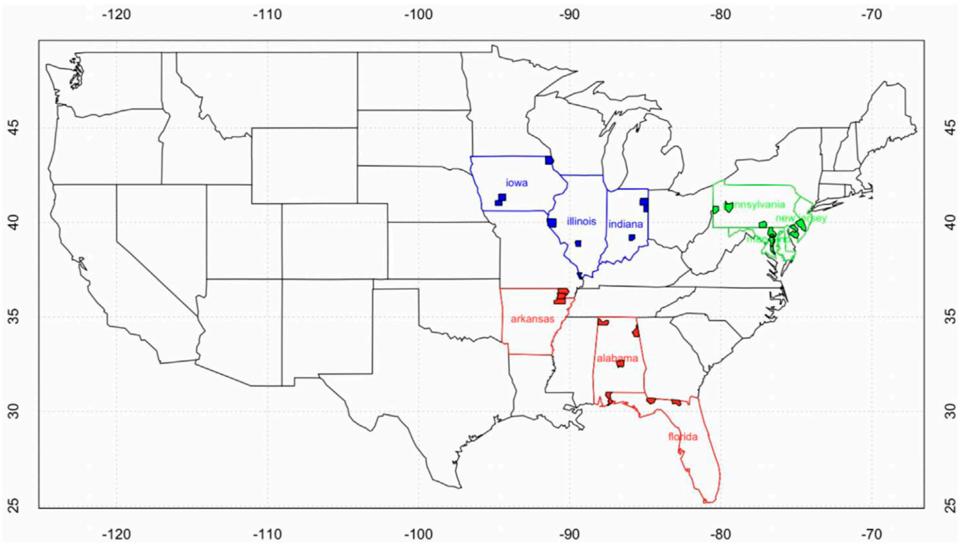

FIGURE 1 | The selected states and counties for Group 1, Group 2 and Group 3.

TABLE 1 | Shares of underwriting gains and losses to insurance companies under the 2021 Standard Reinsurance Agreement.

Losses ratio	**Reinsurance fund**			
	Assigned risk	**Commercial fund**		
	Percentage of losses/Gain			
Losses		Group 1	Group 2	Group 3
1.0–1.6	7.5	65	42.5	42.5
1.6–2.2	6.0	45.0	40.0	40.0
2.2–5.0	3.0	10.0	5.0	5.0
>5.0	0.0	0.0	0.0	0.0
Gains				
0.65–1.0	22.5	75.0	97.5	97.5
0.5–0.65	13.5	40.0	40.0	40.0
<0.5	3.0	5.0	5.0	5.0

FCIC receives 80% of the premium and associated liability in the Assigned Risk Fund, while the company retains 20%. Companies must keep a minimum of 30% (and may retain up to 100%) of the premium and associated liabilities in the commercial fund. FCIC pays increasing shares of indemnities from the liability retained by the company, based on the company's state-level losses ratio (indemnities divided by total premium) in the fund, with FCIC paying the total losses once the losses ratio surpasses 5.0. The proportions of income and losses that fall to private insurance companies vary significantly by the fund (as shown in **Table 1**). For Assigned Risk policies, for example, the highest potential underwriting losses is 16.5 percent (0.6*7.5 + 0.6*6.0 + 2.8*3) of company-retained premium. However, the company's potential for underwriting gains on policies put in the Assigned Risk Fund is likewise relatively small, as11.4 percent of retained premium at most. In comparison, on policies put in the Commercial Fund, Group 1 might earn up to 34.75 percent of the retained premium on Commercial Fund policies. However, the downside risks are also greater, and the maximum permissible underwriting losses is 94 percent of the retained premium.

The main problem addressed here is evaluating the effectiveness of measuring insurance payment methods based on the dependence risk model. We must determine whether there is any potential for dependence between the portfolio's county-level yields, and this dependence could be captured in the insurance losses model to reflect the more accurate fair rates. Then, from a reinsurance perspective, losses evaluation exposed to systematic risk is crucial for determining underwriting terms. Risk assessment at various layers enables us to determine the effect of yield dependence on rate-making.

Crop insurance rate-making involves the simultaneous distribution of prices and yields. To keep things simple, we will focus exclusively on the indemnity under systemic risk and ignore the volatility of the corn price. The indemnity for county i, $indem_i$, for the area yield insurance contract that guarantees the coverage level, say $\lambda\hat{y}_i$, (Ker and Coble 2003) is:

$$indem_i = Pr\left(y_i < \lambda\hat{y}_i\right)\left(\lambda\hat{y}_i - E\left[\left(y_i \middle| y_i < \lambda\hat{y}_i\right)\right]\right) \tag{1}$$

Where y_i is the realized yield, $\hat{y}_i$ is the predicted yield in county i expected yield, and λ is a coverage level between 0 and 1. In this study, we focus on λ = 0.9, which is the most commonly selected coverage level, and it accounts for 95% of the policies (Ker, Tolhurst, and Liu, 2015). Using **Eq. 1**, we can calculate the aggregate losses based on the copula-based and individual models for the related counties portfolio.

The objective of reinsurance is to provide protection for aggregate losses L that exceed some trigger level T based on the level of losses that the insurer can absorb. By contract design, once the aggregate losses exceed this trigger, the reinsurance pays some fixed proportion of aggregate losses L usually up to some predetermined cap C on the reinsurer's exposure. Therefore, if losses are less than the trigger, the contract pays nothing. The contract pays out $L - T$ if losses fall in the range between the trigger and the cap. If losses exceed the cap, the contract pays out the difference between the cap and the trigger, $C - T$. Using this basic structure, one can specify the payout of a layer (a, b] of payout, denoted by $\mathbf{Pay}_{[a,b]}$ of the reinsurance as follows:

$$\mathbf{Pay}_{[a,b]} = Max\ [0,\ Min(L - T,\ C - T)] \tag{2}$$

Therefore, a layer contract covers part of the losses between trigger level T and predetermined cap C, with the maximum payout limited to the difference b − a. It is also referred to as an excess of losses (XOL) insurance policy. The reinsurance program of SRA is based on a modified version of the XOL insurance policy, which covers a certain percentage of the standard layer policy. However, based on minimizing the moral hazard and adverse-selection problems associated with writing company reinsurance. The payout function on these XOL contracts would also be a function of aggregate losses for the different groups. Thus, the expected payout of the contract has the form $\delta\mathbf{Pay}_{[a,b]}$, $0 < \delta < 1$ representing the payout proportion, which depends on the contract. Under the SRA program, there are three different coverage layers: losses ratios between 1.00–1.60, 1.60–2.20, and 2.20–5.00, separately.

Other than estimating the aggregate losses for the regular contract and SRA layers contract, we also estimate the VaR of the aggregate losses, which can be applied to measure the systemic risk inherent to an insurance portfolio. The VaR of aggregate losses for the risk portfolio in each State is:

$$VaR_{AL}(\alpha) = \inf\left\{al\colon \mathrm{P}\left(\sum\nolimits_{i=1}^{3} L(y_i) > al\right) \le \alpha\right\} \tag{3}$$

Herein $L(y_i)$ denotes the losses of county $\boldsymbol{i}$ in the state, which depends on the yield $\boldsymbol{y_i}$ in each county. And $1 - \boldsymbol{\alpha}$ is the confidence level, the $\boldsymbol{\alpha} = 0.1$ at here, it means that 90% of losses are less than the VaR value.

We also consider Expected Shortfall, which measures the average losses over the VaR value. ES takes the average of all the losses greater than the VaR value. Since it is an expectation calculated by integrating over an entire region, it is a much more robust statistic compared to VaR, which is just a single value.

3.2 Simulation of Aggregate Losses Using Copulas

We use the copula-based models to measure the dependence between county-level yields for aggregate losses quantification. Due to the "curse of dimension" associated with an excessive number of variables, a yield portfolio including three counties from each of the nine states is chosen for testing for simplicity and practical reasons. The data sets, which cover the yields of three counties in nine states, are summarized in **Table 2**. We can find that county Allamakee in Group 1 and county Clay in Group 2 has obvious leptokurtic distribution, and most of the counties have negative skewness. **Figure 1** shows the geographical location of the selected counties in each state. The counties in AR, NJ, and MD are adjacent to each other, and the state AL, FL, PA has the most scattered counties portfolio.

Copulas are very flexible with regard to representing the dependent structure of variables. The copula function's fundamental concept is to link the marginal distribution to the joint distribution (Sklar, 1959), avoiding direct estimation of the multivariate distribution function and fitting the multivariate distribution function using parametric or non-parametric methods to estimate the marginal distributions of the variables independently. Copulas have grown in popularity in recent years and have been used to a variety of financial difficulties (Embrechts et al., 1999; Cherubini et al., 2004). They have also been used extensively in agricultural economics, mostly to model spatial dependence in yields or the dependence of random variables in crop revenue insurance, margin insurance, and whole-farm insurance (Vedenov and Power, 2008; Zhu et al., 2008; Bozic et al., 2014; Bulut and J. Collins, 2014; Ahmed and Serra, 2015; Goodwin and Hungerford, 2015; Feng and Hayes, 2016).

Let F be a joint distribution function with univariate marginal distribution functions $F_1, \ldots, F_d$. Then there exists a copula function $C\colon\ [0,1]^d \to [0,1]$ such that

$$F(x_1, \ldots, x_d) = C(F_1(x_1), \ldots, F_d(x_d)), \tag{4}$$

where $x_1, \ldots, x_d \in \mathbb{R}$ are random variables. By inversion of the joint distribution in **Eq. 4**, the copula function can be written as

$$C(u_1, \ldots, u_d) = F\left(F_1^{-1}(u_1), \ldots, F_d^{-1}(u_d)\right), \tag{5}$$

where $F_1^{-1}, \ldots, F_d^{-1}$ are 1-dimensional quantile functions and $u_1, \ldots, u_d \epsilon [0,1]$. The copula function is parameterized by a vector ρ consisting of dependence parameters. Given that the copula is itself a joint distribution function, it satisfies all of the criteria for a joint distribution function.

The copula function's fundamental properties are symmetry and tail dependency (Li and Genton, 2013). Insurance company and financial experts are often interested in the tail characteristic, since they represent the degree to which a portfolio's losses occur in the worst-case scenario (Nelsen, 1999). Tail dependency is an asymptotic concept, and an asymmetric copula function distribution might have either lower or upper dependence, depending on the empirical phenomenon being described. The coefficient of upper-tail dependence is defined as follows:

$$\lambda_U = \lim_{u\to 1} \Pr(U_1 \ge u | U_2 \ge u) = \lim_{\mu\to 1} \frac{1 - 2u + C(u,u)}{1-u}, \tag{6}$$

While the lower-tail dependence coefficient is defined as:

$$\lambda_L = \lim_{u\to 0} \Pr(U_1 \le u | U_2 \le u) = \lim_{\mu\to 0} \frac{C(u,u)}{u}, \tag{7}$$

Copulas exhibit tail dependence if the respective coefficients in **Eqs 6**, **7** are nonzero, and when the tail dependence coefficient is close to 1, large values of the variables occur together.

The copula family chosen is inherently a decision of theoretical tail dependence. The parametric estimating procedure in an empirical investigation involves an *a priori* assumption about the data sets' relationship. The five most often used parametric

TABLE 2 | Summary statistics of average county-level yield (bushel per acre) of corn, by counties.

Group	State	Observations		Summary statistics of crop yield						
		County	Years	Min.	Median	Max.	Std.Dev	CV[3]	Skewness	Kurtosis
Group 1	IL	Adams	30	85.72	151.91	199.96	24.3110	0.1620	−0.5094	3.1834
		Alexander	30	93.68	140.60	178.00	22.4498	0.1631	−0.3542	2.4093
		Bond	30	69.72	133.41	173.96	23.3853	0.1780	−0.5013	2.9523
	IN	Adams	30	102.0	151.9	171.1	17.1990	0.1164	−0.8245	2.9605
		Allen	30	119.3	156.8	170.3	13.0258	0.0859	−0.8696	2.7811
		Bartholomew	30	96.42	149.68	178.92	20.5502	0.1387	−0.6109	2.5246
	IA	Adair	30	99.97	152.71	187.06	20.0485	0.1350	−0.6756	2.9488
		Adams	30	99.82	145.33	174.26	20.9762	0.1476	−0.6395	2.2976
		Allamakee	30	97.54	159.71	180.71	17.7399	0.1132	−1.8518	6.5536
Group 2	AL	Autauga	30	40.00	80.12	126.62	21.5820	0.2740	0.0680	2.3087
		Cherokee	30	35.00	92.09	147.96	28.0576	0.2896	0.0100	2.1373
		Colbert	30	68.38	104.17	167.62	26.6857	0.2444	0.4541	2.0615
	AR	Clay	30	73.68	154.01	179.02	21.5321	0.1439	−1.4126	5.8428
		Craighead	30	68.68	140.55	184.00	26.0007	0.1897	−0.4766	2.8372
		Greene	30	68.68	138.50	172.00	20.3717	0.1522	−1.0445	4.5724
	FL	Escambia	30	64.66	117.38	149.70	22.1617	0.1928	−0.4251	2.3057
		Gadsden	30	64.48	96.83	133.06	18.1695	0.1830	0.2534	2.2667
		Hamilton	30	73.03	99.24	135.00	14.2299	0.1394	0.4311	3.1189
Group 3	PA	Adams	30	63.48	120.13	188.96	27.5589	0.2415	0.0687	3.1202
		Armstrong	30	76.44	122.91	155.06	22.9851	0.1890	−0.3821	2.1000
		Beaver	30	73.43	124.48	150.75	21.3783	0.1761	−0.6073	2.3726
	NJ	Burlington	30	61.54	134.41	149.82	21.5385	0.1705	−1.1812	3.9779
		Cumberland	30	57.27	127.79	160.06	25.4670	0.2037	−0.7255	3.0111
		Gloucester	30	50.27	126.22	153.06	26.7836	0.2221	−0.8964	3.1647
	MD	Anne arundel	30	86.77	129.01	169.28	22.9579	0.1837	−0.0216	1.7190
		Baltimore	30	86.15	137.34	171.18	20.5206	0.1543	−0.5514	2.5109
		Calvert	30	52.07	116.12	167.98	26.4296	0.2282	−0.3819	2.7586

[3]*CV is the Coefficient of Variance.*

copulas (Gaussian, t, Gumbel, Clayton, and Frank) and their various rotations may capture a wide range of bivariate dependent behavior. However, for aggregate losses of coverage yields greater than two counties, the archimedean copula (Gumbel, Clayton, and Frank) cannot accurately simulate multivariate dependence due to its single parameter. In addition to elliptical copulas, the vine and hierarchical copulas can also capture multivariate dependence.

By combining pair-wise copulas, the vine copula enables much more flexibility in multivariate modeling (Bedford and Cooke, 2002; Kurowicka and Cooke, 2006). According to Aas et al. (2009), the factored form of a joint multivariate density function for a set of k random variables is:

$$f(x_1, x_2, \ldots, x_k) = f_k(x_k) \cdot f(x_{k-1}|x_k) \cdot f(x_{k-2}|x_{k-1}, x_k) \ldots \cdot f(x_1|x_2, \ldots, x_k). \tag{8}$$

This density is unique for a given ordering of variables. The joint density can also be expressed in terms of a copula function, as:

$$f(x_1, x_2, \ldots, x_k) = c_{1\ldots k}(F_1(x_1), \ldots, F_k(x_k)) \cdot \prod_{i=1}^{k} f_i(x_i). \tag{9}$$

Joe (1996) shown that each term in **Eq. 9** may be decomposed into the product of a pair-wise copula and a conditional marginal density:

$$f(x|v) = c_{x,v_k|v_{-k}}(F(x|v_{-k}), F(v_k|v_{-k})) \cdot f(x|v_{-k}). \tag{10}$$

Aas et al. (2009) described how to represent a multivariate density as a product of pair-wise copulas. The vine copula functions are best described as a set of "trees," with each variable's distribution represented by conditional distributions at a higher tree level. Bedford and Cooke (2002) presented a "regular vine" representation that enables considerable flexibility in representing multivariate densities in terms of pair-wise copula combinations. Kurowicka and Cooke (2006) identified two distinct types of vine copulas, dubbed the "C-vine" and the "D-vine." When variables have a particular ordering, a D-vine is appropriate, whereas a C-vine is good when variables may be arranged according to their effect on other variables (Aas et al., 2009).

Following Goodwin and Hungerford (2015), we establish county-level yield dependence models using elliptical copulas (Gaussian, t) and vine copulas. To begin, we estimated the corresponding Gaussian and t-copula from detrended county-level crop yield data using the empirical marginal distribution approach. Goodwin and Hungerford (2015) point out that this approach results in less variability than estimation methods based on parametric marginal distributions. We need to estimate three separate coefficients for the Gaussian and t-copula dependence models since each state has three random variables representing county-level yield. Additionally, the t-copula must estimate the

TABLE 3 | Elliptical (Normal and t) copula estimation results for the nine datasets.

	IL		IN		IA	
Parameter	Normal	t	Normal	t	Normal	t
ρ_{12}	0.6862	0.6162	0.8228	0.7254	0.8937	0.8949
ρ_{13}	0.7757	0.8209	0.8706	0.8223	0.7301	0.7263
ρ_{23}	0.5843	0.5818	0.7710	0.6494	0.7637	0.7596
df	NA	2.7526	NA	1.6125	NA	33.8831
AIC	–33.0568	–36.4327	–62.0138	–61.3223	–59.8349	–57.8301
	AL		AR		FL	
Parameter	Normal	t	Normal	t	Normal	t
ρ_{12}	0.7816	0.7869	0.9011	0.9003	0.7020	0.6996
ρ_{13}	0.5671	0.6060	0.8705	0.8692	–0.4843	–0.4819
ρ_{23}	0.7963	0.7914	0.9042	0.9035	–0.4731	–0.4708
df	NA	5.2821	NA	37.0054	NA	138.7882
AIC	–44.8526	–44.0452	–87.7323	–85.5402	–17.3834	–15.2785
	PA		NJ		MD	
Parameter	Normal	t	Normal	t	Normal	t
ρ_{12}	0.5176	0.5187	0.8104	0.8014	0.7328	0.7751
ρ_{13}	0.4244	0.4265	0.8312	0.8211	0.8926	0.9069
ρ_{23}	0.8463	0.8455	0.9211	0.9280	0.7510	0.7582
df	NA	94.9907	NA	4.5455	NA	3.9828
AIC	–34.2009	–32.1208	–77.2285	–77.7075	–58.7623	–62.0529

Note: where 1, 2 and 3 indicate the three selected county, respectively. The estimation method to be used to estimate the dependence parameter is the inversion of Kendall's tau estimator, and df *is the degree of freedom.*

degree of freedom parameter, which converges gradually to the Gaussian copula as the degree of freedom grows (the typical cut-off degree of freedom is 30).

The Gaussian and t-copula maximum likelihood estimation results for the yield data sets are reported in **Table 3**. The first conclusion is that in nine states, the dependencies between county-level yields are all-powerful, and the data sets from IL, IN in Group 1, AL in Group 2, NJ, MD in Group 3 exhibit rather substantial tail dependence. However, the fitted t-copula has a degree of freedom of more than 30 for several states, such as IA in Group 1, AR and FL in Group 2, PA in Group 3, indicating that the tail dependence of these data sets is minor, with essentially no difference from Gaussian copula. Moreover, the county-level yields negatively depend on each other for FL in Group 3. As a result, we cannot determine which copula between Gaussian and t is superior based on the AIC values of Gaussian and t-copulas since the better-fitting copula varies between data sets.

We then estimate the R-vine copulas using a sequential maximum likelihood procedure. Vine copulas are formed of Gaussian, t, Clayton, Gumbel, and Frank copula and their rotating type. Maximum spanning trees are used to pick R-vine trees with respect to certain edge weights. The appropriate pair-wise copula families are selected according to the Akaike Information Criteria (using maximum likelihood estimation) and estimated sequentially (forward selection of trees). The estimation results and AIC value statistics are presented in **Table 4**, and when compared to other vine copula forms (R-vine and D-vine), this approach selects the C-vine copula as the dependence structure for all data sets.

Additionally, we perform a Goodness-of-fit (GOF) test on the fitted results of each portfolio's various copula functions, and the results are provided in **Table 5**. The *p*-values of the GOF test for the fitted copula function are more than 0.05 for all analyzed risk portfolios, indicating that the Gaussian and *t*-copula assumptions are not rejected. **Table 4** also compares the AIC values of several copula forms, and we see that the C-vine copula's AIC values are much fewer than those of the Gaussian and *t*-copula for each portfolio, indicating that the C-vine copula is favored over the Gaussian and *t*-copula.

Then, we need to fit the yield marginal distribution to simulate crop yield losses based on the determined copula-based model. Compared to using a non-parametric marginal distribution to fit the yield distribution, we choose a parametric marginal distribution since it can give an explicit explanation. We estimate the parametric distribution individually for each county yield and then combine it with the copula-based copula model to generate random variables. Numerous parametric distributions have been used to model yield distributions in crop insurance, and we fit the yield using a two-component mixture normal and a Weibull. The distribution hypothesis test and AIC values for the county yield data sets are provided in **Table 6**. As predicted, the Weibull and mixture normal distribution hypotheses are both accepted.

After all, the aggregate losses are fitted based on the estimated copula function and marginal distribution using the approaches outlined above. We emphasize the likelihood of significant indemnity resulting from systemic risk in county-level risk portfolios. Notably, we do not adjust the portfolio for

TABLE 4 | Vine copula estimation results of data sets in each state.

	Factorization	Copula family	Parameter 1	Parameter 2
IL	C_1, C_2	Survival Gumbel	1.83	NA
	C_3, C_1	t	0.81	2.00
	$C_3, C_2 \| C_1$	Clayton	0.40	NA
	C-Vine AIC	−39.62		
IN	C_1, C_2	Survival Gumbel	2.61	NA
	C_3, C_1	Gumbel	3.15	NA
	$C_3, C_2 \| C_1$	Normal	0.22	NA
	C-Vine AIC	−67.91		
IA	C_2, C_1	Survival Gumbel	3.33	NA
	C_3, C_2	Survival Gumbel	2.18	NA
	$C_3, C_1 \| C_2$	Survival Gumbel	0.25	NA
	C-Vine AIC	−62.34		
AL	C_2, C_1	Survival Gumbel	2.36	NA
	C_3, C_2	Gumbel	2.43	NA
	$C_3, C_1 \| C_2$	Normal	−0.06	NA
	C-Vine AIC	−48.71		
AR	C_2, C_1	Normal	0.90	NA
	C_3, C_2	Normal	0.90	NA
	$C_3, C_1 \| C_2$	Clayton	0.53	NA
	C-Vine AIC	−88.4839		
FL	C_1, C_2	Normal	0.70	NA
	C_3, C_1	Normal	−0.48	NA
	$C_3, C_2 \| C_1$	Rotated Gumbel (90°)	−1.14	NA
	C-Vine AIC	−17.4168		
PA	C_2, C_1	Frank	3.69	NA
	C_3, C_2	Frank	9.37	NA
	$C_3, C_1 \| C_2$	Normal	−0.07	NA
	C-Vine AIC	−36.6100		
NJ	C_3, C_1	Survival Gumbel	2.63	NA
	C_3, C_2	Survival Gumbel	4.11	NA
	$C_2, C_1 \| C_3$	Normal	0.25	NA
	C-Vine AIC	−82.7749		
MD	C_3, C_1	Survival Clayton	5.12	NA
	C_3, C_2	Survival Clayton	2.25	NA
	$C_2, C_1 \| C_3$	Gumbel	1.33	NA
	C-Vine AIC	−78.7577		

Note: where 1, 2 and 3 indicate whether the yields of three counties in each state, respectively. Using the inversion of Kendall's tau estimator to estimate the dependence parameter.

TABLE 5 | GOF test results of the data sets in different states.

State	Gaussian		*t*		C-vine
	p-value	AIC	*p*-value	AIC	AIC
IL	0.6628	−33.0568	0.8257	−36.4327	−39.6190
IN	0.3641	−62.0138	0.1444	−61.3223	−67.9088
IA	0.3032	−59.8349	0.2692	−57.8301	−62.3418
AL	0.3601	−44.8526	0.6089	−44.0452	−48.7106
AR	0.3521	−87.7323	0.3212	−85.5402	−88.4839
FL	0.3561	−17.3834	0.3611	−15.2785	−17.4168
PA	0.1164	−34.2009	0.0894	−32.1208	−36.6100
NJ	0.9286	−77.2285	0.9356	−77.7075	−82.7749
MD	0.1703	−58.7623	0.5420	−62.05290	−78.7577

variations in exposure (i.e., various amounts of acreage) between counties and hence assume that all counties have the same level of corn acreage, then we can adjust the total losses by aggregating the average county-level yield losses per acre for each portfolio. Additional loading factors that account for administrative costs are disregarded.

3.3 The Efficacy Tests of Copula-Based Models

The AIC criteria and p-value can only be used to determine the fitted copula's goodness-of-fit (Goodwin and Hungerford, 2015). To assess the efficacy of the copula-based model on the accuracy of losses assessment and insurance pricing, we design a simulation experiment using the Mean Squared Error (MSE), which quantifies the difference between the copula-based model's estimated losses and the "true" losses as defined by Harri et al. (2011). Ker et al. (2016), Yvette Zhang (2017). and Yi et al. (2020) have all employed the MSE measure in the context of agricultural commodity hedging.

We use nonparametric kernel techniques to estimate county-level yield density functions for each portfolio in the 9 states, highlighting that these densities account for county-level yield dependence. Then, assuming that these densities accurately represent the "true" density function, we can generate dependent data samples from these densities. To create data sets based on these "true" densities, an aggregate of 500 samples of sizes $n = 30$ and $n = 50$ is drawn from the "true" distributions for each county-level data set. The mean squared error (MSE) in calculating aggregate losses compared to "true" aggregate losses is used to evaluate the effectiveness of pricing. Premiums are derived for each sample using a Monte Carlo approach based on the individual model with the non-dependence assumption and an estimated copula-based model (Gaussian, t, and C-vine copula). The Weibull and mixture normal distributions obtained in **Section 3** are used to fit the yield distributions of the individual and copula-based models. The following equation is used to obtain their appropriate MSE:

$$MSE(L) = \frac{1}{500}\sum_{i=1}^{500}\left[\hat{\pi}_i - \pi(L)\right]^2 \tag{11}$$

Where π is the "true" losses, and $\hat{\pi}_i$ is the corresponding estimate in the ith experiment. The MSE is calculated by comparing the estimated aggregate losses from the various models to the "true" aggregate losses in each state. The primary role of this simulation experiment is to determine if the copula-based model has an effect on losses measurement by comparing the estimated losses for these two types of models (individual and copula-based) to the "true" losses. We ensure consistency with this large sample size. It makes our estimate consistent and produces the correct result on average.

4 EMPIRICAL RESULTS AND DISCUSSION

Using the procedure outlined in **Section 3**, we collect yield data sets from three counties in each selected states for three groups. We

TABLE 6 | Results of Kolmogorov-Smirnov test (at 5% significance level) and the AIC value of the goodness-of-fit test.

Group 1	IL			IN			IA		
	County	**Weibull**	**Mixture**	**County**	**Weibull**	**Mixture**	**County**	**Weibull**	**Mixture**
p-value	Adams	0.9921	0.9706	Adams	0.9433	0.9674	Adair	0.4624	0.3968
	Alexander	0.9238	0.9647	Allen	0.4586	0.9940	Adams	0.7824	0.8879
	Bond	0.9990	0.9995	Bartholomew	0.8015	0.6246	Allamakee	0.7296	0.2401
AIC	Adams	278.2256	275.1835	Adams	253.9654	250.2059	Adair	265.0451	260.4891
	Alexander	273.6248	271.2883	Allen	236.0602	229.0293	Adams	267.0493	253.3133
	Bond	275.6055	271.5169	Bartholomew	266.2210	257.9925	Allamakee	249.0293	244.8312
Group 2	AL			AR			FL		
	County	Weibull	Mixture	County	Weibull	Mixture	County	Weibull	Mixture
p-value	Autauga	0.9966	0.9955	Clay	0.8303	0.3127	Escambia	0.9027	0.9524
	Cherokee	0.8343	0.9308	Craighead	0.9750	0.7012	Gadsden	0.8805	0.9964
	Colbert	0.7330	0.9995	Greene	0.8286	0.9469	Hamilton	0.4201	0.4335
AIC	Autauga	272.2961	268.1752	Clay	265.9092	262.5262	Escambia	272.2098	269.4284
	Cherokee	287.8535	285.2474	Craighead	282.0591	272.9506	Gadsden	263.8013	258.8797
	Colbert	286.2712	277.1186	Greene	264.9158	257.7720	Hamilton	251.5291	237.1732
Group 3	PA			NJ			MD		
	County	Weibull	Mixture	County	Weibull	Mixture	County	Weibull	Mixture
p-value	Adams	0.4246	0.4854	Burlington	0.4640	0.8507	Anne arundel	0.6400	0.9909
	Armstrong	0.9818	0.9195	Cumberland	0.5786	0.8057	Baltimore	0.7759	0.9861
	Beaver	0.8211	0.9900	Gloucester	0.7634	0.4254	Calvert	0.9977	0.9616
AIC	Adams	287.7737	281.2121	Burlington	266.1494	255.0774	Anne arundel	276.0907	264.7787
	Armstrong	274.4310	269.1059	Cumberland	279.5334	276.3238	Baltimore	266.9404	260.6883
	Beaver	268.7325	262.4391	Gloucester	281.9373	282.8471	Calvert	283.5852	280.0709

estimate SRA policy losses using the random numbers generated by each fitted model. Then we examine if the tail dependency of yield risks affects the aggregate indemnity of crop insurance, such as joint losses due to severe weather occurrences. The asymmetric lower-tail dependency is described by the Rotated Gumbel (180°) and Clayton copulas, which are used to define pair copulas in vine copula. Additionally, t-copula exhibits symmetric tail dependency, while the Gaussian copula does not[4].

The MSE of the aggregate losses between the “true” and the fitted losses (based on the copula and the individual model) is calculated, emphasizing comparing the differences between models with and without dependence. The losses distributions are calculated using 10,000 random samples generated from the estimated losses model. Notably, we use the Weibull and mixture normal as the marginal distributions, and the copula model’s dependence structure varies for each state’s yield data sets. The following are the findings of this experiment:

The mean value of aggregate yield losses is not sensitive to the individual or copula-based model in various risk regions and sample sizes, as shown in **Tables 7–9**. We can determine that the copula-based approach has a negligible effect on the unbiased estimator of aggregate losses accuracy through stochastic simulations. The aggregate losses density distribution plots for the states in **Figures 2–4** help to explain this conclusion. As seen in **Figures 2–4**, the copula-based or individual model may be the most well-fitting model at different losses layers. Due to the fact that the fair premium for crop insurance is determined on the expectation of losses, there is no statistically significant difference between the copula-based and individual models.

TABLE 7 | The average Mean Squared Error of aggregate losses for states in Group 1.

	n = 30		n = 50	
	Weibull	**Mixture**	**Weibull**	**Mixture**
Individual	19.2354	20.7218	13.8076	13.2086
Gaussian	19.2320	20.6700	13.7932	13.3622
t	19.3448	20.8181	13.8149	13.2851
Vine	19.2873	20.7303	13.7933	13.2876

TABLE 8 | The average Mean Squared Error of aggregate losses for states in Group 2.

	n = 30		n = 50	
	Weibull	**Mixture**	**Weibull**	**Mixture**
Individual	9.1846	8.5403	6.9524	4.9648
Gaussian	9.2053	8.5509	7.0002	4.9989
t	9.2302	8.5746	6.9867	5.0089
Vine	9.2216	8.5578	6.9315	4.9918

[4]In the later application we take the following copula families into consideration (some properties are given in brackets): Gaussian (tail-symmetric, no tail dependence). Student-t (tail-symmetric, tail dependence). Gumbel (tail-asymmetric, upper tail dependence) and survival Gumbel (tail-asymmetric, lower tail dependence). Rotated Gumbel by 90°and 270° (tail-asymmetric, no tail dependence). Frank (tail-symmetric, no tail dependence). Clayton (tail-asymmetric, lower tail dependence).

TABLE 9 | The average Mean Squared Error of aggregate losses for states in Group 3.

	n = 30		n = 50	
	Weibull	**Mixture**	**Weibull**	**Mixture**
Individual	26.0669	22.1998	15.7114	14.5431
Gaussian	26.1958	22.2409	15.7976	14.6718
t	26.2791	22.2665	15.8409	14.7108
Vine	26.1050	22.3048	15.8187	14.6373

Nonetheless, as shown in **Tables 10–12**, all copula-based models estimated higher VaR and ES values than the individual model. In Groups 1 and 3, the copula-based model's VaR and ES values are much greater than those of the individual model. VaR is used to measure tail risk by determining the maximum possible losses value for a given probability, and ES takes the average of all the possible losses greater than the VaR value. By comparing the VaR and ES values of "true" distribution, we may infer that the copula-based model is the better-fitting model for VaR and ES values than the individual model in Groups 1 and 3. On the other hand, there is no discernible difference in VaR and ES values between the individual model and the copula-based model in Group 2, which may be due to no obvious tail dependence between the county-level yields in Group 2. It also can be explained in **Figure 3** that the individual model is the most well-fitting model around the tail of the losses for Group 2.

Second, consider the payment situations for various layers. The findings in **Tables 13–15** demonstrate that the individual model's losses MSE is greater than the copula-based model at various levels for all three groups, except for the MSE estimated by using Weibull distribution for the layer of the losses ratio 2.20–5.00 in Group 2. The MSE results reveal that in Groups 1 and 3, the copula-based model may significantly reduce the MSE of losses compared to the individual model, indicating that dependence strongly influences this layer's payment. In Group 2, however, there is no substantial reduction in the MSE of losses between the copula-based model and the individual model since there is no evident tail dependence between the county-level yields (as shown in **Table 4**). Thus, when considerable yield reliance exists in the risk portfolio, the copula-based model beats the individual model for calculating SRA payments.

Additionally, the losses estimations vary across by using the various copula models. For example, in **Table 13**, the measured losses MSE of data sets with a duration of 30 years and Weibull distribution based on the Gaussian, t, and C-vine copula models for the layer of the losses ratio 2.20–5.00 are 7.7005, 7.6656, and 7.2505, respectively. The above findings demonstrate that the accuracy of the losses estimation for the layer of the losses ratio 2.20–5.00 changes based on the using of various alternative copula structures, and the C-vine copula surpasses the Gaussian and t-copula in Group 1, and the reason may be that the IL, IN and IA states' dependence structure has the lower-tail characteristic (survival Gumbel has the upper-tail properties). In comparison, in **Table 14**, the measured losses MSE with a 30-year duration and Weibull distribution based on Gaussian, t, and C-vine copula models for the layer of 2.20–5.00 is 3.4782, 3.4103, and 3.9801, respectively. While the losses MSE for the layer of 1.00–1.60 is 4.8743, 4.9417, and 4.3894, respectively. Thus, adopting the C-vine copula model would result in a more accurate losses measurement at the layer of the losses ratio

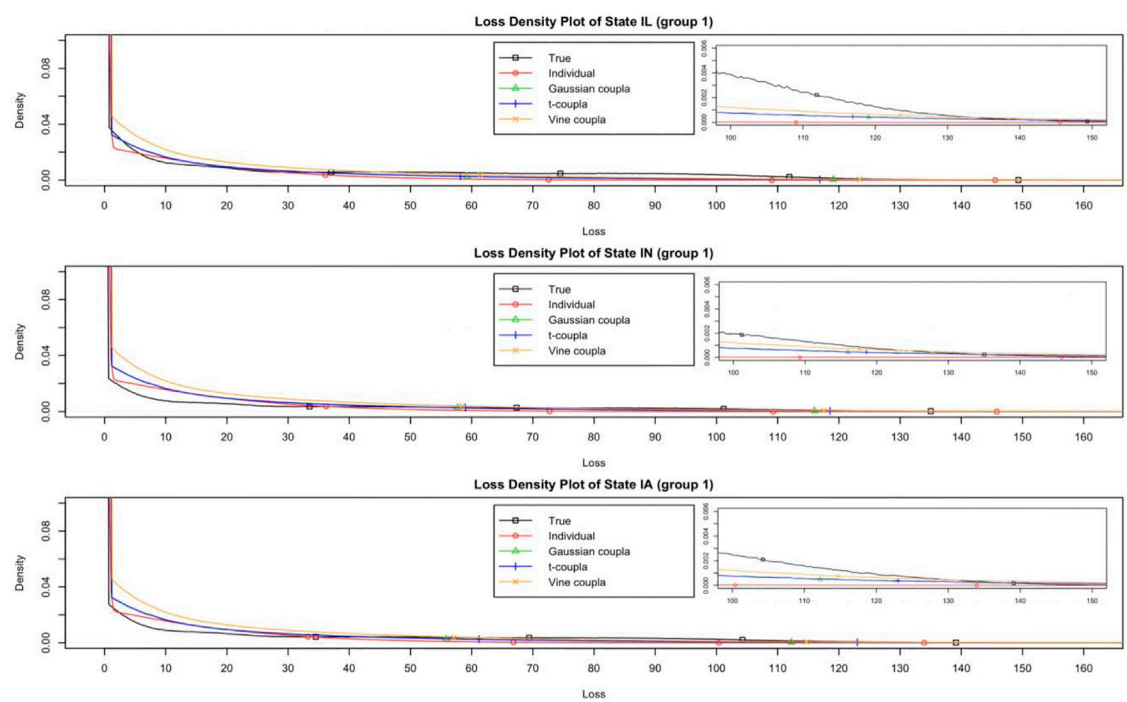

FIGURE 2 | The losses density plot for states in Group 1 (Weibull distribution with a duration of 30 years).

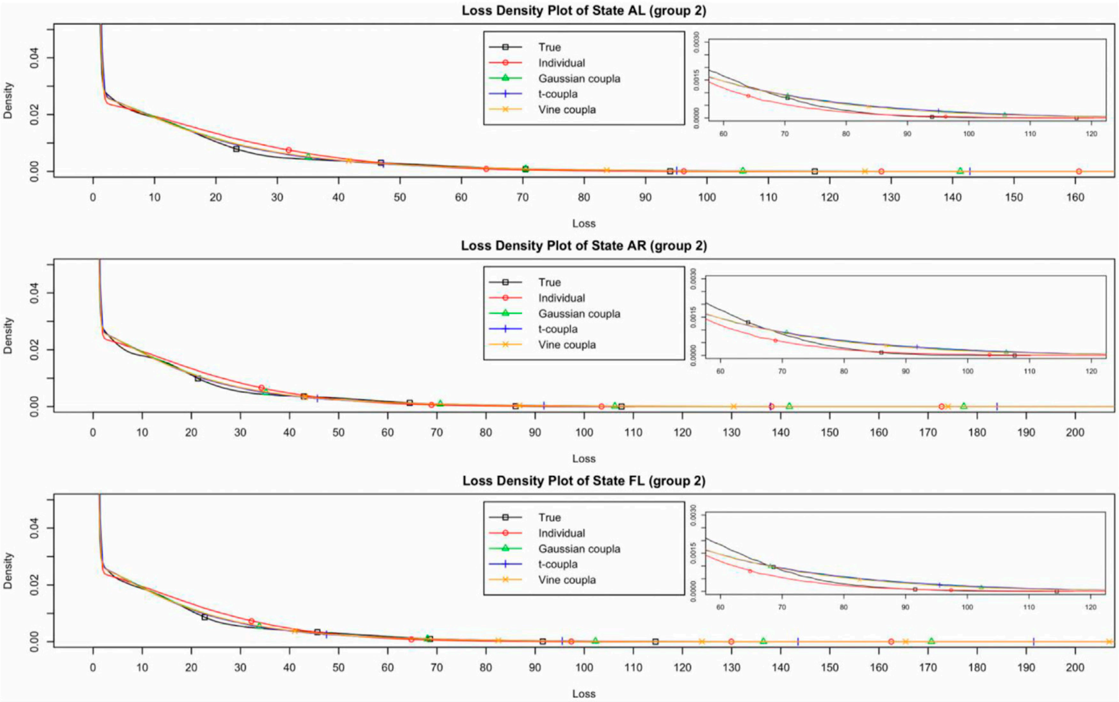

FIGURE 3 | The losses density plot for states in Group 2 (Weibull distribution with a duration of 30 years).

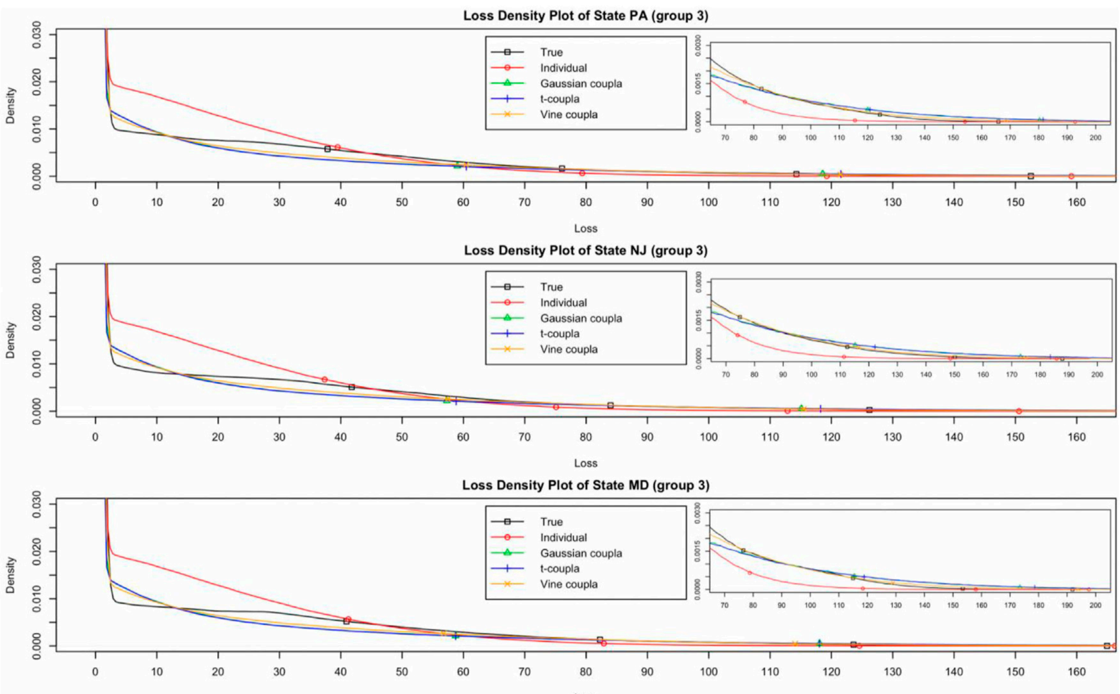

FIGURE 4 | The losses density plot for states in Group 3 (Weibull distribution with a duration of 30 years).

TABLE 10 | The average VaR and ES of aggregate losses for states in Group 1.

		n = 30		*n* = 50	
		Weibull	**Mixture**	**Weibull**	**Mixture**
VaR	"True" distribution	46.9562		48.2575	
	Individual	26.5994	31.6233	26.9795	32.9377
	Gaussian	28.9666	39.1346	29.4282	39.3472
	t	28.7839	38.9980	29.2539	39.1394
	C-vine	28.9486	39.3872	29.2249	38.6265
ES	"True" distribution	79.1993		79.7089	
	Individual	40.0049	43.5855	40.4974	45.6066
	Gaussian	59.0655	66.3426	59.7508	69.1085
	t	59.2127	66.5895	59.8756	69.3212
	C-vine	60.4425	68.6596	61.3516	71.7302

TABLE 11 | The average VaR and ES of aggregate losses for states in Group 2.

		n = 30		*n* = 50	
		Weibull	**Mixture**	**Weibull**	**Mixture**
VaR	"True" distribution	34.3501		33.7988	
	Individual	33.9879	28.4978	34.4625	28.9639
	Gaussian	34.9967	30.7408	35.3239	30.9064
	t	35.128	30.7782	35.3823	30.958
	C-vine	35.1499	30.9079	35.5104	30.7988
ES	"True" distribution	49.3004		49.1049	
	Individual	47.1956	39.0047	47.767	39.759
	Gaussian	53.8759	45.4534	54.1538	46.2313
	t	54.7911	45.9685	54.7368	46.5877
	C-vine	53.717	45.3896	54.1409	46.1026

TABLE 12 | The average VaR and ES of aggregate losses for states in Group 3.

		n = 30		*n* = 50	
		Weibull	**Mixture**	**Weibull**	**Mixture**
VaR	"True" distribution	52.4282		52.6927	
	Individual	41.0873	40.4925	41.8217	40.9976
	Gaussian	51.5542	54.1355	52.4565	54.5344
	t	51.3275	54.0712	52.3422	54.5641
	C-vine	51.4176	53.2053	52.0784	53.4731
ES	"True" distribution	76.3729		76.694	
	Individual	56.6024	54.5455	57.5033	55.4088
	Gaussian	85.9036	81.1081	86.9555	82.5066
	t	86.5183	81.6033	87.7802	83.1246
	C-vine	79.8021	76.1397	80.1034	76.956

between 1.00 and 1.60, and the reason may be that the MD state's dependence structure has the upper-tail characteristic (survival Clayton has the upper-tail properties). From the empirical results of those two groups, we may conclude that if the portfolio contains a substantial tail risk, the C-vine copula model, which provides a more flexible description of yield dependence, is better suited to measure this layer of losses.

Finally, since systemic risks associated with weather will result in concurrent agricultural production losses throughout a large geographic area, for example, the 1988 and 2012 droughts and the 1993 floods in the central and western areas all resulted in widespread crop yield losses. During times of significant yield losses caused by natural catastrophes, there may be greater interdependence between yields in different locations. A generally concerning scenario is that Gaussian copula has a tail reliance of zero, which cannot reflect the tail dependence of risk portfolios as t and vine copula. Nonetheless, the findings of this paper may lead to an intriguing conclusion. According to the above empirical results for Groups 1, 2, and 3, the C-vine copula model can provide a more accurate measurement of losses for layers with tail risk. In addition, the simulation results based on the Gaussian copula model may not differ significantly from those based on the C-vine copula and t-copula mole for the layers that lack strong tail dependence between counties.

TABLE 13 | The average Mean Squared Error of aggregate losses at different layers for states in Group1.

	n = 30		n = 50	
	Weibull	**Mixture**	**Weibull**	**Mixture**
Losses Ratio Between 100 and 160%				
Individual	1.6129	4.0302	1.0581	3.0915
Gaussian	0.9985	1.2076	0.6347	0.7103
t	1.0066	1.2113	0.6465	0.7146
C-vine	1.0370	1.1618	0.6922	0.6980
Losses Ratio Between 160 and 220%				
Individual	3.2074	4.1928	2.3939	2.5521
Gaussian	2.0057	1.9788	1.4758	1.1166
t	2.0144	1.9765	1.4949	1.1218
C-vine	1.9763	1.9117	1.4836	1.1275
Losses Ratio Between 220 and 500%				
Individual	14.3698	11.9700	13.4862	9.4323
Gaussian	7.7005	6.8211	6.5387	4.3115
t	7.6656	6.7546	6.5470	4.2838
C-vine	7.2505	6.4902	6.1143	4.0955

TABLE 14 | The average Mean Squared Error of aggregate losses at different layers for states in Group 2.

	n = 30		n = 50	
	Weibull	**Mixture**	**Weibull**	**Mixture**
Losses Ratio Between 100 and 160%				
Individual	1.4352	1.5407	1.1887	0.9001
Gaussian	0.9680	1.1981	0.6955	0.7269
t	0.9183	1.1930	0.6697	0.7305
C-vine	1.0249	1.2179	0.7280	0.7339
Losses Ratio Between 160 and 220%				
Individual	1.6392	1.9401	1.1451	1.2569
Gaussian	1.1760	1.3799	0.7963	0.8822
t	1.1210	1.3609	0.7766	0.8783
C-vine	1.2244	1.4196	0.8261	0.8903
Losses Ratio Between 220 and 500%				
Individual	1.8717	2.3430	1.1887	1.7412
Gaussian	1.9153	1.7647	1.3531	1.1366
t	1.9080	1.7289	1.3648	1.1130
C-vine	1.9296	1.8503	1.3642	1.1674

TABLE 15 | The average Mean Squared Error of aggregate losses at different layers for states in Group 3.

	n = 30		n = 50	
	Weibull	**Mixture**	**Weibull**	**Mixture**
Losses Ratio Between 100 and 160%				
Individual	6.1879	6.1112	3.5517	3.8775
Gaussian	4.8743	3.6330	3.0748	2.4397
t	4.9417	3.6584	3.1490	2.4429
C-vine	4.3894	3.5051	2.6419	2.2253
Losses Ratio Between 160 and 220%				
Individual	7.7127	8.0662	5.1362	5.6581
Gaussian	3.1998	2.9090	1.8722	1.8003
t	3.2092	2.8849	1.8952	1.7698
C-vine	3.4685	3.3838	2.0679	2.1381
Losses Ratio Between 220 and 500%				
Individual	8.4005	9.0640	6.6696	7.4172
Gaussian	3.4782	4.5983	2.5739	3.3544
t	3.4103	4.5170	2.5572	3.3033
C-vine	3.9801	5.0259	2.8126	3.4737

5 CONCLUSION

The data sets of crop yield in the neighborhood county are affected by systemic risks. Accurate modeling of these systemic risks is essential for determining reliable premium rates of the publicly-subsidized federal crop insurance program. This article detects whether the copula-based models significantly affect losses assessment and insurance pricing. Specifically, we apply the different copula-based models to the losses evaluation of crop insurance. The copulas consider the dependence of yields for adjacent counties—especially the upper and lower tails of the distribution.

To put this into perspective, the unbiased estimation of claims under systemic risk measured by individual and copula-based methods does not significantly differ. Nevertheless, for the different layers of SRA policy, the measuring of dependence significantly impacts aggregate claims. Given the massive scale of the federal crop insurance program, the copula-based model will significantly impact crop reinsurance contracts' pricing, feasibility, and profitability for the insurers, the government, and taxpayers. The vine copula provides a more flexible property in the aggregate losses estimation process in the regions with obviously estimated tail dependence.

DATA AVAILABILITY STATEMENT

All data used in this study are publicly available. The processed data needed to reproduce this study are available at USDA's datasets (https://www.usda.gov/).

AUTHOR CONTRIBUTIONS

YS conceived and designed the study, provided the idea, performed the data analysis, analyzed the results, and wrote the manuscript. KW discussed the idea with YS, and helped design the study and check the results.

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A study on the impact of extreme weather on the poverty vulnerability of farming households—evidence from six counties in the hubei and yunnan provinces of china

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By using micro-farm household survey data from six counties in the Hubei and Yunnan provinces, warm days, heavy precipitation, and consecutive dry days were selected as extreme weather measures, and the RClimDex software was used to empirically examine the impacts of extreme weather on farm household poverty vulnerability by setting percentile thresholds to measure extreme weather indicators in each district and county in 2017. Based on the improved Department for International Development sustainable livelihoods analysis framework, the entropy value method was used to synthesize the variables in the farm household sustainable livelihood capacity to examine their mediating effects. The results were as follows: 1) Extreme weather significantly affected farm household poverty vulnerability. Warm days were significantly and negatively related to farmers' poverty vulnerability, while total heavy precipitation and consecutive dry days were significantly and positively related to farmers' poverty vulnerability. 2) The impacts of extreme weather on farmers with different vulnerability characteristics varied. 3) The sustainable livelihood capacity of farm households played a partially mediating role in the process of extreme weather indicators of persistent drought index affecting the poverty vulnerability of farm households. 4) As compared to rural households engaged in non-agricultural industries, agricultural production and operation-based farming households were more vulnerable to shocks from extreme weather. Accordingly, we recommended that to improve farmers' climate resilience, differentiated policies should be adopted according to local conditions; climate-sensitive vulnerable groups should be identified; agricultural insurance coverage should be expanded; farmers should be guided into entrepreneurship; and equalization of public services should be equalized so as to avoid farmers becoming impoverished due to extreme weather.

KEYWORDS

extreme weather, farm households, poverty vulnerability, sustainable livelihood capacity, adaptive strategy

1 Introduction

As globalization develops, poverty has long been not confined to a single country or region but has become a global problem. Eliminating poverty is the mission of all humanity (Ul Haq, 1995). China is the world's largest developing country and whose poverty alleviation initiatives directly affect the governance of global poverty. By 2020, China's battle against poverty achieved relatively good results and relieved the poverty of 98.99 million rural poor people and removed 832 poor counties and 128,000 poor villages from the poverty list, according to the current standards. China has completed the historic task of eradicating absolute poverty and successfully established a comprehensive well-off society (Huang and Zhu, 2021). However, vulnerability theory suggests that risk, vulnerability, and poverty are closely linked. The livelihoods of the average farm household are vulnerable to shocks from various risks such as climate, health, and disasters that can cause them fall below the poverty line (Azeem et al., 2016). Especially in rural areas, the frequent occurrence of sudden climatic disasters such as floods and droughts intertwined with slow-onset climate changes such as global warming, continuously intensify the harm to agricultural production. Simultaneously, extreme weather can cause severe losses to farmers' natural, physical, human, social, and financial capital, which can leave them impoverished and at increased risk of poverty (Gentle and Maraseni, 2012).

International attention to climate changes such as extreme weather and climate warming has a long history, and scholars and policymakers were originally focused on emission reductions under different scenarios (Füssel, 2007). However, the effects of mitigation policies often take decades to test, so how to adapt to climate change is beginning to attract the attention of scholars and policymakers. The United Nations Framework Convention on Climate Change (UNFFCC), which entered into force in 1994 and was attended by 189 countries, provided the first international policy framework to guide countries in addressing climate change, followed by a wealth of research on how to improve climate change adaptation (Ford et al., 2010). The adaptations concerned abrupt climate changes, including extreme weather and climate disasters that can involve droughts, floods, heatwaves, and cold temperatures. The main characteristic of extreme weather is that it appears quickly and suddenly, and the time elapsed from the perception of the disaster to the appearance of the disaster is relatively short. During its appearance, it can destroy houses and farmland, damage public facilities, and seriously threaten the lives and property of farmers. Meanwhile, it can trigger secondary disasters such as pests and diseases as well as livestock and poultry epidemics, thus forming a chain of disaster networks that have a significant impact on agricultural production and life and be-comes an essential factor leading to poverty among farmers (Nguyen et al., 2020). Consequently, the mechanisms by which sudden climate changes, including extreme weather, affect poverty have also gradually become a focus of scholarly attention.

In academic circles, it is generally acknowledged that individual and household exposure to extreme weather hazards is a key factor in poverty. Extreme weather can exacerbate poverty directly or indirectly through threats to life and property, poverty traps, and "elite capture," especially in less developed countries and regions (Dasgupta and Baschieri, 2010; Leichenko and Silva, 2014; Fagariba et al., 2018; Li et al., 2019; Azzarri and Signorelli, 2020). Rodriguez-Oreggia et al. (2013) argued that extreme weather, especially floods and droughts, could significantly reduce human development and increase poverty. Excessive urbanization, environmental degradation, and weak disaster response capacity could impact poor communities that were already vulnerable to extreme weather events such as floods. Walker (2014) also concluded that drought could plunge an entire country into a natural emergency with the accompanying economic downturn, which could lead to widespread poverty in rural areas. Bui et al. (2014) and Arouri et al. (2015) studied the effects of extreme weather hazards on household income, expenditures, poverty, and inequality through a survey of rural households in Vietnam. They found that all three extreme weather types, including storms, floods, and droughts, negatively impacted household income and expenditure and that climatic hazards increased rural household poverty and inequality. On this basis, Nguyen et al. (2020) collected panel data from approximately 4000 rural households in northeast Thailand and central Vietnam to examine and compare the effects of floods, droughts, and storms on the welfare of rural families in both countries. They pointed out that extreme weather shocks significantly affected household income, consumption, and poverty, in both countries, but with different severity. The aforementioned studies were empirical analyses based on field research data from regions with high climate impacts that verified the direct relationship be-tween weather extremes and poverty. However, many scholars have also explored the mechanisms of extreme weather and their impact on poverty from other theoretical perspectives.

For example, first, there is a non-benign geographic coupling effect between the distribution of poor areas and the ecologically fragile regions of China since environ-mentally weak areas are often those most severely affected by extreme weather so that extreme weather exacerbates poverty through ecological vulnerability (Tong and Long, 2003). Cao et al. (2015) constructed an economic poverty evaluation index system that considered the natural, social, and economic aspects and analyzed the degree of coupling and coordination between ecological assets and economic poverty in the concentrated contiguous hard-ship areas in Qinba, China. They found that most counties and cities in the region had significant coupling between ecological assets and economic poverty. Specifically, the lower the environmental assets, the higher the degree of monetary poverty in the region. Li and Wang (2014) analyzed the coupling characteristics of ecological environment quality and economic poverty in areas with severe environmental degradation and found that there was a high spatial autocorrelation between ecological environment quality and per capita disposable income, but the overall degree of synchronization was poor. Zhang and Feng (2020) explored the correlation, consistency, and coordination between economic poverty alleviation and ecological poverty alleviation by using the entropy value method and coupling coordination degree model in concentrated, contiguous poverty areas in Yunnan Province, China. The results showed that the coupling degree of the four regions in Yunnan Province was high, but the coupling coordination degree was low. Zhou et al. (2021) calculated the coupling degree and coupling coordination of ecosystem services and poverty livelihoods in 717 poor counties in China from 2000 to 2015. They found that ecosystem service functions showed a trend of decreasing, and then in-creasing, while the poverty levels showed an increasing trend, and the degree of conflict in the coupling relationship between ecosystem services and poverty livelihoods was high.

Second, from a sustainable livelihoods perspective, farm households are highly dependent on natural resources for their livelihood activities. Natural disasters such as extreme weather can cause significant losses to farmers' livelihood assets, adverse im-pacts on sustainable income, and even substantial lifestyle changes, leading to poverty among farmers (Motsholapheko et al., 2015). Carter et al. (2007) analyzed the long-term effects of extreme weather on asset stocks and economic growth using the least squares (OLS) method. They showed that extreme weather was likely to deprive the poor of capital, creating a poverty trap from which they would struggle to escape. Nevertheless, some scholars have argued that the impact of natural disasters such as extreme weather on poverty have not always been negative and that poor people in developing countries were more vulnerable to extreme weather (Loayza et al., 2012). Mottaleb et al. (2013) suggested that during natural disasters such as extreme weather, farming households may increase their food expenditures and reduce their education expenditures, thus adversely affecting long-term human capital development. Van den Berg and Burger (2017) studied the impact of hurricanes on household livelihood strategies in rural areas and found that the direct or indirect effects of hurricanes resulted in more than 60% of the rural population choosing low welfare strategies that made them more vulnerable to poverty. Yiridomoh et al. (2021) studied the impact of extreme weather on rural livelihood sustainability using communities along the Black Volta River in Siva State as the unit of analysis and found that short-term, unstable extreme weather such as drought and high temperatures affected the livelihoods of farm households, thereby increasing poverty.

Finally, from a vulnerability perspective, social vulnerability has been closely related to poverty. Poverty increases vulnerability by influencing resource availability, the perceptions of the impact of natural hazards such as extreme weather, and the ability to invest in risk reduction, becoming an essential component of social vulnerability. In general, poorer communities suffer more difficulty in post-disaster recovery (Schmidtlein et al., 2011). A study by Jiang et al. (2012) found that higher agricultural dependence was more likely to trigger poverty, and natural disasters such as extreme weather significantly impacted poverty incidence. Zhang (2011) found that natural hazards such as extreme weather and poverty have overlap and consistency in poor minority communities. There were sequential and cyclical relationships among extreme weather, vulnerability, viability, and poverty. Zhou et al. (2015) constructed the first disaster risk index for China and assessed the relative risk levels at a provincial scale in China, suggesting that reducing vulnerability and population exposure to natural hazards would be an effective measure to mitigate disaster risk in Chinese hotspots. Ding et al. (2014) argued that the education level of household members and household labor capacity would play an essential role in reducing vulnerability. Increasing school attendance and educational background could reduce the vulnerability of farm households.

While all of the above studies have acknowledged poverty as part of social vulnerability, quite a few scholars have considered vulnerability as an essential aspect of poverty and thus proposed the concept of poverty vulnerability (Feng et al., 2017). The World Bank defines poverty vulnerability as the likelihood of falling into poverty in the future. Declining crop harvests, rising food prices, and significant household labor decreases can increase poverty vulnerability. Therefore, poverty should no longer be interpreted limited to fundamental social welfare indicators based on low income but should also include vulnerability to poverty caused by external shocks (W Bank, 2001). Bohua et al. (2013) argued that the main factors affecting the poverty vulnerability in farm households were relatively low economic status, inadequate social security, and poor natural environmental resources. After analyzing the impact of natural disasters such as extreme weather on the vulnerability of farm households to poverty, Thouret et al. (2013) found that maintaining water and soil, increasing the area of greenery, and increasing the proportion of low-income households could effectively counteract the risk of drought and alleviate poverty. Liu et al. (2022) measured the level of poverty vulnerability in farm households and explored the degree of differentiation, taking the Qinba mountainous region as an example. The farmers' exposure risk and resilience were geographically differentiated, and the farmers in the central mountainous areas were at higher risk and more vulnerable to poverty from natural disasters such as extreme weather. Maganga et al. (2021) used panel data from 2010, 2013, and 2016 Living Standards Measurement Surveys in Malawi to examine the extent to which climate change affected the vulnerability of farm households to poverty and the relationship between post-poverty and poverty transition and climate change. From the existing studies, scholars have increasingly focused on the impact of extreme weather and climate changes on the poverty vulnerability of farm households and have focused their research on developing countries that have been most affected. However, their data collection on extreme weather and climate changes have been sourced from local weather stations and farmer perception surveys and have not been considered at the county level (Jalal et al., 2021; Samuels et al., 2022). Li et al. (2022) studied the impact of climate change on individual poverty vulnerability in rural China based on county-level climate data and micro-survey data (CHIPS) and found that extreme temperatures reduced poverty vulnerability. However, they only explored the effect of extreme temperatures on poverty vulnerability and did not consider the relevant role of other extreme weather such as extreme precipitation. The World Meteorological Organization (WMO) and the World Climate Research Program (WCRP), have jointly established the Expert Group on Climate Change Detection and Indices (ETCCDI), which has defined 27 representative climate indices for global and regional studies on extreme climate change (Rodriguez-Sola et al., 2022). Therefore, the inclusion of other extreme weather-related indicators in the discussion could have profound implications for the comprehensive evaluation of extreme weather on the poverty vulnerability of farm households.

The impact of extreme weather on poverty vulnerability is often more pronounced in developing countries or regions, one of which is China (Schmidtlein et al., 2011). China is one of the most at-risk countries for natural disasters. China's meteorological disasters and derived disaster losses have accounted for more than 70% of natural disaster losses, and the average annual direct economic losses account for approximately 75% of natural disaster financial losses, resulting in approximately 80% of the deaths caused by natural disasters (Zhang and Wang, 2022). According to the China Meteorological Ad-ministration disaster database, in 2018, China's meteorological disasters caused 20.81 million hectares of crop damage, 635 deaths and disappearances, and direct economic losses of CYN 264.5 billion. In 2021, Henan, Sichuan, Shanxi, Hebei, Hubei, and Shaanxi suffered severe torrential rainfall and flooding in the second half of the year, causing a total of 59.01 million people affected, 590 deaths and disappearances due to the disaster, 152,000 collapsed houses, and direct economic losses of CYN 245.89 billion. China ranks fourth and second in the world for average annual deaths and economic losses caused by extreme weather, respectively, with an average of more than 1200 deaths per year from extreme weather events (Li and Mao, 2019). Based on the extreme weather statistics in recent years, extreme weather has become a critical risk factor impacting the vulnerability of Chinese farmers, seriously affecting their livelihoods, their safety, and their land. Therefore, studying the impact of extreme weather on farmers' poverty vulnerability in China is of great practical importance for other developing countries to avoid poverty among ordinary farmers and prevent farmers who have left poverty from becoming impoverished again.

In summary, farmers remain at risk of becoming or returning to poverty when faced with risks such as extreme weather. Therefore, exploring the mechanisms of extreme weather on the vulnerability of farm households to poverty and providing policy recommendations are of great importance to consolidate and expand poverty alleviation in China and achieve the goal of rural revitalization. In the meantime, the inclusion of other extreme weather-related indicators in the discussion could have profound implications for the comprehensive evaluation of extreme weather on the poverty vulnerability of farm households. In this paper, the three most representative of the 27 extreme climate indicators, including warm days (TX90p), the sum of heavy precipitation (R95p), and the consecutive dry days (CDD), were selected and calculated with RClimDex software, which was developed by Zhang and Yang (Canadian Meteorological Research Centre) based on the R language environment, to explore the impact of extreme weather on the poverty vulnerability of rural off-poverty farmers in China (Zhang and Yang, 2004). These findings are of great importance to consolidate and expand poverty alleviation in China and achieve the goal of rural revitalization. In the meantime, this study also provides valuable references for other developing countries to avoid poverty among ordinary farmers and prevent farmers who have left poverty from becoming impoverished again.

2 Data and method

2.1 Study areas

More than 70% of meteorological disasters in China have occurred in the central and western poverty areas (Liu, 2019). At the beginning of 2017, there were 25 poor counties in Hubei Province in central China, with 5,721,856 people in poverty and a poverty incidence rate of 14.21%. There were 72 extreme high-temperature events, 22 extreme low-temperature events and 7 extreme precipitation events throughout the year, slightly higher than in previous years. The frequent occurrences of various climatic disasters have posed a severe threat to the safety of people and property. The vulnerability of farmers to climatic disasters has further exacerbated the problem of rural poverty. At the beginning of 2017, there were 33 poor counties in Yunnan Province, with a poor population of 4,630,210 people and a poverty incidence rate of 11.34%. The frequent occurrence of extreme weather events poses a severe threat to the property and security of the poor in these two provinces, further increasing poverty vulnerability. There were 95 extreme high temperature events, 11 extreme low temperature events and 23 extreme precipitation events throughout the year, slightly lower than previous years. Therefore, two poverty counties in Hubei

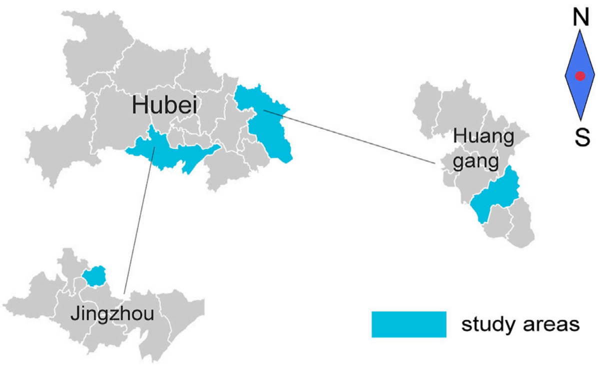

FIGURE 1
Study areas—Qichun County and Shashi District in Hubei Province.

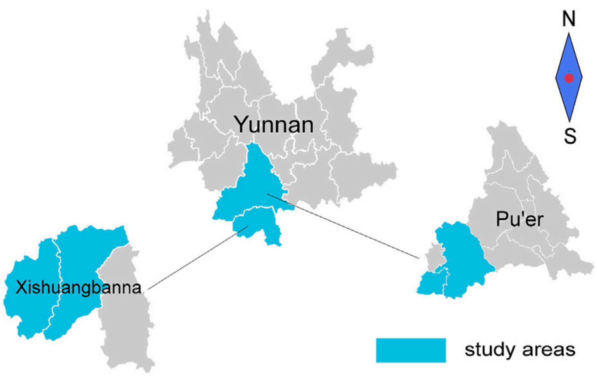

FIGURE 2
Study areas—Lancang County, Menglian County, Menghai Country and Jinghong City in Yunnan Province.

Province and four poverty counties in Yunnan Province in southwestern China were selected as the subjects of this paper (as shown in Figures 1, 2). The geographical locations and climatic characteristics of the six counties were as follows:

Qichun County, Huanggang City, Hubei Province (115°12′–115°56′E, 29°59′–30°40′N), is located in southeastern Hubei Province, north of the middle reaches of the Yangtze River, with an area of approximately 2398 square kilometers and a resident population of 792,101. Qichun County belongs to the subtropical continental monsoon climate, with four distinct seasons, abundant rainfall, a mild climate, an average annual frost-free period of 249.1 days, precipitation of 1341.7 mm, and 2025.8 sunshine hours with an average temperature of 16.8°C.

Shashi District, Jingzhou City, Hubei Province (112°13′–112°31′E, 30°12′–30°25′N) is located in the south of Hubei Province, on the north bank of the Jing River section of the Yangtze River, with an area of approximately 522.75 square kilometers and a resident population of 504,893 people. Shashi District belongs to the subtropical humid monsoon climate zone, with four distinct seasons, excellent heat, and abundant rainfall. The average annual temperature is 16.1°C, the annual frost-free period is 230–270 days long, the annual rainfall is generally between 958 and 1325mm, and the average relative humidity is 80%.

Lancang County, Pu'er City, Yunnan Province (99°29′–100°35′E, 22°01′–23°16′N) is located in the southwest of Yunnan Province, named after the Lancang River in the East, with an area of approximately 8807 square kilometers, the second-largest county in Yunnan Province, and a resident population of approximately 441,455. Located south of the Tropic of Cancer, Lancang County has a southern subtropical mountainous monsoon climate with wet summers and dry winters, abundant rainfall, and sufficient sunshine. Due to the complex topography and altitude difference, the three-dimensional climate is apparent, with high temperature, sufficient heat, an annual average temperature of 19.2°C, annual rainfall of 1624.0 mm, and annual sun-shine of 2098.0 h.

Menglian County, Pu'er City, Yunnan Province (99°9′–99°46′E, 22°15′–22°32′N), located in the southwest of Yunnan Province, is an essential gateway to Myanmar, Thailand, and other Southeast Asian countries. As of the end of 2018, Menglian County has an area of approximately 1893.42 square kilometers and a resident population of 144,693 people. Menglian County has a southern subtropical climate. The climate in the territory has abrupt changes, with no severe cold in winter, no summer heat, and four seasons similar to spring conditions. The average annual temperature is 19.6°C, the average annual rainfall is 1373mm, the annual rainy days are approximately 170, and the average annual sunshine is 2048.6 h. The wind speed is generally 3, with a maximum of 6–7.

Jinghong City, Xishuangbanna, Yunnan Province (100°25′–101°31′E, 21°27′–22°36′N) is located in the south of Yunnan Province, with a land area of approximately 6867 square kilometers and a resident population of 416,054. Jinghong City has a year-round high temperature and low rainfall, which means drought is heavy. The main meteorological disasters are high temperature and drought, wind and hail disasters, and torrential flooding, including winter and spring drought, which is unusually heavy.

Menghai County, Xishuangbanna, Yunnan Province (99°56′–100°41′E, 21°28′–22°28′N), located in the southwest of Yunnan Province, has a land area of 5368.09 square kilometers and a resident population of 353,720. Menghai County belongs to the tropical and subtropical southwest monsoon climate, with no severe cold in winter and summer heat, slight annual temperature differences, and significant daily temperature differences. The average annual temperature is 18.7°C, the average annual sunshine is 2088 h, the average annual rainfall is 1341mm, and the annual frost period is ap-proximately 32 days. There are many fog patches, and the average annual fog is 107.5–160.2 days.

2.2 Data resources

The data used in this study were derived from the survey data of farmers' livelihoods collected by the research team in Hubei and Yunnan provinces in 2017. To ensure the comprehensiveness and reliability of the survey data, the sample areas were selected from two provinces located in relatively rich and relatively poor areas, the questionnaire method was adopted, and a combination of stratified random sampling and targeted sampling was used to conduct the questionnaire survey among households. The specific operation was to first classify the townships in the county into high, medium and low categories according to the depth of poverty; then determine the number of sample farmers from each type of township according to the proportion of the number of farm households in each type of township to the total number of farm households in the county; finally, go to each township to draw samples from the relevant farm households according to the random principle. Eventually, 541, 326, 77, 111, 22 and 37 farming households were sampled in each of the six districts and counties (Qichun County, Shashi District, Lancang County, Menglian County, Jinghong City, Menghai County), and the final number of valid sample farmers was 1,214. The survey included demographic information, natural and physical capital, social and financial capital, agricultural and non-agricultural situations and income, consumption expenditure, agricultural policies, land and homestead status of farm households, etc. After data processing using STATA software and removing the outliers and missing values of vital variable indicators, 1,114 valid respondents were obtained.

The uneven distribution of weather stations in China is manifested by a higher density of weather stations in eastern China and fewer stations in the west, making it difficult to obtain accurate county-level extreme weather data. Therefore, this paper used global climate data from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) to precisely match the geographical locations of six counties in Hubei and Yunnan at a latitude and longitude of 0.1×0.1, solving the problem of inaccurate climate data from local weather stations. We collected more than 10 types of day-by-day climate data such as temperature, precipitation, sunshine, and wind speed, from 1980 to 2017 in 6 counties, keeping 6 indicators: year, month, day, daily maximum temperature, daily minimum temperature, and daily precipitation.

2.3 Variable design and model construction

2.3.1 Variable design

2.3.1.1 Dependent variables

The dependent variables in this study was poverty vulnerability. Poverty vulnerability refers to the likelihood that a household or individual will fall into poverty or persistent poverty in the future. Among the past definitions and measures of poverty vulnerability, there are three main representative ones, which are "vulnerability as expected poverty (VEP)", "vulnerability as low expected utility (VEU)", and "vulnerability as uninsured exposure to risk (VER)". Of these, the VEP is prospective and more applicable to cross-sectional data as it better reflects the dynamic characteristics of poverty than the others (Wang et al., 2020). Therefore, in this paper, the measure of poverty vulnerability of farm households in the data was selected under the definition of VEP, as proposed by Chaudhuri et al. (2002).

The theory of poverty vulnerability measurement under the VEP definition assumes that the magnitude of household poverty vulnerability is associated with the characteristics of the distribution of the household's future welfare level, and thus the likelihood of a household or individual falling into poverty or persistent poverty in the next period is calculated through the current period household or individual characteristics variables (Xiao et al., 2020). The basic equation is shown below.

$$\mathrm{vul}_{h,t} = prob\left(perincome_{h,t+1} < poor\right) \tag{1}$$

where the left-hand side of the equation represents the poverty vulnerability of household h in period t, and the right-hand side of the equation represents the probability that the per capita income level of farm household h in period $t+1$ is less than the poverty line.

Since the future per capita income level of a household usually depends on multiple factors, including both observable individual characteristics such as age, gender, marital status, and household characteristics such as household size, natural capital, physical capital, and social capital, and unobservable variables such as the general environment in which the household is located, the following function can be constructed to measure the future per capita income level of a household:

$$perincome_{h,t+1} = f\left(X_{\mathrm{h}}, \partial_h, \ell_{h,t}\right) \tag{2}$$

where $perincome_{h,t+1}$ denotes the level of household per capita income in period $t+1$, X_{h} denotes a set of individual or household characteristic variables that affect the household's future per capita income, and $\ell_{\mathrm{h},t}$ is an unobservable disturbance term.

Combining Eq. 2–1 yields:

$$vul_{h,t} = prob\left[f\left(X_h, \partial_h, \ell_{h.,t}\right) < poor\right] \tag{3}$$

Assuming that the future per capita income of households follows a normal distribution, this paper drew on the three-step feasible generalized least squared (FGLS) method, as proposed by Amemiya (1977), to achieve a measure of vulnerability to poverty.

First, an OLS regression was performed on the logarithm of the household per capita income level ($\ln perincome_h$), based on individual or household characteristic variables (X_h) and residual terms (ℓ_h), and the estimated equation is as follows:

$$\ln perincome_h = \partial X_h + \ell_h \tag{4}$$

Second, since the fluctuating term of income also depended on a series of individual or household characteristic variables, the equation can be constructed as follows:

$$\ell_{\mathrm{h}}^{2} = \beta X_h + \varepsilon_h \tag{5}$$

Applying the error term obtained from OLS estimation of Eq. 4, 5 yields:

$$\hat{\ell}_h^{\,2} = \hat{\beta}_{ols} X_h + \hat{\varepsilon}_h \tag{6}$$

Furthermore, we obtained the expectation and variance of logarithm of per capita income of farmer households by dividing both sides of Eq. 5 by $\hat{\beta}_{ols} X_h$ and performing OLS estimation to obtain the progressive effective estimate β_{fgls} of β, based on which we obtained $\hat{\ell}_{h,fgls} = \sqrt{\hat{\beta}_{fgls} X_h}$, and applied it to Eq. 4 to estimate the progressive effective estimate ∂_{fgls} of ∂, resulting in the following:

$$\hat{E}\left(\ln perincome_h \mid X_{\mathrm{h}}\right) = X_{\mathrm{h}} \hat{\partial}_{fgls} \tag{7}$$

$$\hat{V}\left(\ln perincome_h \mid X_h\right) = X_h \hat{\beta}_{fgls} \tag{8}$$

Finally, based on the above estimates, the poverty vulnerability of household h in period t was calculated as:

$$\begin{aligned} \hat{v}ul_{h,t} &= \hat{p}rob(\ln perincome < \ln poor) \\ &= \o\left[\frac{\ln poor - \hat{E}\left(\ln perincome_h | X_h\right)}{\hat{D}\left(\ln perincome_h | X_h\right)}\right] \end{aligned} \tag{9}$$

where $\ln poor$ is the natural logarithm of the selected poverty line.

This study used the national poverty line standard household per capita income of RMB 2300/year determined in 2011 in China, the comparable 2017 price of RMB 3449/year extrapolated at constant RMB 2300/year, and the World Bank extreme poverty line standard of USD 1.9/person/day to measure the poverty vulnerability of farm households. In addition, to facilitate the interpretation and analysis of the variables, all poverty vulnerabilities obtained in this paper were multiplied by 100, and the units were uniformly converted to percentages.

2.3.1.2 Independent variables

The various indices (27 in total) of the extreme climate indicator system provided by ETCCDMI have been widely adopted by many scholars in geography, meteorology and agriculture in recent years (Rodriguez-Sola et al., 2022). Eleven of these indicators are related to precipitation, and sixteen are related to temperature. All extreme weather indicators reflect temperature and precipitation extreme events in terms of intensity, frequency, and duration of climate change. Since Hubei and Yunnan provinces are located in central and southwestern China, respectively, the average daily minimum temperature throughout the year rarely falls below 0°C; we did not consider the indicator used to measure shallow temperatures as our dependent variable. Finally, we selected three indicators, warm days (TX90p), the sum of heavy precipitation (R95p), and the consecutive dry days (CDD), as independent variables in this paper, used to study the effects of high temperature, flooding, and drought on poverty vulnerability, respectively. The RClimDex software was then used to calculate the three extreme climate indicators for each county in 2017. The specific process was as follows: for TX90p and R95p, the percentile threshold method was used, using the climate data of each county from 1980 to 2016 as a reference base, ranking the same indicators within this period from smallest to largest, and defining the values higher than the corresponding indicators located at 90% or 95% of the reference year as extreme climate events; for CDD, the maximum number of consecutive days with daily precipitation less than 1 mm was counted. Specific indicators are defined, as shown in Table 1.

2.3.1.3 Mediating variables

The study used the sustainable livelihood capacity of farm households as a mediating variable to test the mechanisms underlying the effect of extreme weather on the vulnerability of farm households to poverty. In the construction of indicators, based on the improved DFID (Department for International Development) sustainable livelihoods analysis framework, 12 indicators in seven dimensions, namely human capital, financial capital, physical capital, natural capital, social capital, information capital, and environmental capital, were selected based on the approach of Liu et al. (2021), and the sustainable livelihood capacity of farm households was comprehensively measured. The measurements were obtained via the entropy method, and the upper and lower 1% of the measured comprehensive values were scaled down using the winsorization. The intermediate variable indicators were used to construct the evaluation system, as shown in Table 2.

2.3.1.4 Control variables

Based on the previous literature, this study applied individual characteristics (gender of household head, health level, marriage status, non-farm working time) and household characteristics (information accessibility, land transfer, number of farm machinery and equipment, and annual household medical expenses) as control variables; the specific definitions and related descriptions of the variables are shown in Table 3.

2.3.2 Model construction

In this study, the baseline regression model, quantile regression model and mediating effect model are constructed respectively, and the impact of extreme weather on farmers' poverty vulnerability and the intrinsic mechanism of action are tested empirically by using STATA software, the models are constructed as follows.

2.3.2.1 Baseline regression model construction

To explore whether there was a significant effect from extreme weather on farmers' poverty vulnerability, this study

TABLE 1 Evaluation system for constructing extreme weather indicators.

Indicator name	Identification	Definitions	Unit
Warm days	TX90p	Number of days with daily maximum temperatures greater than the 90% quantile	d
Heavy precipitation	R95p	Total annual precipitation with daily precipitation greater than the 95th percentile	mm
Consecutive dry days	CDD	Maximum number of consecutive days with daily precipitation less than 1 mm	d

TABLE 2 Evaluation system for constructing indicators of sustainable livelihood capacity of farm households.

Livelihood capital	Indicator name	Definitions
Human capital	Age of household head	Continuous variable, unit: years
	Average education level of the household	Continuous variable, sum of years of education of household members/household size, unit: years
Financial capital	Amount the household can borrow	Continuous variable, unit: rmb
Physical capital	Number of real estate properties	Continuous variable, unit: set
	Housing area	Continuous variable, unit: square meter
Natural capital	Arable land area	Continuous variable, unit: acres
Social capital	Number of families visiting each other in the New Year	Continuous variable, unit: household
	Number of relatives and friends who can provide assistance	Continuous variable, unit: home
Information capital	Number of household electrical and technological products	Continuous variable, unit: pcs
	Number of channels to learn about agricultural support policies	Dummy variable, 1 = three and above, 0 = less than three
Environmental capital	Whether there is pollution in the surrounding water sources	Dummy variables, 0–3: not present - abundantly present
	Presence or absence of pollutants near farmland	Dummy variable, 1 = yes; 0 = no

used OLS regression for empirical testing, and the model was determined, as follows:

$$vul_h = \alpha_0 + \alpha_1 ex\_weather_h + \alpha_2 control_h + \mu_h \tag{10}$$

where vul_h denotes the household poverty vulnerability of farmers h under the poverty line criteria of RMB 2300/year, RMB 3449/year, and USD 1.9/person/day, $ex\_weather_h$ is the core explanatory variable extreme weather (warm days, heavy precipitation, and consecutive dry days), $control_h$ is a series of control variables, and α_0 and μ_h are the intercept and random disturbance terms, respectively.

2.3.2.2 Quantile regression model construction

As traditional OLS regression is essentially a mean regression analysis, the process of performing regression analysis only examined the effect of the explanatory variable x on the conditional expectation $E(Y|X)$ of the explanatory variable y, rather than the overall conditional distribution of $Y|X$. Moreover, as compared to OLS regressions in which the minimized objective function is the sum of squared residuals ($\sum_{h=1}^{n} e_h^2$), which is highly susceptible to extreme values, thus reducing the robustness of the regression results, the quantile regression proposed by Koenker and Bassett (1978) not only captured all the information concerning the effect of x on the overall conditional distribution $Y|X$, but also ensured the robustness of the regression results by using the weighted average of the absolute values of the residuals ($\sum_{h=1}^{n} |e_h|$) as the minimization objective function, avoiding biasing of the results due to the influence of extreme values in the regression analysis (Chen, 2010). Therefore, considering that farmers with different poverty vulnerability levels may have different sensitivities to each influencing factor, the study further used quantile regression based on the above OLS regression to explore the differences in the effects of extreme weather on farmers with different vulnerability characteristics. In the model setting, we referred to the model setting conducted by Yang et al. (2020). The model setting was as follows:

$$Q_t\left(vul|ex\_weather\right) = \beta_{0t} + \beta_{1t} ex\_weather_h + \beta_{2t} control_h + \varepsilon_t \tag{11}$$

where $Q_t\left(vul|ex\_weather\right)$ is the result variable, referring to the household poverty vulnerability of farmers at quartile t; β_{1t} denotes the correlation coefficient at quartile t for parameter estimation of the core explanatory variables (warm days, heavy precipitation, and consecutive dry days), ε_t is a random

TABLE 3 Names and definitions of relevant variables.

Variable category	Variable name		Definitions
Dependent variables	Poverty Vulnerability	vul1	Poverty vulnerability under the national poverty line standard (household income per capita of 2300 RMB/year) determined in 2011 (%)
		vul2	Poverty vulnerability under the 2017 comparable RMB 3449/year poverty line standard extrapolated at constant RMB 2300/year (%)
		vul3	Poverty vulnerability under the World Bank extreme poverty line criterion of USD 1.9/person/day (%)
Independent variables	Extreme weather	warm	Warm days, number of days with daily maximum temperatures greater than the 90% quantile (%)
		precipitation	Heavy precipitation, total annual precipitation with daily precipitation greater than the 95th percentile (mm)
		dry	Consecutive dry days, maximum number of consecutive days with daily precipitation less than 1 mm (days)
Mediating variables	Sustainable livelihood capacity of farm households	sla	Comprehensive measure using entropy method
Control variables	Gender of household head	gender	Gender of household head, 1 = male, 0 = female
	Health level	healthy	1–5: very poor–very good
	Marriage status	marriage	1 = married; 0 = unmarried
	Non-farm working time	unagri	Time engaged in non-farm production and business activities in 2016 (months)
	Information accessibility	information	What are the channels through which you learn about agricultural support policies? 1 = three channels and above, 0 = less than three channels
	Land transfer	transfer	During the past 5 years, did you transfer land to enterprises or large grain farmers? 1 = Yes, 0 = No
	Number of agricultural machinery and equipment	machinery_n	Total number of farm machinery and farm equipment owned by households
	Annual household medical expenses	med_c	Total household expenditure on medical expenses and hospitalization expenses in 2016

disturbance term, and the remaining explanations were consistent with the above.

2.3.2.3 Model construction of mediating effect

This paper adopted a stepwise testing method, as proposed by Wen and Ye (2014), to test the mediating effect of farmers' sustainable livelihood capacity and to identify the mechanism underpinning the effect of extreme weather on farmers' poverty vulnerability. The model was constructed as follows:

$$vul_h = a_1 + b_1 ex\_weather_h + c_1 contril_h + \eta_{1h} \tag{12}$$

$$sla_h = a_2 + b_2 ex\_weather_h + c_2 control_h + \eta_{2h} \tag{13}$$

$$vul_h = a_3 + b_3 ex\_weather_h + b_4 sla_h + c_3 control_h + \eta_{3h} \tag{14}$$

where sla_h denotes the sustainable livelihood capacity of rural household h, b_1 is the total effect of extreme weather on the vulnerability of farm households, b_2 denotes the effect of extreme weather on the sustainable livelihood capacity of farm households, b_3 is the direct effect of extreme weather on the poverty vulnerability of farm households, with b_2*b_4 being the indirect effect of extreme weather on the poverty vulnerability of farm households through the sustainable livelihood capacity of farm households, and the remaining explanations were consistent with the above.

In addition, in the intermediary effect test process, firstly, it was necessary to determine whether the coefficient b_1 was significant; in the case of b_1 significant, secondly, it is necessary to verify whether b_2 and b_4 were significant, and if both were significant, then there was an indirect effect, after which it would be necessary to observe whether b_3 was significant, and if it was significant, then it indicated that there was a direct effect at the same time. If only one was significant, it would be necessary to use the bootstrap method for re-verification; finally, on the basis of determining the existence of an indirect effect, it would be necessary to observe whether the directions of b_2*b_4 and b_3 were consistent, and if they were consistent, it indicated the existence of mediating effect, and the opposite indicated the existence of masking effect.

3 Results

3.1 Variable descriptive statistics

From the descriptive statistics results of each variable in Table 4, as the poverty vulnerability calculation had been uniformly performed by multiplying by 100, the poverty

TABLE 4 Descriptive statistics of variables of related.

Variable name	Obs	Mean	S.D.	Min	Median	Max
vul1	1114	0.1779	0.3119	0.0000	0.0555	2.7578
vul2	1114	0.7425	0.9893	0.0000	0.3719	7.0102
vul3	1114	1.0127	1.2666	0.0000	0.5582	8.5162
Warm	1114	0.1168	0.0127	0.0739	0.1205	0.1260
Precipitation	1114	664.5788	169.5821	503.2000	682.0000	1088.4000
Dry	1114	40.5197	16.2258	21.0000	35.0000	57.0000
Sla	1114	0.0009	0.0007	0.0001	0.0006	0.0034
Gender	1114	0.9273	0.2598	0.0000	1.0000	1.0000
Healthy	1114	3.5799	1.0780	1.0000	4.0000	5.0000
Marriage	1114	0.8932	0.3090	0.0000	1.0000	1.0000
unagri	1114	3.6382	4.8132	0.0000	0.0000	12.0000
information	1114	0.3573	0.4794	0.0000	0.0000	1.0000
transfer	1114	0.1311	0.3376	0.0000	0.0000	1.0000
machinery	1114	1.0242	1.3906	0.0000	1.0000	12.0000
med_c	1114	6988.5862	1.88e+04	0.0000	1200.0000	2.00e+05

incidence corresponding to a poverty line standard of RMB 2300/year per household income was 0.18%, the poverty vulnerability corresponding to a poverty line standard of RMB 3449/year per household income was 0.74%, and the poverty line standard of USD 1.9/person/day corresponded to a poverty incidence of 1.01% for the sample farm households, which showed that the overall poverty vulnerability of the sample farm households was low. Among the extreme weather indicators, the mean value of the percentage of days with a maximum temperature > the 90% quantile was 0.12%, the mean value of total annual precipitation > the 95% quantile was 664.58 mm, and the mean number of the longest consecutive days with daily precipitation < 1 mm was 40.52, on average. The mean value of the control variable sustainable livelihood capacity of farm households was 0.0009. Among the personal characteristics of household heads, the health level of household heads was generally average or relatively good, and 92.73% of the respondents were male, 89.32% of the respondents were married, and the average time spent in non-agricultural production and business activities was 3.64 in months. Among the farm household characteristics, the Internet access rate was 35.73%, the percentage of land transfer households was 13.11%, the average number of farm machinery and equipment was 1.02 pcs, and the average annual household medical expense was RMB 6988.58.

3.2 Analysis of baseline regression results

Before analyzing whether there was a significant effect of extreme weather on farmers' poverty vulnerability, it was necessary to first test the variables for multicollinearity, considering that there could be cointegration problems among the variables that could bias the estimation results. Based on the test results, the maximum value of the variance inflation factor (VIF) and the mean value of VIF were both 1.01, which was less than 10; therefore, there was no multicollinearity between variables.

Based on the multicollinearity test, this study empirically analyzed the impact of extreme weather on farmers' poverty vulnerability through OLS regression. The regression results are shown in Table 5. Mod5-1, mod5-2, and mod5-3 represented the results of the impact of extreme weather on the poverty vulnerability of farm households under the poverty line criteria of RMB 2300, RMB 3449, and USD 1.9/day, respectively.

The regression results showed that the effects of extreme weather indicators (warm days, heavy precipitation, and consecutive dry days) on the poverty vulnerability of farm households under different poverty-line criteria passed the test at 1% significance, and the effects of extreme weather on the poverty vulnerability of farm households increased as the poverty line criteria increased, indicating that there were significant effects from maximum temperature days, total heavy precipitation, and sustained drought days on farmers' poverty vulnerability, i.e., extreme weather significantly affected farmers' poverty vulnerability. Among them, the coefficients of warm days on farmers' poverty vulnerability were negative while the coefficients of total heavy precipitation and consecutive dry days on farmers' poverty vulnerability were positive, which indicated that the increase in high temperature days significantly reduced farmers' poverty vulnerability, while the increase in total precipitation and consecutive dry days significantly increased farmers' poverty vulnerability. In addition, the extreme weather indicator of maximum

TABLE 5 Baseline regression results of the impact of extreme weather on poverty vulnerability of farm households.

Variable name	mod5-1	mod5-2	mod5-3
	Vul1	Vul2	Vul3
warm	−2.0729***	−10.5406***	−14.7611***
	(0.5196)	(1.4006)	(1.7183)
precipitation	0.0006***	0.0025***	0.0034***
	(0.0001)	(0.0002)	(0.0003)
dry	0.0069***	0.0308***	0.0422***
	(0.0009)	(0.0025)	(0.0030)
gender	0.1152***	0.3370***	0.4162***
	(0.0230)	(0.0620)	(0.0760)
healthy	−0.0902***	−0.2985***	−0.3819***
	(0.0056)	(0.0150)	(0.0184)
marriage	−0.5527***	−1.6814***	−2.1105***
	(0.0193)	(0.0521)	(0.0640)
unagri	−0.0141***	−0.0526***	-0.0696***
	(0.0012)	(0.0033)	(0.0041)
Information	−0.0907***	−0.4134***	−0.5725***
	(0.0128)	(0.0346)	(0.0424)
Transfer	0.1292***	0.3880***	0.4865***
	(0.0168)	(0.0451)	(0.0554)
Machinery	−0.0163***	−0.0590***	−0.0778***
	(0.0043)	(0.0117)	(0.0143)
med_c	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)
Constant	0.5514***	1.6573***	2.0833***
	(0.0887)	(0.2391)	(0.2934)
Observations	1,114	1,114	1,114
R-squared	0.645	0.744	0.765

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, same below.

temperature days had a stronger effect on farm household poverty vulnerability than total precipitation and continuous dry days.

In the regression results of the control variables on the poverty vulnerability of farm households, the sex of the household head, the land transfer status of the farm household, and medical expenses all had highly significant positive relationships on the poverty vulnerability of farm households while the health level of the household head, marital status, off-farm working hours, household information accessibility, and the number of farm machinery and equipment significantly and negatively affected the poverty vulnerability of farm households. This indicated that men were more likely to fall into poverty than women; transferring land to enterprises or large grain farmers resulted in the farmers being much more likely to fall into poverty in the future than working on their own land; increasing medical expenses led to a decrease in household disposable income, which changed the household's livelihood decisions and lifestyle, resulting in farmers being more likely to fall into poverty; better health, longer non-farm work time, and being married significantly reduced the probability of poverty in the future; the more comprehensive information regarding the external environment suggested that the richer the household's physical capital, the more resistant the household would be to potential future risks, thus reducing the vulnerability of the household to poverty.

3.3 Analysis of quantile regression results

Table 6 shows the results of the impact of extreme weather on farmers with different degrees of poverty vulnerability under the poverty line of RMB 2300/year per capita household income, and the significance level and direction of each variable were consistent with the results of the full-sample regression (Table 5: mod5-1), which initially verified the robustness of the baseline regression results. Among them, mod6-1, mod6-2, mod6-3, mod6-4, and mod6-5 indicated the effects of extreme weather on the poverty vulnerability of farm households at the 0.1 (low vulnerability), 0.25 (low–medium vulnerability), 0.5 (medium vulnerability), 0.75 (medium–high vulnerability), and 0.90 (high vulnerability) quartiles, respectively. After testing the coefficients at each quantile, we found that $F(4, 1102) = 6.68$, $prob > F = 0.00$, indicating that the correlation coefficients of the explanatory variables in the quantile regressions could be considered not exactly equal at the 1% level of significance, that is, there were differences in the effects of extreme weather on farmers with different levels of vulnerability.

A closer look at the correlation coefficients of the variables at each quantile revealed that, among the effects of warm days on the poverty vulnerability of farm households, the increase in the number of hot days had a stronger impact on households with less than a medium vulnerability, as compared to households with a medium–high vulnerability and high vulnerability, and more significantly reduced the probability of farm households entering poverty. As for the results of the effects of total heavy precipitation and consecutive dry days on the poverty vulnerability of farm households, the coefficients of the effects of total extreme heavy precipitation and persistent drought days increased with the increase in the quantile, indicating that households with high vulnerability were more likely to enter poverty when facing the shock of increased heavy precipitation and persistent drought days, as compared to households with low vulnerability.

Among the control variables, the effects of the sex of the household head, health level, and marital status on the poverty vulnerability of farm households all strengthened as the quantile rose. The effects of off-farm employment time, household information accessibility, and land transfer were stronger for households below-medium vulnerability, that is, the probability

TABLE 6 Impact of extreme weather on farm households with different levels of poverty vulnerability (poor = RMB 2300/year).

Variable name	mod6-1	mod6-2	mod6-3	mod6-4	mod6-5
	q10	q25	q50	q75	q90
warm	−1.1798***	−1.7048***	−1.7901***	−1.3722***	−1.4170**
	(0.1764)	(0.1639)	(0.2409)	(0.3912)	(0.5661)
precipitation	0.0001**	0.0002***	0.0004***	0.0005***	0.0007***
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0002)
dry	0.0021***	0.0034***	0.0054***	0.0058***	0.0068***
	(0.0005)	(0.0005)	(0.0006)	(0.0009)	(0.0018)
gender	0.0477***	0.0516***	0.0604***	0.1088***	0.1457***
	(0.0106)	(0.0123)	(0.0150)	(0.0192)	(0.0424)
healthy	−0.0268***	-0.0334***	−0.0477***	−0.0812***	−0.1256***
	(0.0032)	(0.0028)	(0.0047)	(0.0066)	(0.0101)
marriage	−0.1175***	-0.2037***	−0.4627***	−0.7764***	−1.0741***
	(0.0175)	(0.0443)	(0.0634)	(0.0651)	(0.1013)
Unagri	−0.0066***	−0.0074***	−0.0091***	−0.0090***	−0.0041***
	(0.0007)	(0.0006)	(0.0008)	(0.0010)	(0.0015)
information	−0.0497***	−0.0550***	−0.0657***	−0.0488***	−0.0284**
	(0.0062)	(0.0053)	(0.0059)	(0.0130)	(0.0137)
transfer	0.0477***	0.0521***	0.0576***	0.1160***	0.1624**
	(0.0068)	(0.0060)	(0.0098)	(0.0232)	(0.0690)
machinery	−0.0091***	−0.0101***	−0.0089***	−0.0098**	−0.0070
	(0.0014)	(0.0016)	(0.0027)	(0.0038)	(0.0051)
med_c	0.0000	0.0000*	0.0000***	0.0000**	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.2155***	0.2683***	0.4301***	0.7509***	1.0773***
	(0.0513)	(0.0702)	(0.0797)	(0.1000)	(0.2154)
Observations	1,114	1,114	1,114	1,114	1,114

of entering poverty for households below-medium vulnerability decreased significantly as the off-farm employment time of farmers increased and the Internet access rate rose, while rural households whose land had been transferred to enterprises or large grain growers were more likely to fall into poverty. In addition, the increase in the number of farm machinery and equipment was more likely to reduce households at below-medium and high vulnerability while the impact on households with high vulnerability was relatively weaker.

Table 7 shows the regression results for different levels of vulnerability of farm households due to extreme weather under the poverty line criterion of RMB 3449. Among them, mod7-1, mod7-2, mod7-3, mod7-4, and mod7-5 indicated the impact of extreme weather on the poverty vulnerability of farm households at the 0.1 (low vulnerability), 0.25 (medium–low vulnerability), 0.5 (medium vulnerability), 0.75 (medium–high vulnerability), and 0.90 (high vulnerability) quartiles, respectively.

In terms of significance level and direction, the quantile regression results were generally consistent with the full sample regression results (Table 5, mod 5–2). In terms of the regression results of the control variables, the trend of their impact coefficients at different quartiles was consistent with Table 6. The variation from the previous results was attributed to land transfer having a relatively greater impact on households with high vulnerability, that is, land transfer was less conducive to changing their poverty status for households with high vulnerability.

In the regression results of the core explanatory variables, the coefficient of the impact of high-heat weather on the poverty vulnerability of farm households tended to increase and then decrease as the quantile rose, and the impact of high-heat weather on medium-vulnerable households was significantly higher than that of low-vulnerable households and high-vulnerable households, which could have been due to low-vulnerable households having sufficient resource endowment and stronger risk resilience while the livelihoods of high-vulnerable households were not only affected by weather, but also by their own insufficient livelihood capital and poor sustainable livelihood capacity; therefore, to a certain extent,

TABLE 7 Impact of extreme weather on farm households with different levels of poverty vulnerability (poor = RMB 3449/year).

Variable name	mod7-1	mod7-2	mod7-3	mod7-4	mod7-5
	q10	q25	q50	q75	q90
warm	−7.4172***	−9.5064***	−10.6607***	−7.6661***	−7.3488***
	(0.9624)	(0.9745)	(1.0353)	(1.4849)	(2.2402)
precipitation	0.0009***	0.0015***	0.0025***	0.0024***	0.0027***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0005)
dry	0.0148***	0.0212***	0.0302***	0.0286***	0.0290***
	(0.0029)	(0.0025)	(0.0026)	(0.0035)	(0.0055)
gender	0.2135***	0.2204***	0.2506***	0.3585***	0.4925***
	(0.0478)	(0.0481)	(0.0505)	(0.0632)	(0.1311)
healthy	-0.1398***	−0.1661***	-0.2134***	−0.3197***	−0.4257***
	(0.0157)	(0.0118)	(0.0171)	(0.0214)	(0.0263)
marriage	−0.5965***	−0.9759***	−1.5820***	−2.2716***	−2.8118***
	(0.0742)	(0.1136)	(0.1757)	(0.1507)	(0.1740)
unagri	−0.0369***	-0.0391***	−0.0454***	−0.0448***	−0.0310***
	(0.0031)	(0.0031)	(0.0028)	(0.0038)	(0.0062)
information	−0.3051***	−0.3389***	−0.3400***	−0.2813***	−0.1950***
	(0.0314)	(0.0284)	(0.0250)	(0.0492)	(0.0722)
transfer	0.2401***	0.2555***	0.2515***	0.4407***	0.5246***
	(0.0292)	(0.0305)	(0.0433)	(0.0708)	(0.1119)
machinery	−0.0519***	−0.0504***	−0.0511***	−0.0522***	−0.0449**
	(0.0072)	(0.0081)	(0.0099)	(0.0163)	(0.0218)
med_c	0.0000	0.0000*	0.0000**	0.0000**	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1.0359***	1.1763***	1.2542***	2.1868***	2.9014***
	(0.2812)	(0.2653)	(0.2888)	(0.2902)	(0.5385)
Observations	1,114	1,114	1,114	1,114	1,114

the impact of high-heat weather on the poverty vulnerability of farm households was limited, and eventually the effect was more obvious in medium-vulnerability households. In addition to the effects of high-temperature weather, the effects of total intense precipitation and consecutive drought days on the poverty vulnerability of farm households also differed, with the increase in intense precipitation making high-vulnerability households more vulnerable to poverty, as compared to low-vulnerability households, while the increase in the number of persistent drought days had a stronger effect on medium-vulnerability farm households. This may have been due to the low dependence of agricultural production of low-vulnerability households while high-vulnerability households themselves had less livelihood capital and a scarcity of natural capital such as arable and forest lands, thus reducing the channels through which extreme weather affects the poverty vulnerability of farm households and making the impact relatively low in intensity.

Table 8 shows the impact of extreme weather on farm households with different vulnerability characteristics for a poverty line criterion of USD 1.9/day. Mod8-1, mod8-2, mod8-3, mod8-4, and mod8-5 indicated the impact of extreme weather on the poverty vulnerability of farm households at the 0.1 (low vulnerability), 0.25 (medium–low vulnerability), 0.5 (medium vulnerability), 0.75 (medium–high vulnerability), and 0.90 (high vulnerability) quartiles, respectively.

Observing the impact coefficients corresponding to each quantile variable showed that the quantile regression results were consistent with the full sample regression results in terms of the direction and magnitude of significance (Table 5, mod5-3) while the trend of increase and decrease in each quantile was consistent with Table 7, but the strength of the impact increased significantly, which could be due to the threshold of crossing out of poverty becoming more and more stringent as the poverty line continued to increase, thus making the sample poverty incidence increase significantly and further driving the impact of the variables on the vulnerability of farm households to poverty. The regression results equally verify that extreme weather has a significant impact on farm households poverty

TABLE 8 Impact of extreme weather on farm households with different levels of poverty vulnerability (poor = USD 1.9/day).

Variable name	mod8-1	mod8-2	mod8-3	mod8-4	mod8-5
	q10	q25	q50	q75	q90
Warm	−10.7787***	−13.2306***	−15.1834***	−11.5083***	−11.0276***
	(1.2801)	(1.2689)	(1.4704)	(1.9294)	(2.7120)
precipitation	0.0013***	0.0022***	0.0035***	0.0034***	0.0037***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Dry	0.0212***	0.0303***	0.0429***	0.0403***	0.0414***
	(0.0041)	(0.0039)	(0.0035)	(0.0045)	(0.0064)
Gender	0.2782***	0.2845***	0.3330***	0.4367***	0.6261***
	(0.0615)	(0.0609)	(0.0768)	(0.1009)	(0.1995)
Healthy	−0.1954***	−0.2288***	−0.2945***	−0.4161***	−0.5493***
	(0.0185)	(0.0161)	(0.0226)	(0.0262)	(0.0312)
Marriage	−0.8299***	−1.2495***	−2.0342***	−2.7836***	−3.3914***
	(0.0965)	(0.1342)	(0.1887)	(0.2012)	(0.1902)
Unagri	−0.0516***	−0.0536***	−0.0642***	−0.0632***	−0.0427***
	(0.0038)	(0.0041)	(0.0036)	(0.0057)	(0.0091)
information	−0.4375***	−0.4887***	−0.4842***	−0.4117***	−0.3305***
	(0.0397)	(0.0372)	(0.0333)	(0.0627)	(0.1098)
Transfer	0.3310***	0.3452***	0.3375***	0.5552***	0.6209***
	(0.0349)	(0.0377)	(0.0532)	(0.0873)	(0.1102)
machinery	−0.0769***	−0.0700***	−0.0733***	−0.0706***	−0.0480*
	(0.0106)	(0.0113)	(0.0136)	(0.0211)	(0.0289)
med_c	0.0000	0.0000*	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1.4966***	1.4865***	1.5870***	2.6601***	3.4644***
	(0.3917)	(0.3881)	(0.3740)	(0.3759)	(0.5707)
Observations	1,114	1,114	1,114	1,114	1,114

vulnerability and that the impact differs significantly for farmers with different vulnerability characteristics.

3.4 Analysis of intermediate effect results

The previous empirical results showed that there was a significant effect of extreme weather on the vulnerability of farm households, and there were differences in the impact on farmers with different vulnerability characteristics. Via what mechanism or channel has extreme weather affected farm household vulnerability? To further explore the in-depth logic of the impact of extreme weather on farm household poverty vulnerability, this study selected the sustainable livelihood capacity of farm households as the mediating variable and examined its effect.

Table 9 shows the results of testing the mediating effects of farmers' sustainable livelihood capacity according to different poverty line criteria. Among the extreme weather indicators, the persistent drought days had a significant partial mediating effect on the livelihood sustainability of farm households according to the poverty line household income per capita criteria of CNY 3449 and USD 1.9 per person per day. Among them, the direct effect of continued drought days on farm household poverty vulnerability under the domestic poverty line criterion of per capita household income of RMB 3449 was 0.0053, the indirect effect through farm household sustainable livelihood capacity was 0.0001, and the total effect was 0.0054. Under the international poverty line criterion of USD 1.9 per person per day, the direct effect of the persistent drought days on the poverty vulnerability of farm households was 0.0073, and the indirect effect on the poverty vulnerability of farm households through their sustainable livelihood capacity was 0.0002, for a total effect of 0.0074. This suggested that under the poverty line household income per capita criteria of RMB 3449 and USD 1.90 per person per day, each 1% increase of the persistent drought days indirectly increased the poverty vulnerability of farm households by 0.0001 and 0.0002 percentage points, respectively, by reducing their sustainable livelihood capacity.

TABLE 9 Test results of mediating effects of sustainable livelihood capacity of farm households under different poverty line criteria.

Variable name	Poor = RMB 2300/year			Poor = RMB 3449/year			Poor = USD 1.9/day		
	mod9-1	mod9-2	mod9-3	mod9-4	mod9-5	mod9-6	mod9-7	mod9-8	Mod 9–9
	vul1	Sla	vul1	vul2	Sla	vul2	vul3	Sla	vul3
warm	-0.2484 (0.4711)	0.0004 (0.0018)	−0.2433 (0.4706)	−2.4089* (1.3226)	0.0004 (0.0018)	−2.3924* (1.3207)	−3.6174** (1.6473)	0.0004 (0.0018)	−3.5965** (1.6447)
sla			−14.1720* (7.8481)			-45.6567** (22.0236)			−58.1234** (27.4280)
Control variables	Control	Control	Control	Control	Control	Control	Control	Control	Control
precipitation	0.0004*** (0.0001)	0.0000*** (0.0000)	0.0004*** (0.0001)	0.0018*** (0.0002)	0.0000*** (0.0000)	0.0019*** (0.0002)	0.0024*** (0.0003)	0.0000*** (0.0000)	0.0025*** (0.0003)
sla	−17.5002** (7.7738)		−59.7412*** (21.3034)			−77.0736*** (26.3212)			
Control variables	Control	Control	Control	Control	Control	Control	Control	Control	Control
Dry	0.0013*** (0.0004)	−0.0000** (0.0000)	0.0012*** (0.0004)	0.0054*** (0.0011)	−0.0000** (0.0000)	0.0053*** (0.0011)	0.0074*** (0.0013)	−0.0000** (0.0000)	0.0073*** (0.0013)
Sla	-12.4919 (7.8286)		-38.6119* (21.8587)			-48.5010* (27.1765)			
Control variables	Control	Control	Control	Control	Control	Control	Control	Control	Control

Heavy precipitation under the three poverty lines, as the coefficients $b_2 * b_4$ and b_3 corresponding to the model, were in opposite directions, and both were masking effects although there were indirect effects through the sustainable livelihood capacity of farmers. The coefficients b_2 corresponding to the model for warm days under all three poverty lines were not significant, and needed to be revalidated using the bootstrap method, according to the test proposed by Wen and Ye (2014). The results showed that the 95% confidence interval of the indirect effect contained zero under all three poverty lines, both before and after bias correction, indicating that there was no mediating effect of farmers' sustainable livelihood capacity in the process of extreme weather affecting poverty vulnerability.

3.5 Heterogeneity analysis

Generally, non-farm employment tended to reduce the probability of a household falling into poverty in the future by effectively removing the income uncertainty caused by the variability of the natural environment and the volatility of market prices, reducing the increase in poverty vulnerability due to the risk of agricultural losses, as compared to being engaged in agricultural production (Imai et al., 2015; Sun and Duan, 2019). Therefore, considering that there were differences in the resilience of farm households under different types of employment, this study set a binary dummy variable (1 = working in non-agricultural works related to industry or service industry, 0 = working in agricultural production) with the division of farm households' work industry to explore the impact of extreme weather on the poverty vulnerability of farm households under different employment types to investigate the mechanism of the effect.

The regression results are shown in Table 10, where mod10-1, mod10-2, and mod10-3 reflected the effects of extreme weather on the poverty vulnerability of farm households working in agricultural production, and mod10-4, mod10-5, and mod10-6 reflected the effects of extreme weather on the poverty vulnerability of farm households working in non-agricultural industries. There was a significant difference in the impact of extreme weather on the poverty vulnerability of farm households in different sectors, and rural households working in agricultural production were more vulnerable to the impact from extreme weather than those working in industry and services, that is, this category of farm households were more likely to fall into poverty under extreme weather shocks (e.g., extreme heavy precipitation, consecutive drought days). This could have been due to the higher sensitivity and vulnerability of the agricultural sector due to extreme climate change, where extreme weather shocks tended to affect the livelihood capital of farm households through

TABLE 10 Sub-sample regression results of the impact of extreme weather on poverty vulnerability of farm households (agricultural work vs non-farm employment work).

Variable name	Agricultural work			Non-farm employment work		
	mod10-1	mod10-2	mod10-3	mod10-4	mod10-5	mod10-6
	vul1	vul2	vul3	vul1	vul2	vul3
Warm	−1.9432***	−10.4789***	−14.8055***	−1.5858	−5.6315	−7.3721
	(0.5510)	(1.4574)	(1.7832)	(1.6480)	(4.6077)	(5.7013)
precipitation	0.0006***	0.0026***	0.0035***	0.0002	0.0009	0.0013
	(0.0001)	(0.0002)	(0.0003)	(0.0004)	(0.0010)	(0.0012)
Dry	0.0078***	0.0340***	0.0464***	0.0024	0.0112	0.0157
	(0.0010)	(0.0026)	(0.0032)	(0.0033)	(0.0092)	(0.0114)
gender	0.1499***	0.4266***	0.5240***	−0.0117	0.0120	0.0243
	(0.0258)	(0.0683)	(0.0836)	(0.0391)	(0.1095)	(0.1354)
healthy	−0.1028***	−0.3308***	−0.4200***	−0.0602***	−0.2239***	−0.2954***
	(0.0064)	(0.0170)	(0.0207)	(0.0087)	(0.0244)	(0.0302)
marriage	−0.6300***	−1.8835***	−2.3518***	−0.3143***	−1.0736***	−1.3906***
	(0.0219)	(0.0579)	(0.0708)	(0.0317)	(0.0887)	(0.1098)
unagri	−0.0174***	−0.0627***	−0.0821***	−0.0142***	−0.0519***	−0.0683***
	(0.0020)	(0.0054)	(0.0065)	(0.0020)	(0.0057)	(0.0071)
information	−0.1339***	−0.5516***	−0.7470***	−0.0296	−0.1994***	−0.2960***
	(0.0152)	(0.0403)	(0.0493)	(0.0188)	(0.0527)	(0.0652)
transfer	0.1573***	0.4531***	0.5617***	0.0439*	0.1859***	0.2515***
	(0.0200)	(0.0528)	(0.0646)	(0.0242)	(0.0676)	(0.0836)
machinery	−0.0105**	−0.0415***	−0.0559***	−0.0105	−0.0435*	−0.0599**
	(0.0048)	(0.0127)	(0.0155)	(0.0084)	(0.0235)	(0.0291)
med_c	0.0000***	0.0000***	0.0000***	0.0000**	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.5715***	1.6910***	2.1141***	0.6849*	2.3197**	3.0031**
	(0.0909)	(0.2404)	(0.2941)	(0.3773)	(1.0550)	(1.3054)
Observations	828	828	828	286	286	286
R-squared	0.693	0.779	0.796	0.530	0.663	0.694

agricultural economic output, weakening their sustainable livelihoods and thus significantly increasing their probability of falling into poverty.

3.6 Robustness tests

To ensure the robustness of the model regression results, this study performed a series of robustness tests on the aforementioned model. In previous works, common tests have included replacing the explained or explanatory variables, changing the data source, changing the estimation method or model, adding omitted variables, and tailoring the data. In this study, we re-estimated the poverty vulnerability of farm households by replacing the poverty line and choosing the international general poverty line standard of USD 3.1/person/day (vul4), and used the winsorization method to shrink the estimated vulnerability values by the upper and lower 1%, multiplied the processed values by 100 to transform them into percentage units, and used the constrained logit regression model to regress the effects of extreme weather. In addition, to further ensure the robustness of the regression results, this study applied a stepwise regression for empirical testing. The specific test results are shown in Table 11.

Among them, mod11-1, mod11-2, and mod11-3 were the regression results of the effects of extreme weather indicators (i.e., warm days, total heavy precipitation, and consecutive dry days) on farmers' poverty vulnerability, respectively. Mod11-4 was the regression result of the effects of extreme weather indicators all placed in the same analysis framework on farmers' poverty vulnerability. It can be found that warm days were significantly negatively correlated with poverty vulnerability

TABLE 11 Constrained logit regression estimation results (poor = USD 3.1/day/person).

Variable name	mod11-1	mod11-2	mod11-3	mod11-4
	vul4	vul4	vul4	vul4
warm	−13.4054***			−43.6575***
	(3.2689)			(3.1398)
precipitation		0.0060***		0.0088***
		(0.0005)		(0.0005)
dry		0.0780***	0.0217***	0.1138***
		(0.0053)	(0.0026)	(0.0056)
Control variables	Control	Control	Control	Control

at the 1% level while total heavy precipitation and persistent drought days were significantly positively correlated with poverty vulnerability at the 1% level, and their effects on poverty vulnerability increased with an increase in extreme weather indicators, indicating that the conclusion that extreme weather had significant effects on poverty vulnerability of farmers was robust and reliable.

4 Discussion

Based on the results of the aforementioned empirical tests, extreme weather had a significant impact on the poverty vulnerability of farm households, and those influences varied according to vulnerability characteristics of the farmers. Among them, extreme heat weather represented by warm days significantly and negatively affected farmers' poverty vulnerability while extreme rainfall weather and drought represented by heavy precipitation totals and consecutive dry days significantly and positively affected farmers' poverty vulnerability. The mediating variable of farm household's sustainable livelihood capacity contributed a partial mediating effect in the process of extreme weather indicators of persistent drought days affecting rural household's poverty vulnerability, according to the criteria of a household income per capita of RMB 3449 and USD 1.9 per person per day; each 1% increase in consecutive drought days indirectly increased the poverty vulnerability of farm households by reducing their sustainable livelihood capacity by 0.0001 and 0.0002 percentage points; there was a masking effect in the process of total heavy precipitation affecting the poverty vulnerability of farm households; there was only a direct effect in the process of warm days affecting the poverty vulnerability of farm households, and the indirect effect was not significant. In addition, farmers who were mainly engaged in agricultural production were more vulnerable to shocks from extreme weather than those who were engaged in non-agricultural industries.

The reason for this is that the high suddenness and rapid spread of extreme weather may make the transition time from the initial climate perception to the experience of climate disasters short, resulting in farmers suffering from both the ecological environment and physiological damage. On the one hand, the occurrence of climate extremes causes damage to the physical capital, natural capital, and environmental capital of farmers and threatens their living environment; on the other hand, the impact of extreme weather threatens the health of farmers' family members and leads to the damage of human capital. On the other hand, the health of farm household members is threatened by the extreme weather, which leads to damage to human capital. The increase in medical expenses and the reconstruction of facilities after the disaster increase the impact on the financial capital of farm households. Under the double attack of the internal and external environment, the sustainable livelihood capacity of farming households is severely affected, which increases the possibility of farming households entering into poverty in the future and leads to the increase of farming households' poverty vulnerability. For households with different vulnerability characteristics, households with high poverty vulnerability characteristics, when exposed to shocks from extreme weather, will further lengthen their transition time from disaster experience to climate adaptation, which leads to differences in the impact of extreme weather on households with different vulnerability characteristics under the interaction of different levels of sustainable livelihood capital of households.

As compared to previous studies, there were some similarities and differences in the findings of this paper. In the study by Maganga et al. (2021) on the expected poverty vulnerability of farm households as a result of climate changes, the results indicated that there was a strong correlation between farm household vulnerability and short-term climate stress, with drought, floods, and irregular rainfall all significantly increasing the likelihood of farm households falling into poverty or persistent poverty in the future and that drought had the greatest impact on farmers' welfare losses, followed by floods. This was consistent with the results of the baseline regression test and the robustness test in this paper. Of the positive indicators of the impact of extreme weather exacerbating farmers' poverty vulnerability, persistent drought days had the largest impact on farmers' poverty vulnerability (Table 5, correlation coefficients of 0.0069, 0.0308, and 0.0422), followed by the impact of intense precipitation (Table 5, 0.0006, 0.0025, and 0.0034). This significant relationship had also been verified by Ahmed et al. (2009), Herrera et al. (2018), among others.

However, concerning extreme heat events (warm days) affecting farmers' poverty vulnerability, previous studies have differed from the results of this paper. When exploring the impacts of climate changes on farmers' poverty vulnerability, Li et al. (2022) suggested that extreme heat weather was significantly and positively related to farmers' poverty vulnerability, that is, high temperature weather increased farmers' poverty vulnerability and increased farmer vulnerability to poverty. Ahmed et al. (2009) found via empirical testing that global warming led to an increase in poverty vulnerability in several countries. In addition, domestic scholars such as Zhang (2014) and Cao and Chen (2016) also found the same results. The reason could be attributed to the threshold corresponding to 90% of the maximum temperature of the sample data being lower than the official daily maximum temperature, and the appropriate summer temperature was beneficial to the growth and development of crops (Arouri et al., 2015), which could reduce the poverty vulnerability of farmers to some extent.

The findings of this study provided effective policy recommendations and reference policies for reducing the poverty vulnerability of farm households and improving their sustainable livelihoods at home and abroad, enhancing the climate resilience of the world's agricultural population, and simultaneously promoting the quality of poverty eradication in China and preventing the occurrence of return to poverty on a large scale. At the same time, there were limitations in this study that can be studied and improved upon in the future: 1) The mechanisms of extreme weather on poverty vulnerability of farm households were often varied and complex, and factors such as household consumption expenditure (Herrera et al., 2018), agricultural economic output (Liu et al., 2012), and farm household health level may also have played important roles, which should be considered in future research. 2) Due to the limitation of the data, this study only observed the relationship between poverty vulnerability and extreme weather in the Hubei and Yunnan provinces, but based on previous studies in related fields, the impact of extreme weather on poverty vulnerability of farmers in different regions could also be significantly different. 3) This study empirically examined the impact of extreme weather on the poverty vulnerability of farmers, but based on real-world situations, urban residents and various other groups (e.g., borrowing participant groups, etc.) could be affected by extreme weather and thus fall into poverty.

5 Conclusions and implications

Using micro-farm household survey data from the Hubei and Yunnan provinces, this research empirically explored the impact of extreme weather on the poverty vulnerability of farm households by selecting warm days, heavy precipitation, and consecutive dry days as extreme weather measures. The following were the results: 1) There was a significant effect of extreme weather on the poverty vulnerability of farm households. Among them, warm days were significantly negatively correlated with farmers' poverty vulnerability, while total heavy precipitation and persistent drought days were significantly positively correlated with farmers' poverty vulnerability. 2) The impact of extreme weather on farmers with different vulnerability characteristics were varied. 3) The sustainable livelihood capacity of farm households played a partially mediating effect in the process of extreme weather index consecutive dry days affecting the poverty vulnerability of farm households. Under the criteria of poverty line per capita household income of RMB 3449 and USD 1.9 per person per day, each 1% increase in the persistent drought days indirectly increased the poverty vulnerability of farm households by 0.0001 and 0.0002 percentage points, respectively, through reducing their sustainable livelihood capacity; there was a masking effect in the process of the heavy precipitation total affecting farm households' poverty vulnerability. In the process of warm days affecting farm households' poverty vulnerability, the indirect effect was not significant. 4) As compared to rural households engaged in non-agricultural industries, those engaged in agricultural production and operation were more vulnerable to shocks from extreme weather. The results of this paper clearly indicate the significant relationship between extreme weather and poverty vulnerability of farmers and the mechanisms involved, and point the way for future research, i.e., we still need to continue to think about how to establish extreme weather risk prediction mechanisms, how to improve farmers' adaptive capacity to extreme weather, and how to help farmers build sustainable livelihoods that can cope with extreme weather to ensure they will not return to poverty due to extreme weather. At the same time, this study provides recommendations for governments around the world to deal with extreme weather and prevent poverty return on a large scale, as follows: first, adopting differentiated policies could improve the climate resilience of farmers according to local conditions. Second, identify climate-sensitive vulnerable groups and refine policy implementation. Third, establish a risk warning mechanism to guide farmers in starting their own businesses or transitioning to non-farm employment. Fourth, expand the coverage of agricultural insurance to ensure farmers have relatively stable income when recovering from the effects of extreme weather. Fifth, promote the development of equalizing public services and improving the quality of the public service supply. Sixth, focus on ecological environmental protection, encourage the return of farmland to forests, strengthen the development of ecological compensation for resources, and encourage and focus on the development of ecological and green agriculture.

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

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, ZC; methodology, ZC and HY; software, HY; validation, ZC HY and CY; formal analysis, CY; investigation, ZC and CY; resources, ZC; data curation, ZC; writing—original draft preparation, HY and CY; writing—review and editing, ZC; visualization, CY; supervision, YH; project administration, ZC; funding acquisition, ZC All authors have read and agreed to the published version of the manuscript".

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The impact of climate change on population urbanization: Evidence from china

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Climate change, which is mainly caused by carbon emissions, has attracted attention worldwide. With the continuous increase in temperature, the urban heat island effect, extreme weather, and water shortages have seriously affected the urbanization process. Through an empirical analysis of panel data from 28 provinces in China from 2006 to 2018, this study examines the impact of climate change-induced temperature changes on the urbanization of China's population. The results show that the urbanization level has a significant double-threshold effect on the impact of temperature on urbanization. When the urbanization level crosses the corresponding threshold value, the negative impact of temperature on urbanization is relatively weak. Understanding the impact of climate change on urbanization has become increasingly important as climate warming increases. On the one hand, the climate issue has always been a topic of common concern around the world. On the other hand, studying how climate change affects population urbanization is conducive to identifying the human factors that affect climate change and proposing corresponding solutions. Simultaneously, it also provides a reference for optimizing the distribution of urban and rural populations, and can comprehensively consider the relationship between climate change and urbanization in the formulation and implementation of policies. On this basis, the Chinese government should strengthen financial support for climate change, play a leading role in policies, improve the urban layout and structure, and increase the resilience of cities to climate change.

KEYWORDS

climate change, economic development, environmental protection, threshold regression, urbanization

1 Introduction

Under global warming, extreme weather conditions have become more and more frequent. By 2010, the area affected by extreme heat waves in the world had tripled since 2000 (Zampieri et al., 2016), and by 2018, the frequency and magnitude of extreme high-temperature weather in parts of China had almost doubled (He et al., 2022). Since its reform and opening up, large-scale industrialization and sustained and rapid economic growth have enabled China to experience the largest and fastest urbanization process in the world. According to data from the National Bureau of Statistics of China, China's urban population accounted for 60.9% of the total population as of 2019. According to the 2018 United Nations Urbanization Development Outlook, 55% of the global population currently lives in urban areas, and it is estimated that this ratio will reach 68% by 2050. It is indisputable that large-scale climate change and urbanization on a global scale are prominent issues that the global population must face. With the vigorous development of the economy and the promotion of urbanization, the pursuit of living standards is no longer limited to the satisfaction of basic conditions, such as food, clothing, and warmth, but more to the common development of material conditions and the spiritual world. As the most populous country in the world, and in the process of continuously improving the level of urbanization, various environmental problems are more serious than those in Western countries, particularly the lack of green space per capita caused by a large population density. Climate change caused by human activities has also brought multiple problems to natural systems and urban development (Field et al., 2014). China's carbon dioxide emissions rank first in the world, accounting for 29% of global added value. Natural disasters caused by climate change are becoming increasingly serious. Global warming has caused the melting of glaciers, accelerated evaporation of water resources, and destruction of ecological balance. At present, due to the rising temperature, environmental pollution and deterioration of air quality in certain urban areas of China, there has been a phenomenon of urban population transfer to suburbs, small and medium-sized cities, or rural areas.

Under the influence of climate change, the temperature in Northeast China is increasing annually in winter (Zhou et al., 2020). The most direct reason for the increase in temperature is the increase in greenhouse gases, particularly carbon dioxide emissions. Some scholars believe that urbanization promotes carbon emissions (Huo et al., 2020), but while human socioeconomic activities lead to climate change, climate change also affects human socioeconomic activities, and there is considerable interaction between socioeconomic and climate systems (Karl et al., 1988). The heat island effect brought about by the process of urbanization (Shepherd and Burian, 2003) and the uneven distribution of precipitation will have a severe impact on the local climate (Matsumoto, 2019). The impact of climate change on people's lives is also large, which may lead to nonlinear changes in crop yield (Chen et al., 2016), affect electricity demand (Fan et al., 2019), reduce labor productivity in artificial production caused by changes in ambient temperature, and cause substantial economic losses (Cai et al., 2018). According to reports by the International Energy Agency and the Environment Agency, under the influence of COVID-19, carbon emissions worldwide have been significantly reduced in a short period of time, and China's air quality has significantly improved (Wang et al., 2021). As various industries have been severely impacted by the epidemic, multiple companies face the risk of bankruptcy. When the new crown epidemic has eased, its energy use and greenhouse gas emissions in the process of recovery of industrial production and manufacturing will very likely exceed that before the outbreak (Wang and Su, 2020). If a city's system to deal with climate change is imperfect, it is likely to lead to a sharp decline in air quality, affecting the physical and mental health of residents, thus affecting the level of urbanization. Frameworks for understanding the resilience of cities to the impacts of climate change are still developing (Davoudi et al., 2012; Silva et al., 2012), and cities are still struggling to adapt their policies and institutions to mitigate the adverse impacts of climate change. The spatial distribution pattern of the population will be deeply affected by factors such as resource and environmental constraints and economic and industrial guidance. Currently, China's urbanization process and population density are showing serious regional imbalances, and the eastern coastal areas have formed a large-scale economy. However, urbanization levels in the central and western regions were relatively low. Although regional differences in population urbanization are closely related to regional economic development, differences in climate and the environment also have an important impact on the process of regional urbanization. China should attach great importance to the environment and air quality in the economic development process in order to achieve sustainable development and create a green economy (Chai et al., 2021).

Most studies on climate change have focused on agricultural production and carbon emissions. Few scholars have explored the impact of climate on labor mobility and urbanization. Therefore, this study conducts an empirical analysis on whether climate change can affect China's urbanization, which is expanding perspectives in the field of climate change, and how rational urban planning can improve resilience to climate change. On the one hand, this paper discusses the impact of climate driving on the urbanization level of different Chinese provinces from the perspective of temperature change, which further enriches the research content of climate change. On the other hand, this study first uses the maximum and minimum temperatures as independent variables to improve robustness, and then constructs a GMM regression model, which effectively solves the problem of endogenous variables. In addition, a threshold regression method was used to study the possible nonlinear relationship between climate change and urbanization levels.

2 Literature review and hypothesis

The effects of climate change are manifold. Climate change is an important topic worldwide, and some recent studies have considered the interaction between socioeconomic and climate systems in climate change research (Monier et al., 2018). At the macro level, Nordhaus summarized a large number of macroeconomic studies on the different impacts of climate change, such as damage to agriculture, coastal areas, amenity values, biodiversity, and human health (Nordhaus, 1997). A city is a whole of "society-ecology-technology," composed of closely connected parts, driven and contributed by social, ecological, and technological forces (Monstadt, 2009). When any of these factors change, it will have an impact on urban development and even economic growth. For example, high temperatures will cause economic losses (Rezai et al., 2017; Nagy et al., 2018), and the relationship between GDP loss and global average temperature increase is roughly linear (Jun'Ya et al., 2017). The adverse effects of climate change on urbanization mainly manifest as changes in energy consumption (Giannakopoulos and Psiloglou, 2006), increased mortality and spread of infectious diseases (Alcoforado et al., 2015), coastal city safety issues (Takagi et al., 2016), infrastructure damage (Huong and Pathirana, 2013), and water scarcity (Kummu et al., 2010). At the micro level, climate change will impact the health and mentality of the individual labor force, thus affecting working hours and efficiency (Xiang et al., 2014; Li et al., 2016). Notably, the impact on outdoor workers, such as agricultural workers, is greater than that of indoor workers (Kjellstrom et al., 2009), because the most direct impact of climate change on human health is through the thermal effect of carbon emissions. According to the Intergovernmental Panel on Climate Change forecast, the global average temperature is expected to increase by 2°C by 2100. In the report "Cities and Climate Change" published by the Organization for Economic Co-operation and Development, it is pointed out that compared with rural areas, there is a large amount of concrete and asphalt in cities, as well as equipment such as factory machines, household appliances and urban lighting of residual heat. At the same time, the large area of urban buildings destroys the urban greenspace ecosystem and further aggravates the urban heat island effect. Climate change alters the composition of chemical pollutants in the atmosphere, potentially causing air pollution, particularly in densely populated areas, and adversely affecting urbanization. Based on this, Hypothesis 1 was proposed.

H1. Climate change has a negative impact on population urbanization.

The current political environment in the majority of countries emphasizes economic growth, and cities are under pressure to contribute to national development and innovation processes (Bettencourt et al., 2007; Shearmur, 2012). The level of urban development is crucial for a country's economic growth. In addition to industrialization and policy factors, economic growth and structural adjustment, especially trade opening, are the main drivers of urbanization in China (Zhang, 2002). According to the Paris Agreement, countries have made commitments to control carbon emissions. However, if reducing carbon emissions requires sacrificing economic growth, the motivation and efforts of countries to commit to reducing emissions will be greatly reduced (Wang and Zhang, 2021). Simultaneously, to reduce the spread of COVID-19, many countries have implemented foreign trade restrictions. Therefore, the rise of trade protectionism has brought new challenges to carbon emission reduction in various countries. The world is undergoing a significant urbanization process, while China has made great achievements in urbanization since the reform and opening up (Yy et al., 2019), whose speed and scale are much higher than those of other countries in the same period (Wang and Li, 2019). However, the environmental problems brought about by the extensive economy have gradually emerged, and China is facing enormous pressure to control environmental pollution. Although the government has strengthened its control of environmental pollution by promulgating a series of policies and regulations, there is still a long way to go to control environmental pollution in China (Song et al., 2020). With the further improvement of the urbanization level and the rise of temperature, environmental pollution is bound to become an important factor affecting the health of urban residents (Reiner et al., 2015), which will have an adverse impact on urbanization. In recent years, urbanization in China has been increasing rapidly, however, the problem of the urban population not increasing simultaneously has received a lot of attention. Previous studies have examined the relationship between urbanization, environmental pollution, and residents' health. The impacts of climate change on urbanization are increasingly evident, as urban liveability is becoming vulnerable to extreme weather conditions, such as persistent heatwaves and flooding. Cities provide 80% of jobs worldwide and have long been the main drivers of social innovation and wealth creation, however, cities consume more than 3% of the planet's total resources. Half and three-quarters of total greenhouse gas emissions (Xu et al., 2021). Air pollution and anthropogenic heat from urbanization adversely affect physical and mental health (Michail et al., 2013; Mueller et al., 2017). Because the income level of urban residents is generally higher than that of rural areas, they can more easily choose to live in other areas with a better natural environment when they suffer from environmental problems caused by climate change. The cost of relocation leads to the creation of an environmental poverty trap, which in turn affects the promotion of urbanization. Concurrently, due to the vast territory of China, various climatic and environmental problems caused by urbanization will not be effectively solved due to differences in the regional economy and natural environment, resulting in the emergence of urban populations in some areas, to suburbs, small and medium-sized cities, and rural areas. This phenomenon of transfer is called "counter-urbanization". Chinese researchers have explored "counter-urbanization" according to the specific situation in China's urbanization process. Their results show that, although counter-urbanization has not yet fully arrived in China, residents' concerns about their physical health caused by external adverse conditions, such as environmental pollution and traffic congestion, may affect the influx of the labor force into cities (Wang et al., 2019). For China, which is still in the development stage, the slowdown of urbanization will weaken the driving role of its political and cultural center, which is detrimental to the overall development of the country (De Matteis, 1986). With the increasing pressure of climate change and urban problems, urban functions may be decomposed into livable small- and medium-sized towns and villages, and the urban population will flow to the suburbs and rural areas. However, as provinces with a high level of urbanization have a more complete infrastructure, urban planning may be relatively reasonable, and the scale of the tertiary industry that can attract talent is growing on this basis, therefore, the impact of climate may be different. Simultaneously, owing to temperature differences in different regions, not all regions suffer economic losses due to climate change. Owing to the relative advantages brought about by differences in labor productivity changes between different regions, some regions in medium- and low-temperature areas have achieved positive economic benefits (Matsumoto, 2019). According to the EKC curve hypothesis, environmental quality first declines with economic growth and then gradually improves after economic growth reaches a certain level, showing an inverted U-shaped trend (Renzhi and Baek, 2020; Liu and Lai, 2021). Economic growth and climate change may lead to changes in urbanization, the effects of which may be nonlinear. The three dimensions of sustainable development mentioned in the "2030 Agenda for Sustainable Development" are social, economic, and environmental (Nations, 2015), and they interact with each other. Urbanization, as an important factor at the social level (Yao et al., 2021), will inevitably have an impact on urbanization when climate changes, and ultimately affect the relationship between economic and ecological footprints (Wang et al., 2022). Therefore, Hypothesis 2 is proposed.

H2. Climate change has a nonlinear effect on urbanization. When the urbanization level is greater than the threshold, the negative impact of climate change on urbanization weakens.

Although the scope of this study is similar to that of the existing literature, it contributes to the existing literature in several respects. First, the existing literature mainly studies the relationship between the economy and the environment and seldom examines social factors. This study examines urbanization, an important indicator of the social dimension, and improves relevant research in the field of sustainable development. Second, as temperature is the most intuitive feeling of climate change, this study adds the highest and lowest temperatures on the basis of average temperature, which improves the robustness of the research; alternatively, it can enable the government to utilize more ways to analyze the specific causes of climate change and provide a basis for formulating policies related to environmental protection and urbanization development.

3 Variable definition and model construction

3.1 Variable definition and data selection

Urbanization is the phenomenon or process of population concentration in cities or urban areas and an increase in the density of urban settlements within a given territory. As a process of population migration, first, there is an increase in the proportion of the population living in all urban areas. Second, this proportion of the population is increasingly concentrated in larger urban settlements (Gu, 2019). This is accompanied by migration of the population from rural to urban areas, and rural areas gradually evolve into urban areas. China is the most populous country in the world, and there is a very significant gap between the rich and the poor in the East and the West, which will lead to greater population mobility. Due to the distribution of climate stations and lack of data, this study used panel data of 28 Chinese provinces from 2006 to 2018. Climate data from 28 provincial-level weather stations in China, and other data were obtained from China's National Bureau of Statistics. A base climate station was established with the approval of the local land administration department, the urban and rural construction and environmental protection department, and the National Meteorological Bureau after surveying the site and proposing a plan by the provincial meteorological bureau. The distribution of the base climate stations is based on the distribution of climate zones in China and is determined by the size of the climate zones and spacing requirements of the base climate stations. There is a certain distance requirement according to China's terrain, climate, and other circumstances. The base climate station makes hourly climate observations and submits meteorological records to national and provincial meteorological administrations. Therefore, we used the mean temperature of the climate station located in the province to represent the annual mean, maximum, and minimum temperatures of the province.

3.2 Variable definition

3.2.1 Independent variable

The annual mean, maximum, and minimum temperatures of the climate station located in the province were used to represent climate change.

3.2.2 Dependent variable

In this study, the ratio of the permanent urban population to the total resident population of the region, namely the urbanization rate, was used as a substitute index of the urbanization level as the dependent variable.

TABLE 1 Variable definition.

Variable type	Variable name	Variable measurement
Independent variable	Climate change	Annual mean temperature, annual maximum temperature and annual minimum temperature of the climate station located in the province
Dependent variable	Population urbanization	The proportion of the urban population to the total population
Control Variables	Fdi	Foreign direct investment
	GDPg	GDP growth
	Pg	Natural population growth rate
	Proad	Per capita road area
	Redi	Real estate development investment
	Tti	Proportion of tertiary industry
	Asl	The average wage of urban workers

3.2.3 Control variables

According to Wu et al. (2020), the control variables are the average wage of urban workers, GDP growth rate, natural population growth rate, foreign direct investment, proportion of tertiary industry, and real estate development investment. Table 1 presents a more intuitive description of the variables.

3.3 Basic regression analysis

Before panel threshold regression, random- and fixed-effect models were used for regression analysis. To ensure the robustness of the equation, the annual maximum and minimum temperatures were added to the regression.

$$Ur = \alpha_0 + \alpha_1 At_{it}/Max_{it}/Min_{it} + \alpha_2 Control + \omega_i + \delta_t + \varepsilon_{it} \quad (1)$$

Because of inertia or partial adjustment, an individual's current behavior depends on past behavior. In the panel model, the dynamic panel model takes the lag of the dependent variable as the independent variable and considers the lag effect of the dependent variable (Alvarez and Arellano, 2003). That is, the impact of the urbanization process is temporal, and the climate impact of the current urbanization process is at the beginning of the next stage; therefore, this study adopts a dynamic panel model. To prevent the endogeneity problem, the SYS-GMM model was constructed to investigate whether there is a linear relationship between climate change and urbanization level. According to Wu et al. (2019), urbanization may be affected in the early stages. Therefore, Ur-1 was added to the model as an independent variable to obtain the benchmark model for this study.

$$Ur = \beta_0 + \beta_1 Ur_{it-1} + \beta_2 At_{it}/Max_{it}/Min_{it} + \beta_3 Asl_{it} + \beta_4 GDPg_{it} + \beta_5 Pg_{it} + \beta_6 Tti_{it} + \beta_7 Fdi_{it} + \beta_8 Redi_{it} + \omega_i + \delta_t + \varepsilon_{it} \quad (2)$$

3.4 Threshold regression model

Threshold regression refers to selecting a variable as the threshold variable, dividing the regression model into multiple intervals according to the threshold, classifying the samples after regression, and comparing the coefficients of different intervals (Wang and Wang, 2020). The panel threshold data model proposed by Hansen. (2000) implements parameter estimation and hypothesis testing of the threshold values using strict statistical inference methods. When the climate changes, particularly when the temperature increases due to greenhouse gas emissions, weather problems such as the heat island effect and uneven spatial distribution of precipitation will have adverse effects on urbanization. When urbanization reaches a certain height, the ability of cities to deal with the harm caused by climate change gradually improves, therefore, the adverse impact of climate change on the urbanization process will be alleviated. Therefore, in this study, a panel threshold data model was used to reveal the nonlinear influence of temperature on urbanization. In contrast to the past, this study considers urbanization as the threshold variable, which is also the explained variable in the model. The panel threshold model of the nonlinear correlation between temperature and urbanization was constructed as follows:

$$Ur = \gamma_0 + \gamma_1 At_{it} + \gamma_2 {*} M {*} I(\cdot) + \gamma_3 Control + \omega_i + \varepsilon_{it} \quad (3)$$

where i represents province; t represents year; ω and δ represent the individual effect, time effect, and random effect; α_0, β_0, and γ_0 are constant terms of each model; α_1 and β_1 correspond to the explanatory variable coefficients of each model; γ_1 is the coefficient vector of the explanatory variable of the threshold model; and M is the vector of the explanatory variable. $I(\cdot)$ is the threshold condition indicator function to be analyzed.

TABLE 2 Descriptive statistics.

Variable	Obs	Mean	Std.Dev	Min	Max
Ur	364	53.010	12.690	27.490	89.600
At	364	12.770	7.720	−3.060	25.380
Max	364	36.070	3.470	20.400	44.000
Min	364	−12.820	15.780	−42.800	11.100
Asl	364	45559.570	20423.940	15370.000	140000.000
GDPg	364	13.060	7.120	−22.400	32.270
Pg	364	0.740	1.370	−6.740	17.030
Tti	364	42.440	7.190	28.600	70.940
Fdi	364	610000.000	733000.000	71.070	3580000.000
Redi	364	2305.230	2203.650	31.180	14412.190

TABLE 3 Stationarity test.

Variable	IPS test	LLC test	Result
Ur	−7.113***	−26.601***	Stable
At	−5.249***	−19.503***	Stable
Max	−5.194***	−19.217***	Stable
Min	−5.066***	−18.961***	Stable
Asl	−7.593***	−28.653***	Stable
GDPg	−5.263***	−19.611***	Stable
Pg	−6.644***	−25.231***	Stable
Tti	−5.259***	−19.620***	Stable
Fdi	−4.813***	−17.897***	Stable
Redi	−3.994***	−14.734***	Stable

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4 Results and discussion

4.1 Descriptive statistics and stationarity test

Table 2 presents the descriptive statistics. It can be seen from the table that the maximum urbanization level of the sample provinces is 89.600 and the minimum is 53.010, indicating a large gap in urbanization level across the country. The maximum annual average temperature is 25.380, the minimum is −3.060, the maximum annual maximum temperature is 44, and the minimum temperature is −42.800. Thus, owing to the large latitude in China, the annual average temperature of each province is very different.

The GMM is a common parameter estimation model. Arellano proposed the first-order difference GMM method and has continuously improved it to form a system GMM, which can solve the shortcomings of the estimation of the endogeneity problem of the original variables. By combining the horizontal and difference regression equations, the lag level was used as the instrumental variable of the first-order difference, and the first-order difference was used as the instrumental variable of the horizontal variable to obtain an unbiased estimation result. In this study, a systematic GMM with a lag term was established to study the impact of temperature change on urbanization. The unit root test is an important method for determining the stationarity of variables, which is the premise of time series modeling. Since most macroeconomic variables are non-stationary, their stability of economic variables must be tested before further analysis (Wu et al., 2019). As a test method for panel data, the unit root test was proposed by Levin and Lin (Andrew et al., 2002), who relaxed the original assumption of independence and the same distribution, proposed a test method of independence and different distributions, and allowed the existence of heteroscedasticity.

LLC and IPS tests were used to test the stability of the relevant variables. From Table 3, we can see that all relevant variables reject the 1% unit root hypothesis.

From Table 4, it can be concluded that the VIF test is performed on the variables, and there is no multicollinearity among the variables, indicating that the regression results are reasonable and valid.

At the same time, in order to test the possible cross-sectional correlation problems in the process, this paper adopts the CD test to analyze the data.

From the data results in Table 5, it can be seen that each CD test statistic rejects the null hypothesis that the cross-sectional units are independent of each other at the 1% significant level. CIPS (Second Generation Panel Unit Root Test) test. It can be seen from Table 6 that each variable rejects the 1% unit root hypothesis, indicating that the experimental results are stable.

4.2 Regression analysis

Based on the results in Table 7, we used the fixed- and random-effect models to conduct regression analysis on average, annual maximum, and annual minimum temperatures, and concluded that air temperature was negatively correlated with urbanization, which was significant at the 1% level, which improved the robustness to a certain extent. According to the model R-squared, it can be judged that the interpretation results of the fixed effect model and the random effect model are valid, the results of the fixed effect are stronger than the random effect, and the fitting effect is better. In the subsequent threshold regression results, the R-squared value is also relatively high.

As shown in Table 8, regarding the validity of the tool variables, the model selected the Hansen test as the over-identification constraint test. The model utilizes the observed values of the threshold variables to estimate the appropriate threshold, thus avoiding the insufficiency of subjective judgment partitions and yielding more accurate results (Shao et al., 2022). The model also verifies whether the residual term is autocorrelated with the first- and second-order sequences by

TABLE 4 VIF test.

Variables	VIF	1/VIF	Variables	VIF	1/VIF	Variables	VIF	1/VIF
Asl	3.455	0.289	Asl	3.353	0.298	Asl	3.532	0.283
Redi	3.26	0.307	Redi	3.115	0.321	Redi	3.349	0.299
Tti	2.641	0.379	Tti	2.588	0.386	Tti	2.663	0.376
Fdi	2.37	0.422	Fdi	2.357	0.424	Fdi	2.385	0.419
GDPg	1.51	0.662	GDPg	1.502	0.666	GDPg	1.509	0.663
Pg	1.07	0.935	Pg	1.067	0.937	Pg	1.069	0.936
At	1.11	0.901	Max	1.019	0.981	Min	1.153	0.868
Mean VIF	2.202		Mean VIF	2.143		Mean VIF	2.237	

TABLE 5 CD test.

Variable	CD-test	*p*-value
Ur	46.24	0.000
At	46.42	0.000
Max	40.02	0.000
Min	45.94	0.000
Asl	45.10	0.000
GDPg	9.27	0.000
Fdi	40.60	0.000
Pg	22.41	0.000
Tti	38.27	0.000
Redi	43.19	0.000

TABLE 6 CIPS test.

Variable	CIPS test	Result
Ur	−4.986***	Stable
At	−5.090***	Stable
Max	−4.259***	Stable
Min	−4.890***	Stable
Asl	−4.201***	Stable
GDPg	−4.469***	Stable
Pg	−4.548***	Stable
Tti	−4.424***	Stable
Fdi	−3.531***	Stable
Redi	−5.201***	Stable

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

judging the *p*-value of AR (He et al., 2022). It can be seen from the results in Table 5 that the Hansen test cannot reject the null hypothesis and the *p*-value of AR (He et al., 2022) is large, indicating that the tool variables are not over-identified and there is no second-order sequence correlation between the correlation estimation equation. Therefore, the use of the Hansen test in this study is sufficient to demonstrate the reliability of the results, indicating that the regression results of the system GMM estimation method adopted in this study are reliable and effective.

The regression coefficients of the explained variables are significantly negative during the lag period, indicating that urbanization is significantly affected by the lag period. From the regression model of the national sample, the average, maximum, and minimum temperatures all have a significant negative correlation effect on urbanization level, which proves that the result is robust, indicating that temperature will hurt China's urbanization in China. This shows that, in the face of climate change, China's urban problems need to be further rationally planned to reduce the potential urban problems caused by climate or environment, thus limiting economic growth. Thus, Hypothesis 1 is verified.

According to the results in Table 9, urbanization threshold variables all pass the single and double thresholds at a significance level of 1%.

It can be seen from Table 10 that the thresholds of urbanization for the average temperature are 38.500 and 49.380.

As shown in Table 11, when the urbanization level was <38.50, the increase in average temperature had the greatest negative effect on urbanization, with a correlation coefficient of −0.906. When the urbanization level was >38.50 and ≤49.38, the negative impact degree decreased to −0.496. When the urbanization level was >49.38, the influence intensity further decreased to -0.119. All these passed the 1% significance level test. It can be seen that increasing temperatures will promote the occurrence of de-urbanization; however, with the increase in urbanization level, the impact of temperature decreases. This may be because places with high levels of urbanization have relatively complete infrastructure and are less affected by climate. However, when urbanization is less than a certain level, the cost of leaving the city may be relatively low; therefore, people are more willing to flee the city. Therefore, temperature had a greater negative impact on urbanization in

TABLE 7 Regression analysis results.

Variables	RE	FE	RE	FE	RE	FE
At	−0.532***	−0.466***				
Max			−0.551***	−0.441***		
Min					−0.253***	−0.229***
Asl	0.000***	0.001***	0.000***	0.001***	0.000***	0.001***
GDPg	0.099	−0.313***	0.037	−0.485***	0.105*	−0.317***
Pg	2.084***	1.586***	2.350***	1.787***	2.126***	1.590***
Tti	0.733***	0.536***	0.603***	0.377***	0.755***	0.551***
Fdi	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Redi	−0.001***	0.000**	-0.001***	0.000***	−0.001***	0.000
Observations	364	364	364	364	364	364
R-squared	0.716	0.769	0.630	0.701	0.721	0.768
F-test		163.369		114.960		162.406

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 8 Dynamic panel regression results.

Variables	SYS-GMM	SYS-GMM	SYS-GMM
L.Ur	−0.110**	−0.259***	−0.117***
At	−0.464***		
Max		−0.761***	
Min			−0.215***
Asl	0.000	0.000	0.000
GDPg	−0.023	−0.110	−0.054
Pg	2.255	2.866***	2.781
Tti	0.502***	0.541**	0.547***
Fdi	0.000***	0.000***	0.000***
Redi	0.000***	−0.001***	0.000***
Obs	351	351	351
AR(1)	−2.980***	−2.780***	−3.290***
AR(2)	−1.330 (0.18)	−1.410 (0.15)	−1.570 (0.11)
Hansen test	12.720 (1.00)	11.940 (1.00)	12.660 (1.00)

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

this case. Simultaneously, climate change has also had a great effect on the development of the economy; on the one hand, China's carbon dioxide emissions increased by 29% of the world's increase, although on the issue of greenhouse gas emissions, China presented a highly responsible attitude to the world, in the international community, particularly in developed countries. The highly developed economies that developed countries enjoy today have gone through a process of high carbon dioxide emissions. China's PER capita emissions of carbon dioxide are now at the level of Britain and the US at the beginning of the 20th century; China's PER capita GDP only reached the level of some developed countries in 1960. These numbers indicate that emissions are a developmental problem. If emissions are cut on a large scale, China faces a large-scale reform of its energy structure, and it is doomed to spend a lot of manpower material resources; on the other hand, climate change leads to frequent extreme weather to a certain extent, the temperature increase will warm the ocean, resulting in a large amount of water vapor, which will result in more frequent rainfall and snowfall, and an increase in rainfall will result in flooding. As a result, buildings and infrastructure will be damaged, as floods also cause great disturbance to economic activities, and thus adversely affect economic development.

TABLE 10 Threshold estimation results.

	Threshold value	95% confidence interval
Threshold1	38.500	[37.0900,38.6800]
Threshold2	49.380	[48.5100,49.7000]

TABLE 9 Threshold test.

Model	F-value	*p*-value	Crit10	Crit5	Crit1
Single threshold model	91.47***	0.000	28.664	33.153	40.143
Double threshold model	50.01***	0.000	25.514	27.635	36.055

$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 11 Panel regression results.

Variables	OLS	Threshold regression
Asl	0.001**	0.000***
GDPg	0.099*	−0.357***
Pg	2.084***	1.242***
Tti	0.733***	0.496***
Fdi	0.001***	0.001***
Redi	−0.001***	−0.001***
At1(Ur ≤ 38.50)		−0.906***
At2 (38.50 < Ur ≤ 49.38)		−0.496***
At3(Ur > 49.38)		−0.119**
At	−0.532***	
Constant	15.369***	18.570***
Observations	364.000	364.000
R-squared	0.730	0.840

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5 Conclusions and policy recommendations

5.1 Conclusions

First, the stochastic effect model, fixed effect model, and systematic GMM regression analysis show that temperature will negatively affect urbanization, and the same conclusion is reached by adding annual maximum and minimum temperatures to improve robustness. Second, by introducing urbanization as a threshold variable, the panel threshold model was used to study the impact of temperature on urbanization. We concluded that Hypothesis 2 is satisfied. When the urbanization level was lower than the first threshold of 38.50, the increase in average temperature had a significant negative effect on urbanization. When the urbanization level between the two thresholds was >38.50 and ≤49.38, the negative impact degree decreased. When the urbanization level was greater than the second threshold value of 49.38, the negative impact caused by temperature further decreased, and all of the above passed the significance level test of 1%. A possible reason for this phenomenon is that, when the level of urbanization is low, the infrastructure construction is not suitable, and the city does not have sufficient strength to quickly and effectively formulate countermeasures in the face of environmental damage caused by temperature changes. When the level of urbanization reaches a certain level, the economic strength of the city itself is relatively strong, and the ability of the city to cope with climate change has been strengthened, resulting in a decrease in the negative impact of temperature change on urbanization. Increasingly high, the city’s ability to deal with risks and related system construction will be further improved, therefore, the negative impact of temperature on urbanization will be further reduced.

The current understanding of the relationship between climate change and urbanization is still in the exploratory stage. Climate change is continuously affected by urbanization and other human activities, and climate change impacts urbanization and human activities. The timetable for China to achieve its carbon neutrality goal by 2060 has been clarified, and it is necessary to formulate a roadmap for a set of concrete plans to achieve this goal. In-depth exploration of the interaction, impact mechanism, and implementation path of climate change, carbon emissions, and urbanization are important aspects for realizing a green economy and sustainable development. This study examined the relationship between climate change and population urbanization in China. On the one hand, the average, maximum, and minimum temperatures were selected for research on the measurement of temperature, and economic factors were considered in the selection of control variables, which enriched the research content of the sustainable development agenda. On the other hand, it can make the government pay more attention to observing the most intuitive manifestations of climate change, explore its causes, and take relevant measures to solve environmental problems in a timely manner.

5.2 Policy recommendations

Urbanization is an inevitable choice for society to deal with climate change, and is also an important stage of economic development. Establishing environmental awareness, building green communities, developing a low-carbon and innovation-driven economy, and advocating sustainable social concepts such as moderate consumption are ways to achieve climate-resilient cities and sustainable human development goals. This study makes recommendations from three aspects: urban planning, innovative development, and narrowing the urban-rural gap.

First, optimize urban planning and promote a combination of ecology and urban construction. China’s urban planning to address climate change focuses mainly on the systematic and hierarchical construction of low-carbon urban planning frameworks to explore mitigation and adaptation technologies to address climate change. Given the increasingly prominent contradiction between climate change, human activities and environment, ecology, and resource carrying capacity, megacities and urban agglomerations need to realize harmonious coexistence between nature and humans and sustainable development of the regional economy through urban planning and construction. It is necessary to evaluate the climate and environmental effects of urban planning implementation, provide scientific support for the construction of a green and livable environment, adjust the relationship between urban development and the ecological

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environment, and maximize the social and economic benefits. Second, strengthen innovation capacity. Technological innovation forms the basis for developing zero-carbon energy and improving energy efficiency. Therefore, technological progress can fundamentally solve the problems of emissions and climate change. Third, pay attention to balanced development between urban and rural areas and narrow the income gap between urban and rural areas. The government can release preferential measures to encourage the development of township enterprises, encourage farmers to work in cities, and promote the construction of small towns. Finally, popularize energy conservation education. The state should vigorously increase publicity and education in energy conservation, incorporate energy conservation knowledge into the national education and training system, popularize scientific knowledge of energy conservation, arouse the public's sense of crisis and urgency in energy conservation and environmental protection, create an atmosphere of public opinion to save resources and slow global warming, attach great importance to energy conservation and emission reduction, and make the public truly realize the importance of energy conservation and emission reduction.

Although this study uses an econometric model based on panel data to explore the impact of climate change on urbanization in China, it still has certain limitations. For example, annual data do not fully reflect the impact of seasonal climate fluctuations on urbanization. Therefore, we will attempt to collect more detailed data in the future to address these issues. Simultaneously, there are multiple factors that affect the urbanization process, and this study only considers the climate change factor. Climate change can affect urbanization in several ways. In addition to the most obvious temperature changes, it also affects the urbanization process by changing the energy structure, affecting the spatial distribution of precipitation, and causing natural disasters. In the follow-up, we will investigate the internal mechanisms of climate impact on urbanization from multiple perspectives and propose policies. In addition, the results only reflect the direction of the influence of temperature on urbanization; cities are a system, and further research on more microscopic aspects of the system should be considered.

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

Ku-CC: project administration. X-RM, YY and Y-JL: investigation and validation. Ku-CC, X-RM, YY, Y-JL: formal analysis. Ke-CC: conceptualization and supervision. All authors designed and conducted the study, analyzed the data, and wrote the draft. All authors contributed to the interpretation of results, critically reviewed draft, and approved the final manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The contribution of weather forecast information to agriculture, water, and energy sectors in East and West Africa: A systematic review

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The provision of timely and precise weather information could reduce the vulnerability of people to climate change risks. In this study, we conduct a systematic review to synthesize the existing evidence on weather information services for the agriculture, water, and energy sectors of East and West Africa and identify priorities for future research. This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement checklist. The review identified relevant peer-reviewed publications using ScienceDirect and Scopus databases for original research articles published in English from 2000 to 2022. After applying the eligibility criteria, 25 articles were included in the final review. The themes emerging from the articles were extracted, and a summary was provided to illustrate each theme. The review revealed that weather information studies focus more on the agriculture sector than energy production and water resource management. Users of weather information mainly accessed information related to rainfall and temperature, and the information was accessed mainly through radio, mobile phones, and television. Most of the information provided focused on generic meteorological forecasts instead of tailored impact-based forecasts. Only very few users can access, or benefit from the information produced due to poor communication and technical understanding of weather information. In addition, a lack of downscaled information, logistics, and trust hinders the uptake and use of climate information. Consequently, mainstreaming capacity-building of key stakeholders is required to promote effective adoption and strengthening of climate information services across East and West Africa.

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climate change, decision-making, climate change adaptation, extreme events, food security, climate vulnerability

Introduction

There has been a surge in climate change-induced extreme weather events such as floods, droughts, and storms in the past decade (2010—2020), particularly in tropical regions such as sub-Saharan Africa (Codjoe and Atiglo, 2020; Dube et al., 2021). The effects of such extreme events are more profound in Africa due to limited capacity to manage risks, weaker revenue capability, and lower institutional ability to upgrade infrastructure (Kayaga et al., 2013; Horne et al., 2018). Extreme events can result in the loss of human lives and livelihoods, decreased crop productivity, destruction of electricity distribution infrastructure, and interruption to water supplies (Connolly-Boutin and Smit, 2016; Curtis et al., 2017; Ife-Adediran and Aboyewa, 2020; Intergovernmental Panel on Climate Change, 2021).

One way to minimize the impact of extreme weather is by improving weather forecasting and better communication of weather warnings. The ability to provide timely and precise weather forecasts offers the potential to reduce the vulnerability of people to the impacts of extreme weather (Singh et al., 2018; Alley et al., 2019; Nost, 2019; Antwi-Agyei et al., 2021a). However, accurate forecasting of weather variables remains a major challenge for the scientific community (Mani and Mukherjee, 2016), especially in tropical regions. The need to safeguard lives and livelihoods from extreme weather events has made the provision of timely weather forecasts an essential adaptation initiative (Oyekale, 2015). Improving the weather forecast's accuracy is crucial for people's safety and protecting key economic sectors, including agriculture, aviation, water, energy, and emergency response (Parker et al., 2021). In addition, availability, accessibility, and usability of accurate weather information are key for climate-informed decision-making (Dinku et al., 2014; Mabe et al., 2014; Nkiaka et al., 2019). As weather forecasts become progressively more accurate and timelier, their use can inform climate change risk mitigation strategies. However, the benefits linked to these improvements will only be appreciated if the forecasts are used directly in management decisions (Blum and Miller, 2019).

There is an urgent need to assess the forecasting of high-impact weather in sub-Saharan Africa to minimize the devastating effects of extreme events on the economy and livelihoods (Woodhams et al., 2018; Carter et al., 2019). With improved warning systems, it is possible to reduce the extent of damage by improving the resilience of at-risk populations and reinforcing the preparedness of the population to cope with extreme events (Anaman et al., 2017). The production and use of improved weather information to deliver early warnings and adequately manage these extreme events are essential in societal preparedness against extreme weather events (Anaman et al., 2017).

Studies have highlighted the importance of weather and climate services in mitigating risks such as drought, flooding, and loss of lives and livelihoods (Mabe et al., 2014; Sena et al., 2014; Oyekale, 2015; Mittal, 2016; Guido et al., 2021; Kayaga et al., 2021). These studies have considered the effects of extreme weather events on agriculture, health, water, and energy sectors in South America, Asia, and Africa. Despite the plethora of information on climate services, the effect of observations of climate change on using weather forecasts has not been investigated in depth in East and West Africa regions (Seo, 2014; Nkiaka et al., 2019). Studies have not synthesized all of the evidence on the contribution of weather and climate information in Africa into a single study to enhance decision-making. The choice of East and West Africa was influenced by the geographic and socioeconomic characteristics, which make these regions most vulnerable to climate change. In addition, gaps remain between the production of climate services, its use in decision-making, and the societal benefits derived from climate services (Webber, 2019; Harvey et al., 2021).

This review focused on the agricultural, energy, and water resource sectors. These sectors are critically important as they contribute significantly to the gross domestic product (GDP) of the East and West Africa regions (Coers and Sanders, 2013; Food and Agriculture Organisation and African Development Bank, 2015; Nhemachena et al., 2018; Gashu et al., 2019) and are highly prone to climate variability and change (Cervigni et al., 2015; Butterfield et al., 2017).

With respect to water resources, many African countries encounter numerous difficulties in the acquisition of sustainable and sufficient quality water to meet the needs of a rapidly increasing population and socioeconomic development without compromising on safeguarding the essential ecosystems that water resources depend on (Global Water Partnership, 2015). Water scarcity in these two regions has risen due to climate change and other factors, with negative consequences projected at the river basin level (Yomo et al., 2019). It is predicted that water security will be significantly affected due to urbanization and rapid population growth in various continents (United Nations, 2019), as more water is required for domestic water supply, agriculture, and business. General Circulation Models (GCMs) in East Africa predict a 10–20% surge in rainfall and a shift in rainfall distribution. For example, in Uganda, the impact of climate change on seasonal rainfall is projected to be more significant compared to variations in annual rainfall (Kisakye and Van der Bruggen, 2018). In addition, rapid population growth, usage of agrochemicals, industrialization, urbanization, soil steepness, and land-use and cover changes threaten water quality (Mukanyandwi et al., 2018). Similarly, West Africa is dependent on rain-fed agriculture and already prone to extreme weather events such as floods and droughts. The region is projected to face a declining crop yield by 2050 if the large-scale water cycle changes already observed deteriorate (International Water Management Institute, 2022). An assessment of available water resources in Burkina Faso indicates that the country is heading toward water scarcity with ever-increasing demands for water. This situation could affect key sectors that are important for socioeconomic development, such as agriculture, and endanger the well-being of more than 340 million people in the region (WaterAid, 2021). However, water resource management and development have primarily paid less attention to the interdependence of the various uses of water—for agriculture, domestic, and industrial use and for maintaining the ecosystems and hydrological services. Inadequate data and information on the state of renewable water resources further worsen water planning and governance (Global Water Partnership, 2015).

The agriculture sector is the backbone of many African countries' economies. The sector employs about 65–70% of the labor force, supports 90% of household livelihoods, and is responsible for about one-fourth of the continent's gross domestic product (OECD/FAO, 2016; World Bank, 2016). The growth in the agriculture sector is more effective in easing poverty than growth in non-agricultural sectors (Mukasa et al., 2017). The agriculture sector is by nature subtle to climate conditions and is also prone to the impacts of climate change (Parker et al., 2019). In most African countries, agriculture is largely small scale and rain-fed, thus making it vulnerable to climate variability and change (Ochieng et al., 2016; Hlophe-Ginindza and Mpandeli, 2021). The economy and the livelihoods of many households in East and West Africa have become vulnerable to climate change owing to heavy dependence on rain-fed agriculture and natural resources (Ochieng et al., 2016; Sultan and Gaetani, 2016; Kalai et al., 2017). Due to climate change, observed and projected disruptions in precipitation patterns are likely to reduce growing seasons and negatively affect crop yield (Guido et al., 2020). The agriculture sector is predominated by smallholder farmers with limited access to the resources and technology needed to cope with the impacts of extreme events (Abdul-Razak and Kruse, 2017). To cope with the devastating effects of climate change on food production, farmers have been adopting new farming technologies and practices. These practices include improved management systems such as introducing microcatchments, crop cover, crop rotations, ridges, planting trees, improved pastures, and innovative technologies such as shorter cycle varieties, improved seeds, and drought-tolerant varieties (Kristjanson et al., 2012; Anuga and Gordon, 2016). East and West Africa are key producers of the African continent's food; therefore, strengthening the resilience of the agricultural system to climate change is crucial to reducing poverty (SDG1) and averting hunger (SDG 2) (FAO, 2015).

The review also focused on the energy sector of East and West Africa. The economy and energy systems of East Africa are extremely reliant on natural resources and thus very prone to current and projected effects of climate change (Ddamulira, 2016). The region's present energy state is marked by a high reliance on biofuels in rural areas. While biofuels are renewable clean energy options, their use remains traditional, with major environmental and health consequences (Waindi and Khalid, 2011). Heavy system losses also harm the electricity sector in East Africa. This is owing to a high reliance on hydropower for electricity generation. However, the climate in the region has an impact on this reliance since the occurrence of severe drought results in significant losses in electricity output (Waindi and Khalid, 2011). This results in widespread power rationing which has negative impacts on the socioeconomic livelihoods of the people across space and time. The West African region is similarly faced with the realities of energy vulnerability, system unreliability, and fuel price volatility. Energy poverty (lack of access to modern energy services) and its effects on local economies and social development are projected to remain the predominant challenge through 2030 (Merem et al., 2017). The potential impacts of climate change on the energy sector could include substantial stress on the production, distribution, and utilization of energy. This may lead to increased use of fossil fuels or reinforced infrastructure, and increasing greenhouse gas (GHG) emissions, for instance, reduced efficiency of power stations, reduction in renewable energy resources, or increased risks of storm damage to coastal infrastructure (Cronin et al., 2018). These would undermine all of the achievements made in the energy sector.

These sectors (water resources, agriculture, and energy) are inextricably connected because the usage in one sector influences the availability and usage in the other sectors (Mpandeli et al., 2018). It is crucial to assess the influence of weather information on how users can use the information to make important decisions. In this study, weather information users are defined as managers, policymakers, engineers, students, researchers, farmers, and the general public that use weather information and knowledge to inform decision-making (Nkiaka et al., 2019). As yet, there is no comprehensive review of studies evaluating the effects of weather forecasts on these key economic sectors in Africa. Specifically, this review sought to

- identify the type of weather and climate information being accessed by water, agriculture, and energy users across East and West Africa;
- assess the influence of weather and climate information on users' ability to make important decisions with respect to water, agriculture, and energy sectors; and
- identify key barriers to the uptake of weather information in the energy, water, and agriculture sectors in East and West Africa.

Methods

The systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009).

Eligibility criteria

We focused on studies that considered the contribution of weather forecast information to agriculture, water, and energy sectors in East and West Africa. Studies were included for this review if they met all of the underlisted criteria:

1) conducted in either East or West Africa;
2) focused on either agriculture, energy, or water resource sectors;
3) assessed whether weather forecast information helped users to make informed decisions;
4) assessed the barriers to the uptake of weather information;
5) assessed the synergies and trade-offs between the water–energy–food nexus; and
6) original peer-reviewed publications.

We excluded studies that were conducted in other regions, focused on sectors other than those of interest, and considered outcomes not relevant to this study. In addition, papers were excluded if they were not published in English or published before 2000. Reviews, book sections, opinions, letters to the editor, and papers reporting only mathematical models were excluded from this review.

Information sources and search strategy

The review targeted peer-reviewed articles published in English from January 2000 to January 2022. The year 2000 marked a surge of pilot-scale studies with African farmers ensuing the much-publicized 1997/1998 El Nino (Hansen et al., 2011). Articles were searched from two major databases, ScienceDirect and Scopus, due to their broad coverage and quality of content. The search terms included search strings such as ("weather forecast" OR "weather information" OR "weather service") AND ("Agriculture" OR "water resource" OR "energy") AND ("Africa"). Furthermore, we manually searched the reference list of selected articles for articles pertinent to the study but were not captured during The electronic search. Supplementary Table S1 shows the search strategy and results of the various databases.

Study selection

Articles obtained using the search terms were exported into the EndNote reference manager (version X20), and duplicates were removed. Two reviewers (TPA and PA-A) independently screened titles and abstracts of the articles retrieved from the electronic databases and hand searches. Articles that failed to meet the inclusion criteria were excluded. We then downloaded the full-text articles and reviewed them for inclusion. At this stage, studies were excluded for reasons (Supplementary Table S2). Any disagreements in the screening and selection of articles were resolved by dialogue and involvement of a third reviewer.

Data extraction and analysis

A data-extraction form was designed and piloted to gather information according to the focus of the study. The form captured information on the author's name and year of publication, the title of the article, country and region, sector, weather information accessed, whether the information helped make decisions, and key barriers to the uptake of climate information. Regarding data analysis, descriptive statistics were used to present information on study countries and the medium of receiving weather and climate information. Included studies were analyzed using thematic analysis. The themes emerging from the articles were extracted, and a summary was provided to illustrate each theme. These themes include information accessed, user decision-making, and key barriers. Quality assessment of the included papers was not done due to the heterogeneity of the papers.

Results

Search results

Using the search terms, 38,636 and 348 articles were retrieved from ScienceDirect and Scopus databases, respectively. Fourteen (14) additional papers were obtained through random Google search and manual screening of the reference lists of included studies. After removing duplicates, 35,349 records were retained. The titles and abstracts were then screened to obtain 52 records to be included for full-text assessment. Twenty-seven (27) articles were excluded for reasons (Supplementary Table S2), while 25 articles fully met the inclusion criteria (Figure 1).

Study setting

Of the 25 included studies, 20 reported findings from only West Africa, four from East Africa, and one article reported findings from East and West Africa. These studies were conducted in 11 countries across East and West Africa, with the majority of the studies reporting findings from Ghana ($n = 9$), followed by Burkina Faso and Senegal ($n = 5$), Kenya and Tanzania ($n = 3$), Benin, Ethiopia, Niger and Uganda ($n = 2$), and Mali and Nigeria ($n = 1$) (Figure 2). All of the 25 studies focused on the agriculture sector (Table 1).

Information accessed

Twenty-one studies reported on different types of weather information accessed by users. Most of the weather and climate information provided focused on generic meteorological forecasts instead of a tailored impact-based forecast. Though all of the included studies focused on agriculture, the information

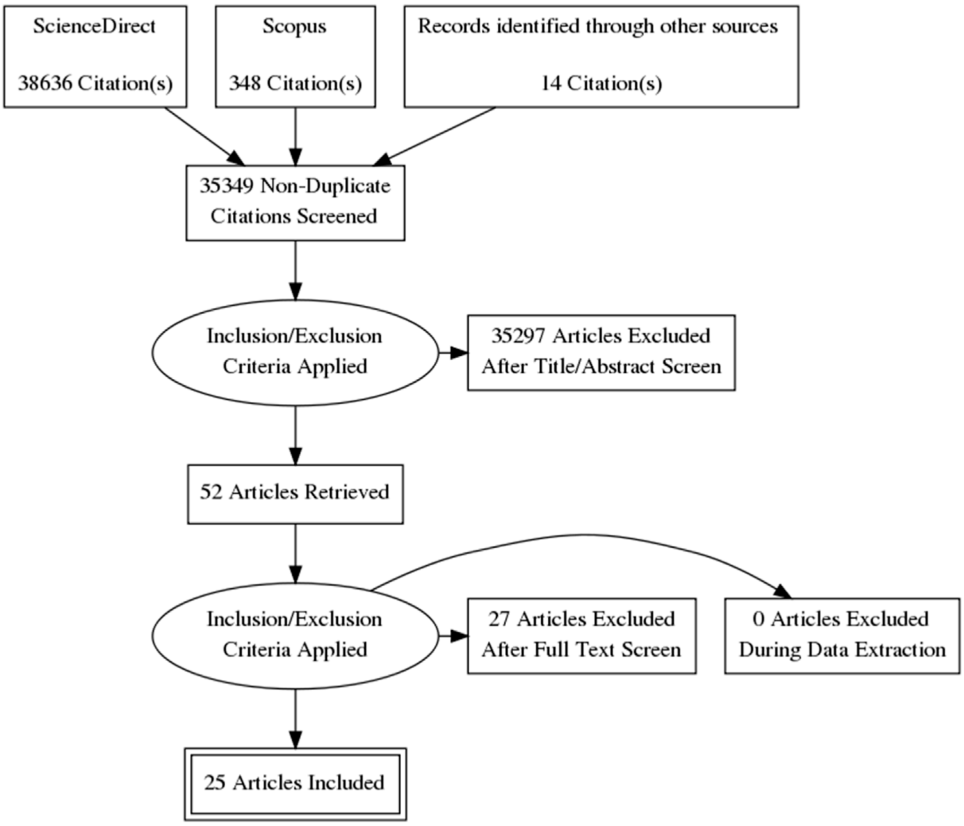

FIGURE 1
Flow diagram of included and excluded studies in the review.

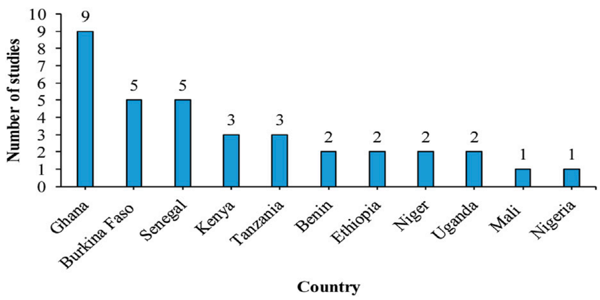

FIGURE 2
Breakdown of the included studies by country.

accessed by users differed based on whether they were into animal husbandry or crop farming. The majority of the studies reported that for users in crop farming, the climate information needed or accessed was related to rainfall and temperature, such as the onset of rains, rainfall distribution and amount, end of rains, the intensity of the dry season, dry spells, and the speed of winds during the rainy season (Rasmussen et al., 2015; Amegnaglo et al., 2017; Diouf et al., 2019; Radeny et al., 2019; Bacci et al., 2020; Partey et al., 2020; Antwi-Agyei et al., 2021c). Some studies reported that pastoralists needed or accessed extra information such as the outbreak of livestock and crop pests/diseases (Oyekale, 2015) and the availability of grazing resources (Rasmussen et al., 2015). However, four studies did not mention the specific type of weather information needed by users. For example, Chiputwa et al. (2022) reported that users needed or accessed information on daily forecasts, early warning system (EWS), and seasonal forecasts, while Wamalwa et al. (2016) reported that users had access to agro-weather and climate information. In addition, disaster forecasts such as flooding, wind and windstorms, dry/wet spells, and drought were reported by eight studies (Rasmussen et al., 2015; Amegnaglo et al., 2017; Ouedraogo et al., 2018; Diouf et al., 2019; Radeny et al., 2019; Bacci et al., 2020; Antwi-Agyei et al., 2021c; Ouedraogo et al., 2021) (Table 2).

The medium through which weather and climate information was received was also assessed. The most common means of accessing climate information included radio, mobile phone (text messages and voice calls), television, and extension officers (Figure 3).

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TABLE 1 Characteristics of included studies.

Sn	Author, year	Title	Country	Sector
1	Amegnaglo et al. (2017)	Contingent valuation study of the benefits of seasonal climate forecasts for maize farmers in the Republic of Benin, West Africa	Benin[a]	Agriculture
2	Antwi-Agyei et al. (2021b)	Predictors of access to and willingness to pay for climate information services in north-eastern Ghana: A gendered perspective	Ghana[a]	Agriculture
3	Antwi-Agyei et al. (2021c)	Opportunities and barriers for using climate information for building resilient agricultural systems in Sudan savannah agro-ecological zone of north-eastern Ghana	Ghana[a]	Agriculture
4	Bacci et al. (2020)	Agrometeorological forecast for smallholder farmers: A powerful tool for weather-informed crops management in the Sahel	Niger[a]	Agriculture
5	Chiputwa et al. (2022)	Co-production, uptake of weather and climate services, and welfare impacts on farmers in Senegal: A panel data approach	Senegal[a]	Agriculture
6	Diouf et al. (2019)	Factors influencing gendered access to climate information services for farming in Senegal	Senegal[a]	Agriculture
7	Ebhuoma and Simatele (2019)	"We know our Terrain": indigenous knowledge preferred to scientific systems of weather forecasting in the Delta State of Nigeria	Nigeria[a]	Agriculture
8	Naab et al. (2019)	The role of climate services in agricultural productivity in Ghana: The perspectives of farmers and institutions	Ghana[a]	Agriculture
9	Nyadzi et al. (2018)	Diagnosing the potential of hydro-climatic information services to support rice farming in northern Ghana	Ghana[a]	Agriculture
10	Nyambo and Chengula (2017)	Dissemination of agricultural weather forecasts under weather and climate variability: a case of the smallholder farmers in Moshi rural district, Tanzania	Tanzania[b]	Agriculture
11	Nyang'au et al. (2021)	Smallholder farmers' perception of climate change and adoption of climate smart agriculture practices in Masaba South subcounty, Kisii, Kenya	Kenya[b]	Agriculture
12	Ouedraogo et al. (2021)	Utility and triggers in uptake of agricultural weather and climate information services in Senegal, West Africa	Senegal[a]	Agriculture
13	Ouedraogo et al. (2018)	Closing the gap between climate information producers and users: Assessment of needs and uptake in Senegal	Senegal[a]	Agriculture
14	Oyekale (2015)	Access to risk mitigating weather forecasts and changes in farming operations in east and west Africa: Evidence from a baseline survey	Ethiopia[b], Kenya[b], Tanzania[b], Uganda[b]	Agriculture
			Burkina Faso[a], Ghana[a], Mali[a], Niger[a], Senegal[a]	
15	Partey et al. (2020)	Gender and climate risk management: evidence of climate information use in Ghana	Ghana[a]	Agriculture
16	Radeny et al. (2019)	Indigenous knowledge for seasonal weather and climate forecasting across East Africa	Ethiopia[b], Tanzania[b,] and Uganda[b]	Agriculture
17	Rasmussen et al. (2015)	Improving how meteorological information is used by pastoralists through adequate communication tools	Burkina Faso[a]	Agriculture
18	Sanfo et al. (2022)	Effects of customised climate services on land and labour productivity in Burkina Faso and Ghana	Burkina Faso[a], Ghana[a]	Agriculture
19	Sarku et al. (2021)	Tracing hybridity in the provision of ICT-enabled agricultural weather information services in Ghana	Ghana[a]	Agriculture
20	Sarku et al. (2022)	Usability of weather information services for decision-making in farming: Evidence from the Ada East District, Ghana	Ghana[a]	Agriculture
21	Tall (2010)	Climate Forecasting to Serve Communities in West Africa	-	Agriculture
22	Tarchiani et al. (2021)	Access, uptake, use and impacts of agrometeorological services in Sahelian rural areas: The case of Burkina Faso	Burkina Faso[a]	Agriculture
23	Wamalwa et al. (2016)	Agro weather and climate information dissemination and its influence on adoption of climate smart practices among small scale farmers of Kisii country, Kenya	Kenya[b]	Agriculture
24	Yegbemey et al. (2021)	The Impact of Short Message Services (SMS) Weather Forecasts on Cost, Yield and Income in Maize Production	Benin[a]	Agriculture
25	Zongo et al. (2016)	Farmers' perception and willingness to pay for climate information in Burkina Faso	Burkina Faso[a]	Agriculture

NB.
[a]West Africa.
[b]East Africa.

TABLE 2 Summary of the type of weather information accessed by users.

Author, year	Weather information accessed
Amegnaglo et al. (2017)	Onset of rains, rainfall distribution and amount, end of rains, the intensity of the dry season, and the speed of winds during the rainy season
Antwi-Agyei et al. (2021b)	Information on rainfall and temperature
Antwi-Agyei et al. (2021c)	Information on rainfall (onset, distribution, amount, and cessation of the rains), temperature (expected average temperatures), and windstorm (intensity of the storms)
Bacci et al. (2020)	Information on rainfall and temperature
Chiputwa et al. (2022)	Information on the daily forecast, early warning system (EWS), and seasonal forecast
Diouf et al. (2019)	Onset date of rains, cessation date, daily rain forecast, and dry spells
Naab et al. (2019)	General daily, monthly, and seasonal rainfall and temperature forecast
Nyadzi et al. (2018)	Information on rainfall and temperature
Nyambo and Chengula (2017)	Information on rainfall and temperature
Nyang'au et al. (2021)	Information on rainfall and temperature
Ouedraogo et al. (2021)	Information on rainfall, wind, flood, and dry spell
Ouedraogo et al. (2018)	Seasonal forecast, the onset and cessation dates, the optimal sowing dates, daily rainfall forecasts, the false starts, the cumulative rainfall, and the dry and wet spells
Oyekale (2015)	Information on the outbreak of livestock and crop pests/diseases and the start of the rainfall
Partey et al. (2020)	Information on rainfall and temperature
Radeny et al. (2019)	Amount of rainfall, the onset of rainfall, rainfall distribution, cessation of rainfall, duration of cropping/rainy season, drought occurrence, the severity of weather events
Rasmussen et al. (2015)	Onset date of the rains, flooding events, availability of grazing resources in various areas, and fine-scale information on rainfall amount during the first weeks of the rainy season
Sanfo et al. (2022)	Information on rainfall and temperature
Sarku et al. (2021)	General forecast, farming-specific forecasts, and temporal forecasts
Wamalwa et al. (2016)	Farmers had access to agro-weather and climate information
Yegbemey et al. (2021)	Farmers received weather-related information
Zongo et al. (2016)	Farmers had access to official seasonal forecasts prior to the agricultural campaign

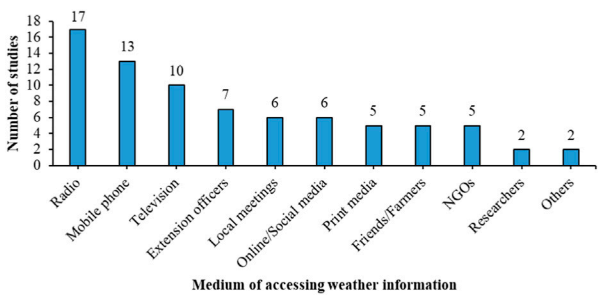

FIGURE 3
Medium of accessing weather information.

User's decision-making

Decisions made due to the access to weather and climate information ranged from land preparation to harvesting time. One study reported that most of the respondents who received the information used it to make decisions such as preparing farmlands, selecting crop varieties, varying cropping patterns, and harvesting time (Antwi-Agyei et al., 2021c). Furthermore, farmers who received seasonal, daily, and early warning systems (EWS) made significantly more farm management decisions and had a higher yield of crops than non-users of weather and climate information services (Chiputwa et al., 2022) (Table 3). In the fisheries sector, climate information helped fishers postpone their activities on the sea or go to sea while using their life jacket (Ouedraogo et al., 2018). However, the proportion of fishers who used weather information in decision-making was low. Of those who had access to weather and climate information, only a few utilized the information to decide on various activities (Oyekale, 2015; Nyang'au et al., 2021). In some instances, users combined indigenous and scientific forecasts. Though they acknowledge the limitations in using indigenous forecasts, they considered it better for decision-making than the scientific forecast provided by the state agency responsible for the forecast (Nyadzi et al., 2018) (Table 3).

Key barriers to the uptake of weather information

The production and delivery of weather information is not an assurance that the information will automatically inform

TABLE 3 Summary of decisions made by users after accessing weather information.

Author, year	Decision made
Amegnaglo et al. (2017)	Farmers believed that access to climate information can inform their farming decisions. The vast majority of farmers (95%) will respond to the introduction of seasonal climate forecasts by adopting at least one strategy (either intensified or nonintensified).
Antwi-Agyei et al. (2021c)	1) About 79% of the respondents receiving climate information indicated that they used such information to make decisions on land preparations.
	2) Female farmers reported using climate information for equally important decisions, including crop variety selection (50%), changing cropping patterns (36%), and harvesting-time decisions (21%).
Bacci et al. (2020)	1) Forecasts could correctly predict the weather for the next decade with a percentage of 87.5. This information is crucial for farmers because they can plan their agricultural activities or take measures against dry spells in the coming decade (delay of sowing, use of fertilizers, etc.).
	2) Users perceived the agrometeorological 10-day forecasts as important for their decision-making processes, even if they were not quantitatively accurate.
Chiputwa et al. (2022)	1) Households in locations with a multidisciplinary working group (MWG) used significantly more combinations of different types of seasonal and daily forecasts to inform farming decisions than households in locations with no MWG.
	2) Farmers with access to a MWG made significantly more farm management decisions after receiving seasonal, daily, and early warning systems (EWSs) than farmers without access to an MWG.
	3) Farmers who used weather and climate information services (WCIS) had a significantly higher yield of crops than nonusers of WCI.
Diouf et al. (2019)	The climate information service was useful for farmers in determining sowing periods.
Nyadzi et al. (2018)	The survey revealed that adaptive farm decisions of farmers are generally based on information generated from indigenous and scientific forecasts. While farmers were quick to acknowledge the limitations in their personal forecast, they considered it better for decision-making than the scientific forecast provided by Ghana Meteorological Agency as this was perceived to be generic and not locally specific to their community and needs.
Nyang'au et al. (2021)	Seventy-four percent of the total sampled households had access to weather and climate information from multiple sources. Of those who gained access, only 34.2% of them utilized the information in deciding on various farming activities.
Ouedraogo et al. (2021)	Farmers use weather and climate information services (WCIS) to make decisions on crop choice and sowing dates during the offset of the growing season. These WCIS also guide the farmers to identify crop varieties that are suitable for the length and quality of the season. The type of croplands (topography and soil type), as well as the cropland size, are decided based on the WCIS disseminated during the period.
Ouedraogo et al. (2018)	1) Majority of farmers who received climate information services (CIS) took decisions related to the choice of croplands, crop varieties, sowing, plowing, and fertilizer-spreading dates.
	2) At the end of the rainy season, the evaluation revealed that 95.7% of the respondent farmers were very satisfied with the decision that they had taken following the reception of the CIS and 78.4% certified that their crop yield had been substantially improved.
	3) In the fisheries sector, the evaluation showed that about 45% of the respondents decided to postpone their activities on the sea after they received the warning; 15% decided to go to sea while using their life jackets.
Oyekale (2015)	1) 33.2 and 44.2% of the farmers from East Africa were able to take some specific farm decisions based on pieces of advice received on the outbreak of pests/diseases and the start of rainfall, respectively.
	2) Among West African farmers, 13.3 and 34.0% of the farmers were able to use weather forecasts received on the outbreak of pests/diseases and the start of rainfall, respectively.
Partey et al. (2020)	Increased rainfall variability and increased drought frequency in the study area significantly influenced farmers' use of climate information services (CIS).
Sanfo et al. (2022)	The customized climate service (CCS) positively impacted corn, cowpea, and sorghum productivity. Farmers who received CCS recorded higher yields than those who did not.
Tarchiani et al. (2021)	Most farmers with access to the information used seasonal forecast (SF) to choose crop varieties and toposequences to exploit and prepare the land, choose the seeding time, and other cropping practices.
Yegbemey et al. (2021)	Providing smallholders with weather-related information through mobile phone SMS can help them reduce labor costs and positively affect yield and farm income.
Zongo et al. (2016)	Farmers believed that weather information could help them make informed decisions as most (93%) farmers want to integrate climate information in their decision process for agricultural production.

decision-making because barriers can hinder the use of information. In the studies reviewed, 18 studies reported barriers to the uptake and use of weather information in East and West Africa. The four key barriers reported include; poor communication and understanding of weather information (n = 12), lack of downscaled information (n = 8), lack of logistics (n = 5) and lack of trust (n = 4). Other barriers include meteorological information not tailored to meet the information needs of vulnerable group decision-makers at the sub-national level

TABLE 4 Summary of key barriers to the uptake of weather or climate information.

Key barrier	Details	References
Poor communication and understanding of weather information (*n* = 12)	1) Uncertainty of obtaining information on time, continuously, and of difficulties in understanding the information 2) Inadequate information on seasonal forecast for long-term planning, low accessibility of climate information, high levels of illiteracy, misalignment between the climate information provided and what is needed by smallholder farmers and timeliness of climate forecast/information, and the technical language used in communicating climate information 3) The inability to comprehend how anthropogenic activities contribute to climate change have also been identified as a key factor that impedes the uptake of seasonal climate forecast 4) Available information is not communicated to the understanding of all, and there is a lack of collaboration between local institutions in the production and dissemination of climate service 5) Challenges in information access and interpretation are faced by illiterate farmers who cannot read a text, and even literate farmers lack the necessary skills to understand technical information because of the format they are presented 6) Missing climate information service (CIS) and the untimely delivery of CIS. 7) The paucity of communication channels between national-level producers of climate knowledge and community-level users 8) Farmers' inability to understand the necessity of climate information to make their decisions in terms of agricultural production	(Tall, 2010; Oyekale, 2015; Zongo et al., 2016; Amegnaglo et al., 2017; Nyadzi et al., 2018; Ouedraogo et al., 2018; Ebhuoma and Simatele, 2019; Naab et al., 2019; Antwi-Agyei et al., 2021c; Ouedraogo et al., 2021; Tarchiani et al., 2021; Sarku et al., 2022)
Lack of downscaled information (*n* = 8)	1) Lack of downscaled information (farmers emphasized that they would like to get downscaled information to allow them to take site-specific decisions) 2) Seasonal climate forecasts are not usually tailored to meet end-user needs 3) Not reliable and area-specific and difficult to interpret by ordinary people 4) Seasonal weather forecasts are often not downscaled and are provided for wide areas and generalized	(Rasmussen et al., 2015; Nyambo and Chengula, 2017; Ouedraogo et al., 2018; Diouf et al., 2019; Ebhuoma and Simatele, 2019; Radeny et al., 2019; Ouedraogo et al., 2021; Sarku et al., 2022)
Lack of logistics (*n* = 5)	1) Unavailability of dissemination technology and technical expertise 2) Lack of permanent funding sources and relevant training on the ground 3) Inadequate access as a result of limitations in transmission equipment 4) Lack of training on interpretation of the information and limited participatory sharing and interpretation of weather and climate forecasts	(Oyekale, 2015; Wamalwa et al., 2016; Ouedraogo et al., 2018; Bacci et al., 2020; Partey et al., 2020)
Lack of trust (*n* = 4)	1) The lack of management options and trust in the information source 2) Loss of confidence due to previous imprecise forecast that affected farmer productivity 3) Lack of trust in the 'unknown voices that communicated the information' hindered the willingness to rely on weather/climate information 4) The origin of the information is a factor that affected usable WIS, as farmers preferred to know the source of information and how it is produced	(Rasmussen et al., 2015; Amegnaglo et al., 2017; Ebhuoma and Simatele, 2019; Sarku et al., 2022)
Others (*n* = 5)	1) Agrometeorological services are given less priority from the Ghana Meteorological Agency (GMA) compared to other services such as aviation and military 2) Lack of interest in the information and inadequate and inconvenient time slot allocated for seasonal climate forecasts (SCFs) broadcasting in relation to farm activity schedules of the rural people 3) The belief in indigenous knowledge 4) Meteorological information is in most cases not tailored to meet the information needs of vulnerable group decision-makers at the subnational level 5) The low information uptake was also attributed to delay in forecasts, development of advisories, and subsequent dissemination of advisories	(Tall, 2010; Wamalwa et al., 2016; Nyambo and Chengula, 2017; Naab et al., 2019; Ouedraogo et al., 2021)

NB: n means the number of studies.

and the belief in indigenous knowledge (Table 4). One study reported that the inability to comprehend how anthropogenic activities contribute to climate change impeded the uptake of seasonal climate forecasts (Ebhuoma and Simatele, 2019). Regarding logistics and training, the inability to interpret climate information and convert it into actions affected the user's ability to use the information in decision-making (Partey et al., 2020).

Discussion

This study reviewed and assessed literature for evidence on the uptake, use and adoption of weather and climate information in the Agriculture, Water and Energy sectors in East and West Africa. The review revealed many research gaps and highlighted significant findings for policy-making.

Our review showed that studies on weather information services had focused predominantly on West Africa than East Africa. The dominance of studies in West Africa, especially Ghana, could be attributed to the region's vulnerability to climate risks (Karambiri et al., 2011; Sultan and Gaetani, 2016; Akinsanola and Zhou, 2019). Most of the studies were conducted in rural communities without focusing on users in urban communities. Future studies are needed to identify the weather and climate information needs of urban users (especially farmers) and evaluate the influence of the information on users' ability to make informed decisions. Further studies are also needed to identify the type of weather and climate information needed by users in sectors such as fisheries, energy, and water resources.

Regarding the type of weather information accessed by users, our results revealed that the information accessed differs even within a specific sector. Most farmers were more interested in accessing rainfall (such as the likely amount and distribution of rainfall) and temperature (such as the intensity of the dry season) forecasts. The findings are consistent with other results from South Africa, Europe, and Asia (Lebel, 2013; Mudombi and Nhamo, 2014; Shackleton et al., 2015), highlighting rainfall and temperature information as crucial information needed by users to manage climate risks. Many households in East and West Africa regions rely on agro-based livelihoods that are extremely vulnerable to the adverse impacts of climate change. Forecast on rainfall and temperature helps farmers to plan what to plant and when to do it. In addition, it helps them put measures in place to reduce the devastating impacts of extreme events on their livelihoods. However, most of the information received by users was a daily forecast instead of a seasonal forecast. This is in agreement with the findings of Baffour-Ata et al. (2022) who observed that few farmers received seasonal forecasts. They attributed this to the possibility of farmers encountering a digital divide (i.e., a gap between demographics and regions with access to modern information and communications technology and those that do not or have restricted access) in the access to seasonal forecasts. It is also important to stress the space–time relevance of seasonal forecasts to the needs of decision-makers. This has often been attributed to the greater uncertainty and probabilistic information associated with seasonal forecasts provided by national meteorological agencies (see Antwi-Agyei et al., 2021c). There is a need to build the capacity of meteorological agencies in the provision of accurate seasonal forecasts to aid decision-making. The availability of seasonal forecasts could provide advanced early warning of rainfall variability and help users plan ahead of time (Young et al., 2020).

The review further showed that few studies reported on impact-based forecasts such as drought, windstorms, and floods. Impact-based forecasts bridge the gap between forecasts and possible impacts of impending hazards [World Meteorological Organisation (WMO), 2015]. The provision of an impact-based forecast helps farmers to act before disasters in order to minimize the effects of weather and climate hazards on their livelihoods. The medium of communicating weather and climate information is important as it ensures users access the required information to make the right decisions. Our review revealed that the key media for communicating weather and climate information included radio, mobile phones, and television. Findings are consistent with other studies (Ajani, 2014; Coulier et al., 2018; Sikhondze, 2020; Henriksson et al., 2021), reporting radio as the most preferred medium of receiving weather and climate information. However, in rural areas that do not have electricity, farmers have to purchase batteries to enable them to operate their radios, and this places an extra financial burden on them. This could discourage farmers from using radios, thus denying them access to weather and climate information. Therefore, policymakers should prioritize extending electricity to rural farming communities or providing them with alternative effective means of accessing weather and climate information.

The significance of weather and climate information depends on mainly the ability to produce information that is usable and delivered in ways that can be incorporated into decision-making processes (Singh et al., 2018). The review showed that users who had access to weather and climate information used it to make several decisions related to land preparation, crop variety selection, varying cropping patterns, and harvesting time. Farmers also made key farm management decisions such as the application of fertilizers and pesticides, irrigation, and drying of crops based on weather and seasonal forecasts (Antwi-Agyei et al., 2021c). The decisions often lead to a significant increase in crop yields and farmer income and welfare. However, the review also highlights that few users utilized the information accessed. One fundamental gap identified is that most of the included studies did not have a comparison group (who did not use weather and climate information) in their analysis, making it difficult to assess the impact of using the information in decision-making.

The production and delivery of weather and climate service do not necessarily warrant that the information will be used or is even helpful for decision-making (Nkiaka et al., 2019). Our review revealed several challenges confronting the uptake, use, and adoption of weather and climate information. Key among them include poor communication and understanding of weather and climate information, lack of downscaled information, and lack of logistics. These findings support the findings of other studies in Europe, North America, and South Africa (Bolson et al., 2013; Bruno Soares and Dessai, 2016; Singh et al., 2018), where farmers and other users of weather and climate information identified barriers that prevented them from making better decisions using weather and climate information. Other studies have documented similar challenges affecting the use of climate and weather information for the implementation of climate-smart agricultural practices in Ghana (Antwi-Agyei et al., 2022). These barriers, if not addressed, could erode the efforts made in the provision of weather and climate information to aid farmers in planning their farming activities and also build their resilience to climate change. The review noted that there is a need to integrate scientific and indigenous knowledge to ensure locally appropriate framing of communications and use of weather and climate information services. Studies on cost–benefit analysis of the reliance on indigenous knowledge and scientific weather and climate information are needed. Further studies are required to explore the effectiveness of integrating indigenous knowledge of climate information into scientific weather and climate information to increase the uptake, use, and adoption of weather and climate information.

The use of weather and climate information in the agriculture sector could present some synergies and trade-offs in other sectors such as the energy and water resource sectors. For instance, cultivating plants that require low water will reduce water withdrawal for irrigation. In addition, the use of solar-powered pumps, promotion of microirrigation, and other forms of farming, such as hydroponics, would address the trade-offs associated with increasing food production (Mpandeli et al., 2018). Weather and climate information services can play a substantial role in guiding nexus-related decision-making (Conway et al., 2015). Unfortunately, studies on weather and climate information have not explored the synergies and trade-offs between the water–energy–food (WEF) nexus. Implementing measures that enhance the synergies and reduce the trade-offs between the WEF nexus is crucial in attenuating the devastating impacts of climate change on livelihoods (Mpandeli et al., 2018).

Conclusion and policy implications

This review reveals that studies on weather and climate information have to date focused more on West Africa than East African countries. The uptake, use, and adoption of climate information helped users to take key decisions to reduce the impact of extreme weather events. However, few studies reported on the impact-based forecast, and few users could access or benefit from the information produced due to poor communication and understanding of weather and climate information, lack of downscaled information, lack of logistics and trust, etc. These challenges, if not addressed, may regress the achievements made in the provision of weather and climate information. Therefore, sustainable efforts should be made to address these challenges through practical training and capacity building of end-users. This will facilitate the creation of awareness and understanding of climate information to help mitigate the impacts of stern climate events on livelihoods.

There is a need for weather and climate information that is easily accessible, understandable, and tailored to meet the needs of users. Weather and climate information delivery should be a key factor in policy discussions at all levels to improve climate risk management. Investors and governments could also increase their revenue base by expanding and diversifying technology in the delivery of impact-based forecasts specific to key sectors of the economy. Future studies are required to evaluate the production of the impact-based forecast, its performance, uncertainties, and how it translates into farmers' decision-making.

Data availability statement

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

Author contributions

TA conceived the study design and drafted the manuscript. PA-A and AD participated in the study design, critically revised important intellectual content, and acquired the funding for this study. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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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.2022.935696/full#supplementary-material

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The impact of natural disasters on rural household wealth: Micro evidence from China

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Examining the factors that influence rural households' wealth facilitates enhancing poor households' happiness, improving their overall welfare, and narrowing the wealth gap between different households. Thus, this study analyzed data from the China Family Panel Survey (CFPS) using multiple linear regression and propensity score matching methods to examine the impact of natural disasters on rural household wealth. Our findings showed that natural disasters have a significant negative impact on rural household wealth, with a medium-to long-term effect. Additionally, the heterogeneity analysis indicated that natural disasters have a greater effect on the wealth of larger households and households with high-consumption levels. Mechanism results suggest that natural disasters affect rural household wealth by reducing household income and harming individual's physical and mental health.

KEYWORDS

natural disasters, household wealth, income, physical health, mental health

1 Introduction

Natural disasters, such as hurricanes, earthquakes, droughts, mudslides, and floods, not only worsen the living conditions of a region's inhabitants, but also result in huge expenses for the government, businesses, and individual residents, directly or indirectly reducing the local population's wealth growth rate. Economic inequality includes both income and wealth inequality. In most countries, current wealth inequality is much higher than income inequality, averaging more than 0.6 and the share of wealth held by minorities continues to expand (Yang and Gan, 2020). The Credit Suisse Global Wealth Report 2021 stated that the global wealth gap has continued its sharp rise, with the richest 1% owning nearly half (45%) of the wealth. Data from the Wind database showed Chinese residents' 2021 per capita disposable income to be 35,128 RMB, slightly above the global average. Nearly 900 million people in China (approximately 60% of the country's total population) belong to the lower-middle-income group. Among them, the proportion of rural residents in the low- and middle-income groups is over 90%. Eliminating the wealth gap and narrowing the gap between the low- and high-income groups is a key point. Examining the determinants of rural households' wealth levels and exploring the focus points for wealth growth of the middle- and low-income groups facilitate improving farmers' welfare and narrowing the wealth gaps between income groups, which could enhance the happiness of low-income families and improve the overall welfare of society.

With its vast territory and diverse terrain, China is more seriously affected by natural disasters than other regions. The Ministry of Emergency Management of China reported that, in 2021, natural disasters in China affected 107 million people, damaged or directly caused the collapse of 2,143,100 houses, affected up to 11,739 thousand hectares of crops, and caused direct economic losses of up to 334.02 billion yuan.[1] It is clear that natural disasters in China cover a wide area, are devastating, and inflict serious losses that significantly impact the economic behavior of the country's residents. In China's rural areas, most residents still largely depend on crops for their economic resources. Thus, the impact of natural disasters on the wealth of rural Chinese house-holds is particularly profound.

Given that natural hazards affect residents' work and lives in different ways, many studies have examined the impact of natural disasters on individual and household economic behavior. Existing research found that natural disasters affect individuals' well-being (Rehdanz et al., 2015), investor sentiment (Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Kaplanski and Levy, 2010), migration (Saldaña-Zorrilla and Sandberg, 2009; Warner and Afifi, 2014; Cattaneo and Peri, 2016; Pajaron and Vasquez, 2020), risk preferences (Bourdeau-Brien and Kryzanowski, 2020), mental health (Shultz, 2014; Graham et al., 2019; Zhang et al., 2022), and children's development (Rabassa et al., 2012; Deuchert and Felfe, 2015). Furthermore, studies have examined the impact of natural disasters on household income inequality (Yamamura, 2015; Abdullah et al., 2016; Keerthiratne and Tol, 2017), household savings (Filipski et al., 2019), household debt (Gallagher and Hartley, 2017), household consumption (Arndt et al., 2004; Wahdat, et al., 2021), and other household behaviors. Natural disasters cause direct or indirect economic losses to households. Therefore, several studies have investigated the impact of natural disasters on household income (Bayudan-Dacuycuy and Lim, 2013; Bui et al., 2014; Arouri et al., 2015). Arouri et al. (2015) found that natural disasters can dampen household income growth. However, other studies revealed that natural disasters do not affect the population's income, which may be because government transfers to the affected areas compensate for the population's income loss (Tatyana, 2017). Household wealth is a more comprehensive reflection of a household's economic situation (Pollack, et al., 2007). Therefore, examining the impact of natural disasters on household wealth can provide a more comprehensive understanding of natural disasters' impact on households' economic status.

Existing literature that examines natural disasters' effects on household wealth is relatively scarce. We did not find any studies that examined the effects of natural disasters on household wealth in rural China. Hence, this study examined the effects of natural disasters on rural household wealth based on data from the 2014, 2016, and 2018 CFPS. This study contributes to the existing literature by: 1) enriching knowledge of the factors that influence household wealth and providing empirical evidence that identifies natural disasters' effects on household financial behavior; 2) examining the heterogeneity of natural disasters' effects on rural households' wealth for different size households and different consumption levels, to enhance understanding of natural disasters' heterogeneous effects on rural households' wealth; 3) clarifying the mechanism through which natural disasters affect rural households' wealth by reducing residents' income and health status, which provides policy insights for the government to mitigate rural households' wealth loss caused by natural disasters, and thereby enhance social welfare.

2 Theoretical analysis and research hypotheses

Natural disasters are characterized by suddenness, urgency, clustering, and concomitance. Therefore, natural disasters, while negatively affecting families in the area, also cause serious damage to the local infrastructure, resulting in the regional economy's collapse and even social disruption. Therefore, natural disasters usually bring unpredictable negative exogenous shocks to individuals or households, affecting normal life and the macroeconomy's stable operation. Previous studies found that natural disasters cause casualties and significant physical damage (Toya and Skidmore, 2007), and affect foreign direct investment (Neise et al., 2022) and government debt (Borensztein et al., 2009; Lis and Nickel, 2010; Melecky and Raddatz, 2015; Klomp, 2017).

Many studies also found that natural disasters significantly negatively impact economic development (Cavallo et al., 2013; Abbas Khan et al., 2019; Qureshi et al., 2019; Deng et al., 2022), making it difficult for individuals to maintain normal economic activities in a poor external environment, thereby indirectly affecting household wealth accumulation. More importantly, natural disasters also directly affect household wealth. Most farming households rely on agricultural production for income; however, natural disasters may destroy crops and cause significant losses to farming households (Huigen and Jens, 2006; Huang, et al., 2022). Additionally, natural disasters may destroy houses and the means of production (Jia et al., 2018), causing direct wealth losses to households. Natural disasters also cause panic and price increases, which increases household expenditures. Increased economic losses and expenditures, in turn, hinder rural households' wealth accumulation. Based on these factors, we proposed the following hypothesis.

1 Link to data source: https://www.mem.gov.cn/xw/yjglbgzdt/202201/t20220123_407204.shtml.

TABLE 1 Variable definitions.

Variable	Variable name	Variable definition
Wealth	Family wealth	Difference between total household wealth and liabilities
Disaster_d	Natural disaster	Individuals whose villages have experienced any natural disaster are coded 1, and 0 otherwise
Disaster_n	Natural disaster intensity	Number of natural disasters experienced by the individual's village in the last four years
Male	Male	Males are coded 1, and females are coded 0
Age	Age	Age of the individual
Education	Level of education	Number of years of education of an individual
Marital	Marital status	Married is coded 1, and 0 otherwise
Math	Math skills	Higher scores indicate higher math ability
Language	Language skills	Higher scores indicate higher verbal ability
Insurance	Social security	Individuals who have purchased social security are coded 1, and 0 otherwise
Agricultural	Agricultural production	Individuals whose households are engaged in agricultural production are coded 1, and 0 otherwise
Size	Family size	Number of family members
Consumption	Household consumption per capita	Annual per capita household consumption

hypothesis 1. Natural disasters may harm rural household wealth.

Natural disasters might impact rural household wealth through harming population health. For example, previous studies have found that natural disasters, such as typhoons, mudslides, and hailstorms, may adversely affect the physical health of individuals, sometimes causing death (Kahn, 2005; Han et al., 2021), and may also negatively affect individuals' mental health (Graham et al., 2019; Zhang et al., 2022). Residents need to spend time and money to improve ill health. However, the penetration of agricultural mechanization is low in rural China; most areas are planted and harvested through manual labor. When agricultural workers' health deteriorates, crop cultivation is reduced. Additionally, individuals with disaster related disabilities cannot engage in agricultural production, thus reducing household income. Individuals with deteriorating health conditions may also need to increase their health care expenditures or sell their fixed assets to pay for high medical expenses, thus reducing household wealth. Based on these factors, we proposed the following hypothesis.

Hypothesis 2. Natural disasters may harm population health, and thus affect rural households' wealth.

Natural disasters might impact rural household wealth though their effect on household income. Natural disasters can destroy crops, homes, and arable land, reducing household property income. Natural disasters may also damage irrigation facilities and transportation infrastructure, thus affecting crop yields and crop sales, which indirectly affects household incomes. Additionally, natural disasters may damage farmers' means of production, which is time-consuming and costly to repair or purchase, affecting the normal agricultural production cycle. Many studies have shown that natural disasters significantly negatively impact the population's income (Bayudan-Dacuycuy and Lim, 2013; Bui et al., 2014; Arouri et al., 2015), which is an important sources of household wealth accumulation. Decreased household income inevitably affects household wealth accumulation. Given these factors, we proposed the following hypothesis.

Hypothesis 3. Natural disasters may reduce the household income and thus affect rural households' wealth.

3 Materials and methods

3.1 Data sources

This study used data from the 2014, 2016, and 2018 CFPS, which conducted a detailed study of individuals, households, and communities in 25 provinces/municipalities/autonomous regions in China, including Beijing, Sichuan, Shanghai, Guangdong, and Jiangsu. Its wide sample coverage and scientific sampling method helped to ensure a representative sample by collecting both individual information, such as birthdates, gender, marital status, household registration, and health status, and household information, such as household wealth, consumption, and size. This allowed us to examine the impact of natural disasters on rural residents' household wealth by excluding data from cities. We also excluded samples with missing values, resulting in a sample comprising 6,144 households and 15,063 individuals.

3.2 Variable definitions and descriptive statistics

3.2.1 Household wealth

The dependent variable was household net wealth. Referring to existing relevant studies (Hurst and Lusardi, 2004; Piketty and Zucman, 2014), we used household net assets to measure

TABLE 2 Descriptive statistics.

Variable	Full sample			Control group			Processing group		
	Observations	Mean	Standard deviation	Observations	Mean	Standard deviation	Observations	Mean	Standard deviation
Wealth	15,063	1.612	2.431	3,702	2.220	3.257	11,361	1.414	2.055
Male	15,063	0.496	0.500	3,702	0.487	0.500	11,361	0.499	0.500
Age	15,063	46.509	16.535	3,702	46.327	16.747	11,361	46.568	16.466
Education	15,063	6.166	4.431	3,702	6.600	4.511	11,361	6.024	4.395
Marital	15,063	0.803	0.398	3,702	0.803	0.398	11,361	0.803	0.398
Math	15,063	6.559	5.675	3,702	7.060	5.737	11,361	6.395	5.645
Language	15,063	14.064	11.349	3,702	15.211	11.286	11,361	13.690	11.345
Insurance	15,063	0.895	0.307	3,702	0.833	0.373	11,361	0.915	0.279
Agricultural	15,063	0.840	0.367	3,702	0.715	0.451	11,361	0.881	0.324
Size	15,063	4.638	2.004	3,702	4.471	2.122	11,361	4.693	1.961
Consumption	15,063	8.975	0.854	3,702	9.094	0.907	11,361	8.937	0.832

household net wealth, including financial assets, such as stocks, bonds, and funds, and non-financial assets, such as real estate and buildings. Our study does not include household appliances, automobiles, IV, washing machine or wealth that is difficult to quantify in numerical terms, and we don't include the government's transfer payment (the pension that an individual can receive after retirement) in the future. We summed the total household assets and deducted them from the total household liabilities to determine each household's net wealth.

3.2.2 Natural disasters

The core explanatory variables in this study were natural disasters. Drawing on existing research (Zhang et al., 2022), we constructed two core explanatory variables based on the 2014 CFPS questionnaire, which asked individuals, "Has your village experienced the following natural disasters in the past four years?" The options included nine types of natural disasters, such as drought, flood, forest fire, hail, typhoon, mudslide, agricultural, and forestry pests and diseases, earthquake, and infectious diseases. Based on these questions, we constructed the first core explanatory variable (Disaster_d), a dummy variable that indicates whether an individual experienced natural disaster. If the individual's village experienced any kind of natural disaster in the past four years, Disaster_d was coded 1; otherwise, it was coded 0. The second core explanatory variable was natural disaster intensity (Disaster_n), which used the number of natural disasters experienced by the individual's village as a proxy variable, where a greater number of natural disasters in the past four years indicated a greater natural disaster intensity.

3.2.3 Relevant variable descriptive statistics

To alleviate the endogeneity problem caused by omitted variables, we controlled for a series of variables. Individual-level control variables included gender, age, education, marital status, cognitive ability, and social security. Household-level control variables included whether a household member was engaged in agricultural production, household size, and household consumption. Considering that households' annual per capita consumption is relatively large, we used logarithmic processing of household consumption. Table 1 shows the variable definitions.

Descriptive statistics for household wealth, natural disasters, and the control variables are shown in Table 2. Mean household wealth was 16,120 RMB, indicating that rural households have low net wealth. Mean household wealth for the control group was 22,220 RMB, with a mean of 14,140 RMB for households that experienced at least one natural disaster was. Therefore, on average, households that experienced natural disasters had lower levels of wealth accumulation than households that did not. These results suggest that natural disasters may harm rural households' level of wealth.

3.3 Econometric models

This study used a multiple linear regression model to examine the impact of natural disasters on household wealth.[2] The model is as follows.

$$Wealth_i = \alpha_i + \beta_0 disaster\_d_i + \beta X + \varepsilon_i \tag{1}$$

$$Wealth_i = \rho_i + \beta_1 disaster\_n_i + \lambda X + \mu_i \tag{2}$$

$Wealth_i$ represents the dependent variable, household wealth; α_i and ρ_i is the intercept term for model estimation. Disaster_d and

2 This paper does not examine the impact of natural disasters on household wealth using a panel fixed effects model, as data related to natural disasters are not included for 2016 as well as 2018.

TABLE 3 Impact of natural disasters on household wealth.

Variable	(1)	(2)	(3)	(4)
	Family wealth	Family wealth	Family wealth	Family wealth
Disaster_d	−0.806***	−0.537***		
	(0.057)	(0.050)		
Disaster_n			−0.186***	−0.123***
			(0.013)	(0.012)
Male		−0.127***		−0.122***
		(0.039)		(0.039)
Age		0.012***		0.012***
		(0.001)		(0.001)
Education		0.057***		0.054***
		(0.006)		(0.006)
Marital		0.151***		0.153***
		(0.047)		(0.047)
Math		0.009		0.010*
		(0.006)		(0.006)
Language		0.004		0.004
		(0.003)		(0.003)
Insurance		−0.351***		−0.379***
		(0.081)		(0.081)
Agricultural		−0.864***		−0.902***
		(0.071)		(0.071)
Size		0.029***		0.029***
		(0.011)		(0.011)
Consumption		0.671***		0.678***
		(0.028)		(0.028)
Constant	2.220***	−5.157***	1.940***	−5.337***
	(0.054)	(0.293)	(0.035)	(0.294)
Observations	15,063	15,063	15,063	15,063
Adjusted R2	0.020	0.131	0.013	0.128

Note: *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Standard errors for clustering at the individual level are in parentheses.

disaster_n are core explanatory variables and reflect natural disaster occurrence and intensity, respectively. X represents the control variables, gender, age, education level, marital status, cognitive ability, health insurance participation, whether the household is engaged in agricultural production, household size, and household consumption. ε_i and μ_i is the random error term for model estimation.

4 Results

4.1 Regression results

Table 3 reports the estimated impact of natural disasters on household wealth. Columns 1) and 3) show the results without controlling for gender, age, and other control variables; the estimated coefficients of natural disasters' impact and intensity on household wealth, were −0.806 and −0.186, respectively. Both were negatively significant at the 1% significance level, indicating that natural disasters have a significant negative impact on household wealth. Table 3, columns 2) and 4) include the control variables; the estimated coefficients of natural disaster impact and intensity on household wealth remain negatively significant, further indicating that natural disasters have a significant negative impact on household wealth. The above results are consistent with Hypothesis 1. Analyzing the estimated coefficients for the control variables revealed that agricultural production, social insurance, and gender estimated coefficients were all adversely significant at the 1% level of significance. The estimated coefficients of age, education, marital status, household size, and household consumption on household wealth were also significant, indicating that these factors significantly impact household wealth.

TABLE 4 Balance test.

Variable	(1)	(2)	(3)	(4)	(5)
	Matching Status	Average value		T value	*p* value
		Processing group	Control group		
Male	pre-match	0.499	0.487	1.31	0.190
	post-match	0.498	0.495	0.44	0.660
Age	pre-match	46.568	46.327	0.77	0.443
	post-match	46.574	46.737	−0.75	0.455
Education	pre-match	6.025	6.601	−6.88	0.000
	post-match	6.030	6.055	−0.42	0.671
Marital	pre-match	0.803	0.803	0.03	0.979
	post-match	0.805	0.805	−0.15	0.881
Math	pre-match	6.395	7.060	−6.20	0.000
	post-match	6.402	6.408	−0.08	0.935
Language	pre-match	13.690	15.211	−7.09	0.000
	post-match	13.697	13.743	−0.30	0.761
Insurance	pre-match	0.915	0.833	14.08	0.000
	post-match	0.918	0.918	−0.24	0.812
Agricultural	pre-match	0.881	0.716	24.31	0.000
	post-match	0.882	0.884	−0.48	0.630
Size	pre-match	4.693	4.471	5.85	0.000
	post-match	4.687	4.610	2.85	0.004
Consumption	pre-match	8.937	9.094	−9.79	0.000
	post-match	8.937	8.927	0.87	0.384

4.2 Robustness tests

4.2.1 Estimation using the propensity score matching method

Individuals choose their own place of residence according to the natural environment or the occurrence of historical natural disasters. This may introduce a sample self-selection problem. Referring to existing research (Zhang et al., 2022), we used propensity score matching (PSM) to alleviate this source of bias. Before using PSM, it was necessary to test the common support assumption and whether the balance test was satisfied. The equilibrium test showed no significant differences in individual or household characteristics between the treatment group (individuals affected by natural disasters) and the control group (individuals not affected by natural disasters) after matching. Satisfying the common support assumption implies that the propensity scores of the treatment and control groups are mostly in the same range after matching, ensuring that there is a large enough sample to estimate the impact of natural disasters on household wealth.

The balance test results in Table 4 show that all control variables except for family size support the original hypothesis of no systematic difference between the control and treatment groups after matching, indicating that the data satisfy the balance test. In addition, the propensity scores' probability density plots before and after matching (Figures 1,2) showed that 172 samples were lost after matching; the propensity score values of both the treatment and control groups intersected and were in the same range after matching. This illustrates the effectiveness of using propensity score matching.

Drawing on existing research (Zhang et al., 2022), we examined the impact of experiencing a natural disaster on household wealth using five different matching methods, including radius matching, kernel matching, K-nearest neighbor matching ($K = 1$ and $K = 4$), and spline matching. Table 5 shows the impact of natural disasters on household wealth obtained using the propensity score matching method. Analyzing the natural disaster coefficients shows that regardless of matching method, the estimated coefficients of natural disasters' impact on rural household wealth were negative and significant, which is consistent with the above estimation results, further indicating that natural disasters have a significant negative impact on rural household wealth.

4.2.2 Substitution of the explanatory variables

In the above model, the dependent variable, family wealth, was continuous. We then established a dummy variable: if family wealth is greater than the average value of the net wealth of all families in the data, the family is considered to have a relatively high level of wealth,

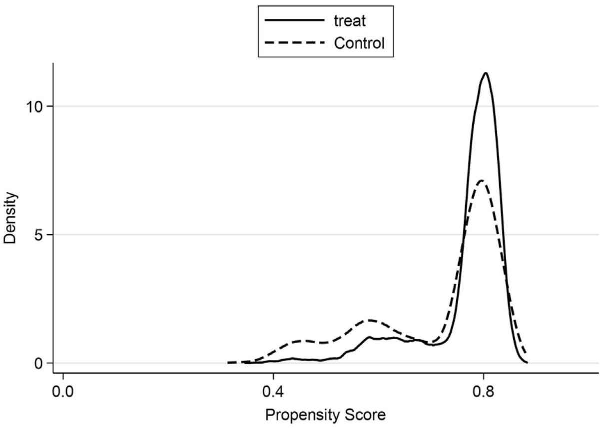

FIGURE 1
Propensity score—probability density plot (before matching).

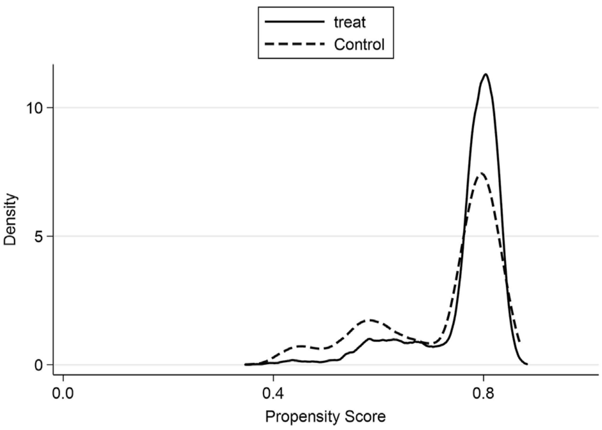

FIGURE 2
Propensity score—probability density plot (after matching).

and is coded 1; otherwise, it is coded 0. We then used a probit model to examine the impact of natural disasters on household wealth. As shown by the estimation results in Table 6, the estimated coefficients of natural disaster occurrence and intensity on household wealth were negatively significant. In addition, columns 3) and 4) of Table 6 report the marginal effects of the impact of natural disasters on household wealth. Both the natural disaster occurrence and intensity marginal effects on the impact of household wealth were negatively significant. These results further illustrate the robustness of the finding that natural disasters significantly negatively affect rural household wealth.

TABLE 6 Robustness tests.

Variable	(1)	(2)	(3)	(4)
	Probit	Probit	Margin	Margin
Disaster_d	−0.224***		−0.074***	
	(−8.788)		(0.008)	
Disaster_n		−0.066***		−0.022***
		(−8.619)		(0.002)
Control variable	YES	YES	YES	YES
Observations	15,063	15,063	15,063	15,063

Note: *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Standard errors of coefficients are in parentheses.

4.3 Heterogeneity analysis

4.3.1 Heterogeneity in the impact of households at different levels of consumption

To examine the heterogeneity of natural disasters' impact on the wealth of households with different consumption levels, we divided the sample into high- and low-consumption households and used a multiple linear regression model to examine the impact of natural disasters on high- and low-consumption households' wealth. Households were considered high consumption if their consumption level was greater than the mean consumption value of all sample households, and vice versa for low-consumption households. The estimation results in Table 7 show that the effect of natural disasters on the wealth of high- and low-consumption households is negatively significant. This indicates that natural disasters harm the wealth of both low- and high-consumption households. The

TABLE 5 Impact of natural disasters on household wealth (considering self-selection).

Variable	(1)	(2)	(3)	(4)	(5)
	Radius matching	Nuclear matching	K-nearest neighbor matching (k = 1)	K-nearest neighbor matching (k = 4)	Local linear regression matching
Natural disaster	−0.433***	−0.432***	−0.439***	−0.439***	−0.418***
	(0.062)	(0.062)	(0.073)	(0.073)	(0.073)
Observations	15,036	15,036	15,036	15,036	15,036

Note: *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. Standard errors of coefficients are in parentheses.

TABLE 7 Heterogeneity in the impact of natural disasters on households at different levels of consumption.

Variable	(1)	(2)	(3)	(4)
	High consumption	Low consumption	High consumption	Low consumption
Disaster_d	−0.633***	−0.363***		
	(0.081)	(0.054)		
Disaster_n			−0.151***	−0.089***
			(0.020)	(0.013)
Control variable	YES	YES	YES	YES
Constant	−8.315***	−2.987***	-8.601***	−3.026***
	(0.800)	(0.281)	(0.802)	(0.281)
Observations	7,493	7,570	7,493	7,570
Adjusted R^2	0.121	0.076	0.118	0.075

Note: *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Standard errors for clustering at the individual level are in parentheses.

TABLE 8 Heterogeneity in the impact of natural disasters on households of different sizes.

Variable	(1)	(2)	(3)	(4)
	Large-scale families	Small-scale families	Large-scale families	Small-scale families
Disaster_d	−0.760***	−0.338***		
	(0.078)	(0.064)		
Disaster_n			−0.159***	−0.085***
			(0.018)	(0.016)
Control variable	YES	YES	YES	YES
Constant	−4.030***	−5.143***	−4.245***	−5.271***
	(0.418)	(0.423)	(0.419)	(0.425)
Observations	7,570	7,493	7,570	7,493
Adjusted R^2	0.129	0.133	0.123	0.132

Note: *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Standard errors for clustering at the individual level are in parentheses.

absolute value of the estimated coefficient of natural disasters' impact on high-consuming households was greater than that of low-consuming households, indicating a larger impact on high-consuming households.

4.3.2 Heterogeneity in the impact of different household sizes

To examine the impact of natural disasters on the wealth of different sized households, we divided the sample into larger and smaller households, where a household was considered large if it was larger than the average of all household sizes, and small if the opposite was true. We then used a multiple linear regression model to examine the impact of natural disasters on the wealth of large- and small-scale households. As shown in Table 8, the estimated effect of natural disasters on both large-scale and small-scale households was negatively significant, indicating that natural disasters have a significant negative effect on both large-scale and small-scale households. Comparing the wealth effects on large-scale and small-scale households showed that the estimated coefficient absolute value of the natural disasters' impact on large-scale household wealth was greater than that on small-scale households.

4.4 Mechanism of action test

4.4.1 Impact of natural disasters on the physical and mental health of the population

To test Hypothesis 2, we examined natural disasters' effects on individuals' physical and mental health. The CFPS asked individuals, "How healthy do you think you are?" with possible responses, 1. Unhealthy, 2. Fair, 3. Relatively healthy, 4. Good healthy, and 5. Excellent healthy. Each response was assigned an

TABLE 9 Impact of natural disasters on individuals' physical and mental health.

Variable	(1)	(2)	(3)	(4)
	Mental health	Mental health	Physical health	Physical health
Disaster_d	−0.050***		−0.120***	
	(0.011)		(0.020)	
Disaster_n		−0.036***		−0.068***
		(0.003)		(0.006)
Control variable	YES	YES	YES	YES
Observations	15,063	15,063	15,063	15,063

Note: *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Standard errors for clustering at the individual level are in parentheses.

integer value from 1 to 5, with higher scores indicating better physical health. Following existing studies (Gu et al., 2020; Zhang et al., 2022), we measured individuals' mental health based on the 2014 Flow Center Depression Scale (CES-D). The CFPS CES-D scale included six questions about mental health.[3] We used factor analysis method measure mental health. The Kaiser–Meyer–Olkin (KMO) test values were greater than 0.8, and Bartlett's spherical test results all rejected the original hypothesis of no correlation between variables at the 1% significance level. Cronbach's alpha was 0.856. These results indicate that it is reasonable to use factor analysis to measure individuals' mental health, where higher scores reflect better mental health.

We used the ordinary least square to investigate the impact of natural disasters on individual mental health. Given the physical health is an ordinal variable, we employed the oprobit model to estimate the impact of natural disasters on population physical health. Results are shown in Table 9. The estimates show that natural disasters' effects on individuals' physical and mental health were negatively significant. These results are consistent with Hypothesis 2, indicating that natural disasters can affect household wealth by harming individuals' physical and mental health.

4.4.2 Impact of natural disasters on individual incomes

To test Hypothesis 3, we used the ordinary least square to examine the impact of natural disasters on individual annual income. The specific question about the household income is "In the past one year, what was your household's total income, which include operational income, property income, wage income, and financial support or government subsidies from others." The estimation results are shown on Table 10. The estimated coefficients of natural disasters' impact and intensity on individual income were −0.075 and −0.031, respectively, which are negatively significant at the 1% significance level. This indicates that natural disasters have a significant negative impact on residents' income, which validates Hypothesis 3, and further indicates that natural disasters affect rural household wealth by reducing the population's income.

4.5 Further analysis

To examine the medium- and long-term impacts of natural disasters on household wealth, we matched the household wealth variables in rural China in 2016 and 2018 with the CFPS in 2014, and used multiple linear regression to examine the medium- and long-term impacts. Table 11 shows that the estimated coefficients of natural disasters' impact on household wealth levels after two and four years were negatively significant, indicating that natural disasters have both a short-term impact on rural household wealth and a medium-to long-term impact.

5 Discussion

Numerous studies have examined the impact of natural disasters on individual or household income (Bui et al., 2014; Arouri et al., 2015; Park and Wang, 2017). However, studies on the impact of natural disasters on household wealth are rare. Fang et al. (2019) examined the impact of natural disasters on inclusive wealth based on macro data for G20 countries from 1990 to 2010, but the study was conducted from a macro perspective and did not examine the impact of natural disasters on household wealth. However, other studies examined the impact of natural disasters on household wealth.

3 The six questions were 1) In the last month, how often did you feel emotionally depressed, de-pressed, and unable to do anything to cheer you up? 2) In the last month, how often did you feel nervous? 3) In the last month, how often did you feel restless and had difficulty staying calm? 4) In the last month, how often did you feel that there is no hope for the future? 5) In the last month, how often did you find it difficult to do anything? 6) In the last month, how often did you think life is meaningless?.

TABLE 10 Impact of natural disasters on individual income.

Variable	(1)	(2)
	Individual income	Individual income
Disaster_d	−0.075***	
	(0.027)	
Disaster_n		−0.031***
		(0.008)
Control variable	YES	YES
Constant	4.604***	4.596***
	(0.188)	(0.190)
Observations	15,063	15,063
Adjusted R2	0.161	0.162

Note: *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Standard errors for clustering at the individual level are in parentheses.

For example, Howell and Elliott (2019) examined the impact of natural disasters on the relative wealth of households (wealth gap) based on Panel Study of Income Dynamics (PSID) data. Unlike these studies, the present study did not explore the causal relationship between natural disaster experience and household relative wealth, but instead focused on the short-term and mid-to long-term effects of natural disasters on household absolute wealth. Our findings suggest that natural disasters have a significant negative impact on household wealth, which is consistent with the findings of Arouri et al. (2015).

Starting from household differences, we examined the heterogeneity of natural disasters on household wealth with different consumption and different family sizes. This is beneficial to understanding the heterogeneous impact of natural disasters on household wealth. The findings show that natural disasters have a greater impact on households with higher levels of consumption. This may be because households with higher consumption levels may have relatively higher asset levels, and may own more productive equipment and fixed assets. In contrast, natural disasters such as typhoons, mudslides, and hailstorms, may damage buildings; therefore, this household group is more vulnerable to natural disasters. In addition, natural disasters may reduce residents' income, and it is difficult for individuals to change high-consumption habits when their income is reduced. Some households may rely on their pre-disaster savings or the sale of fixed assets to maintain high consumption. Thus, natural disasters affect high-consuming households more than low-consuming households. In addition, the heterogeneity analysis results suggest that natural disasters' impact on the wealth of larger households is also greater. This may be because larger rural households may expand their acreage and purchase more means of production to revive their livelihoods compared to smaller rural households. However, these households also take greater risks, and when natural disasters occur, they may be more vulnerable to the effects and may suffer more wealth losses. Thus, natural disasters have a greater impact on the wealth of larger households than on smaller ones.

This study theoretically analyzed the role of residents' income and health status in natural disasters' effects on household economic status, and conducted a corresponding mechanism test, providing empirical evidence for understanding the mechanism by which natural disasters affect household wealth. The mechanism analysis results suggest that natural disasters may reduce household income and decrease individual physical and mental health. This result is consistent with the findings of Kokai et al. (2004), Udomratn (2008), and Zhang et al. (2022). The mechanism analysis also examined the effect of natural disasters on household income, and showed that natural disasters can significantly negatively affect income, which is consistent with the findings obtained by Arouri et al. (2015) and Pleninger (2022).

Further analysis revealed that natural disasters not only impact household wealth in the short term, but have

TABLE 11 Medium- and long-term effects of natural disasters on household wealth.

Variable	(1)	(2)	(3)	(4)
	T+2 Year wealth	T+2 Year wealth	T+4 Year wealth	T+4 Year wealth
Disaster_d	−0.701***		−0.956***	
	(0.081)		(0.104)	
Disaster_n		−0.187***		−0.207***
		(0.017)		(0.023)
Control variable	YES	YES	YES	YES
Constant	−5.212***	−5.434***	−6.087***	−6.438***
	(0.451)	(0.450)	(0.570)	(0.570)
Observations	14,115	14,115	13,944	13,944
Adjusted R^2	0.111	0.110	0.113	0.110

Note: *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Standard errors for clustering at the individual level are in parentheses.

significant medium-to long-term effects as well. This could be because natural disasters reduce residents' income and harm their health status. The health status of residents is not necessarily reversible. When individuals' health status deteriorates, it may be difficult to recover and may even worsen, which inevitably affects their long-term income. It can also increase household medical expenditures, making it difficult for a family to accumulate wealth long after a natural disaster, and resulting in a significant loss of family wealth. Natural disasters can also destroy crops and the means of production on which households depend. Poorer households may lack funds to purchase appropriate agricultural means of production. They may also face credit constraints that prevent borrowing funds, making it difficult to regain their previous production scale, which affects the household's long-term income. Thus, natural disasters may affect household wealth levels in the near term, and also household wealth accumulation in the medium-to long-term.

This study has limitations. First, in constructing the model, individual and household-level control variables were included as much as possible. However, it was not possible to control for every variable that may affect household wealth. Second, the net household wealth measure is underestimated because some high-wealth net worth households were unwilling to disclose their true household wealth. Future research can improve the models by obtaining the true wealth of high-income households. Third, we examined the relationship between natural disasters and rural households' absolute wealth, and indirectly analyzed natural disasters' effects on household wealth inequality. Future research could explore the effect of natural disasters on the relative gap in household wealth to analyze the direct effect of natural disasters on household wealth inequality.

The following policy implications can be drawn from the study findings. First, natural disasters have a significant negative impact on rural households' wealth. Therefore, it is necessary to focus on providing social security and policy assistance to the affected groups to reduce household wealth loss, help affected farmers accumulate wealth, and reduce the wealth gap between the affected and wealthy groups. Second, it is important to improve natural disaster prevention and response; strengthen monitoring and early warning systems; increase research on the effects of natural disasters, such as catastrophic weather, floods, and earthquakes; and improve the rural infrastructure to substantially reduce household wealth loss. Third, the government should increase its disaster prevention and mitigation efforts to enhance rural households' ability to cope with natural disasters, which can effectively reduce residents' wealth loss when natural disasters occur. Fourth, our findings show that natural disasters affect household wealth by reducing residents' income and harming individual's health. Therefore, the government should focus on rural households' physical and mental health, and provide economic support by increasing their income. This will prevent individuals from falling into the poverty trap because of health problems.

6 Conclusion

As the widening wealth gap has become more prominent worldwide, many scholars have examined and analyzed the impact of natural disasters on households' economic status and welfare. Based on 15,063 observations from the CFPS database, we examined the causal relationship between natural disasters and rural household wealth, leading to our study's core conclusions: 1) natural disasters have a significant negative effect on rural household wealth, and this effect remains over the long run; 2) natural disasters have a greater negative effect on the wealth of high consumption and larger households; and 3) natural disasters affect rural household wealth by reducing residents' income and harming individual's physical and mental health.

Data availability statement

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

Author contributions

Conceptualization, SW and RZ; methodology, SW, RZ, and DF; software, SW and RZ; validation, SW, RZ, CW, and DF; formal analysis, SW and RZ; investigation, SW, CW, and DF; resources, RZ; data curation, SW and DF; writing—original draft preparation, SW, RZ, CW, and DF; writing—review and editing, SW and CW visualization, RZ and DF; supervision, SW, CW, and RZ; project administration, SW, RZ, and DF. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Alleviating impacts of climate change on fishing communities using weather information to improve fishers' resilience

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This study contributes new knowledge in evaluating actions aimed at alleviating impacts of climate change on small-scale fishers and enhancing resilience in their households in West Africa. Evidence of the damage caused by climate change to the artisanal fisheries sector in West African countries is accumulating. Current measures in place for artisanal fishers to adapt to these changes include broad long-term pro-poor strategies designed to manage the persistent problem of overfishing and declining fish stocks. However, one immediate coping strategy is beginning to emerge, the more active use of reliable weather information. Based on 80 semi-structured interviews conducted in Senegal, Ghana, and Nigeria between 2021 and 2022, this study investigates claims that the use of weather information (WI) is helping West African artisanal fishers and those involved in secondary fishery activities to build more climate-resilient household income and food security. Unlike the long-term measures for mitigating the impact of climate change, results from the study show that by assessing the risk, their marine capture activities using weather information, fishers are immediately benefitting. Using the diffusion of the innovation theory to investigate the pattern of fishers' adoption and usage of weather information, we found that Senegalese marine artisanal fishers can be classified as "Early Adopters" of this innovation. However, this is not the case with inland fishers who remain skeptical and will only use weather information if they can ascertain its reliability. West Africa's inland fisheries sector is often neglected in climate change strategies: there is a lack of coordinated action to understand the weather information needs of these vulnerable fishers in order to coassess and codevelop bespoke weather products that offer benefits to them. However, West Africa's fisheries, especially those inland, are too important to ignore if the United Nations Sustainable Development Goals (UNSDGs), including no poverty and zero hunger, are to be achieved. To help this sector fully benefit from the use of weather information, this study recommends detailed research into the weather information needs of these fishers and user-friendly ways to engage with the fishers to transmit the information.

KEYWORDS

West Africa, inland artisanal fishers, marine artisanal fishers, weather information, diffusion of innovation

1 Introduction

West Africa is endowed with substantial marine and inland fisheries, broadly divided into industrial and artisanal sectors, both of which play major roles in the daily lives of communities (FAO Fisheries Department, 1996; Teh et al., 2016; Okeke-Ogbuafor et al., 2020). The industrial sector is an important foreign exchange earner for West African countries: most of their exportable fish are sold to European Union (EU) countries (Okafor-Yarwood et al., 2022). Unlike the industrial sector, which is mechanized, the artisanal fisheries sector is labor intensive and employs more people (Belhabib et al., 2015). However, due to the poor fishery management, including inadequate record keeping, it is difficult to estimate the actual number of people employed by the artisanal fisheries in West Africa (Belhabib et al., 2015; USAID, 2018). Nonetheless, it is claimed that about 6.7 million West Africans directly depend on this sector for food and income (Belhabib et al., 2015).

West Africa's fishery sectors are particularly vulnerable to the impacts of climate change. The complex links between the biogeochemical properties of West African waters, fish productivity, and distribution is poorly understood, and this complexity is compounded by the impact of climate change (Belhabib et al., 2016; Wilson et al., 2021). Extreme weather conditions linked to climate change are becoming more frequent and difficult to predict resulting in negative impacts on fisheries, fishers' livelihoods, and their associated communities. For example, adverse weather conditions damage fishing equipment, cause the loss of gear, and negatively affect the fish post-harvest sector (Monnereau and Oxenford, 2017). Rising sea temperature decreases fish reproduction and growth causing fish stocks to migrate toward colder waters away from the equator (White et al., 2022). Most artisanal fishers are now fishing further offshore to follow the migrating fish and moving to new fishing grounds in their own and other countries, thereby increasing the operational costs of fishing (Belhabib et al., 2016). Many fishers have also changed from small-sized to medium-sized boats (Monnereau and Oxenford, 2017).

The impact of climate change on West African fishers when combined with the persistent problem of overfishing increases the fishers' rates of poverty (Bahri et al., 2021; Belhabib et al., 2016; Sumaila and Tai, 2020; Stead, 2019). As the impact of climate change continues to soar globally, fish catches are predicted to decrease by 7.7% worldwide but could fall by over 50% in Nigeria and 60% in Ghana (Coalition for Fair Fisheries Arrangements, 2021). A total of four broad long-term measures have been proposed that could help reverse this decrease—marine protected areas (MPAs); co-management; wealth-creation strategies; and social welfare policies. The aim of MPAs is to protect breeding grounds for fish, thus replenishing declining fish stocks (Assis et al., 2021; Marcos et al., 2021). However, globally the value of MPAs for conserving fisheries is contested and the results are highly context-dependent (Caveen et al., 2014; Di Franco et al., 2016; Kituyi and Thomson, 2018; Trégarot et al., 2020). The second measure that has been taken to mitigate the impact of climate change is the promotion of co-management to strengthen relationships and trust between stakeholders in the fisheries, and for the collective action toward sustainable fisheries management and climate change adaptation for artisanal fisheries (Pittman et al., 2019). However, co-management is not a panacea (Bown et al., 2013). It raises many practical issues like which stakeholders should participate in decision making and how to prevent stronger stakeholder groups from dominating co-decision-making. The outcome of fisheries co-management arrangements are sometimes the products of internal or even external manipulations and discrimination of vulnerable stakeholders (artisanal fishers) by more influential stakeholders (industrial fishers) (Kaluma and Umar, 2021; Okafor-Yarwood et al., 2022).

The third approach is a wealth-creation strategy or fishing for profit, which focuses on the economic gains obtained directly or indirectly from industrial marine capture fisheries (Dyck and Sumaila, 2010; Okeke-Ogbuafor and Gray, 2021). But this trickle-down theory has been heavily criticized for the lack of evidence that it works. The fourth approach is the social welfare model which is designed to promote the well-being of fishers and their households, improving their income, nutrition, and food security (Belhabib et al., 2015; Cohen et al., 2019). One way of doing this is by scaling back the industrial fleet to stop fish just outside the inshore area from being vacuumed up by large-scale vessels. However, instead of boosting fishers' income and food security, such a policy may encourage overfishing by artisanal fishers (Okeke-Ogbuafor et al., 2020; Okeke-Ogbuafor et al., 2021). Therefore, despite these four measures taken to mitigate against climate change by communities, national governments, and international organizations, West African artisanal fishers and their households remain one of the worst-hit by the impact of climate change (Ojea et al., 2020). The African Science for Weather Information and Forecasting Technique (African-SWIFT) provides a fifth approach focused on the improved accuracy and communication of weather forecast information across a range of timescales (Parker et al., 2021). SWIFT, through its Testbed 3, says that the use of weather information by fishers and those involved in secondary activities can help West African fishers build resilience to climate change (Fletcher, 2021; Hill, 2021). Weather information is becoming more accurate as the skills of predictive models are improved by scientific and monitoring advances (Fletcher, 2021; Hill, 2021; Parker et al., 2021). Weather information is used by farmers to enhance their resilience to climate change. For example, pastoral, cash, and food crop farmers in West Africa are increasingly dependent on the accurate weather information to make management decisions, including when to plant their seedlings or the type of seedlings to plant, thus integrating weather information into their decision making (Nkiaka et al., 2019; Ouedraogo et al., 2021; Sarku et al., 2022). The value of weather information for fishers' safety at sea (Diouf et al., 2020; Mbaye et al., 2021; Opemo, 2018) has long been known, but its utility for the livelihood and income of West African fishers and those involved in secondary activities has been less researched and is not well-understood (Katikiro and Macusi, 2012; Lovei, 2017; Monnereau and Oxenford, 2017). This study fills this gap by examining the impact of climate change on livelihood and household income of West African artisanal fishers and the benefits of weather information to artisanal fishers and those involved in secondary activities.

2 Theoretical framework

The theoretical framework presented in this study is the diffusion of innovation theory pioneered by Everett Rogers (2003). Innovation is about an idea, process, discovery, or technology which is new to individuals and their communities. Diffusion is the process through which awareness of an innovation spreads over time within social structures or organizations. The diffusion of innovation theory developed by Rogers integrates communication and sociological theories of behavioral change to explain how an idea passes through different stages of adoption by its potential users. The structure of a social system influences how individuals make decisions about the adoption and usage of innovation and the speed of its diffusion. Rogers (2003) classifies individuals in a social system into five groups based on their attitude toward innovation. The "Innovators" are the first group to accept the innovation, and they are highly skilled in creating new ideas and technologies. The "Early Adopters" are the second group to accept the innovation, and they are more integrated into the social system than are the "Innovators." They are also more informed about the innovation than are the other members of the community. The "Early Majority" are followed by the "Late Majority" into adopting the innovation. The Late Majority group are reluctant to accept innovations because they are highly risk averse. This set is always the last to adopt innovation—they pick it up only when it has spread throughout the social system (Blythe et al., 2017; Ferster, 2017). Time plays an important role in the spread and adoption of new ideas. Socio-economic characteristics such as gender, income, and the level of education can also influence peoples' decisions about innovation (Blythe et al., 2017). The diffusion of innovation theory is used to analyze the spread of new ideas and technologies in a range of sectors, including health (Zhang et al., 2015; Dearing and Cox, 2018), agriculture (Dan et al., 2019; Lavoie et al., 2021), and aquaculture (Blythe et al., 2017; Kumar et al., 2018). For artisanal fisheries, our study will use this theory to frame the context and analyze the adoption of weather information by fishers in the three case-study countries.

With regard to the factors that motivate people to adopt innovations, according to Rogers (2003), there are five user-perceived qualities: relative advantage, trialability, observability, compatibility, and complexity. Relative advantage is seen as the most important determinant of an innovation adoption rate because it explains the degree to which a user perceives an innovation to be better or more useful than the existing alternatives (Sahin, 2006). Trialability is the capacity for an innovation to be tested with minimal investment and commitment. Innovations with a higher trialability are more likely to be adopted. Observability is about how visible the results of an innovation are to their users. Potential users are unlikely to adopt an innovation if they cannot see it being used by their peers or people within their network. Compatibility is how an innovation fits into the existing technical knowledge and within the values, beliefs, culture, and needs of potential users. The more an innovation can co-exist or integrate with the existing values, beliefs, and needs of potential users, the greater the chances for diffusion and adoption (Tornatzky and Klein, 1982; Scott et al., 2008; Wisdom et al., 2014). Last, complexity is the degree to which an innovation is perceived as difficult to understand and use (Rogers, 2003). Innovations that are hard to understand and use are less likely to be adopted by the potential users.

Traditionally, the agricultural and fishery sectors have used extension workers as change agents to promote the diffusion of new ideas and innovation (Blythe et al., 2017). However, persuading individuals and communities to accept weather information does not only require the services of trained knowledge brokers but also requires a regular supply of weather information and the match of weather information with the needs of artisanal fishers (Nkiaka et al., 2020; Singh and Singh, 2017; Sultan et al., 2020). As the impact of climate change on fishers and fisheries continues to rise and following the failure of marine protected areas, co-management the wealth-creation, and social welfare strategies to significantly alleviate the impact of climate change on fishers' and their households, this study investigates the patterns of adoption and usage of weather information by fishers, encouraged by change agents to assess the extent to which weather information (WI) is helping fishers build resilient livelihoods.

3 Research design and methods

This study makes use of the qualitative data collected in two phases from three case-study countries. The first phase of data collection was in December 2021, when a total of 50 semi-structured

TABLE 1 Number and composition of participants across case countries.

Category of participants	Senegal	Ghana	Nigeria
Primary sector			
Artisanal marine capture fishers and inland fishers	18	15	17
Secondary sector			
Fish mammies and fishmongers	3	9	8
National Agencies			
Staff of fishery agencies	2	2	1
Staff of meteorological agencies	2	1	2
Total number of participants	25	27	28

interviews were conducted with key informants (KIs) in Senegal, Ghana, and Nigeria. All 50 participants were recruited through snowball sampling and based on their knowledge or use of WI and willingness to participate in this study. Relying on snowball sampling to recruit participants can be biased as respondents are likely to recommend people who hold similar views to themselves. Thus, to encourage heterogeneity and obtain a variety of perspectives, a wide range of respondents were recruited from the fishery sectors and the meteorological agencies (Kirchherr and Charles, 2018; Allen, 2022). During this first phase, we interviewed five staff from the Ministries of Fisheries in the case countries; five staff from the meteorological agencies; 29 marine fishermen; and 11 fishmongers and women fish investors who finance fishers (fish mammies). A total of 20 interviews were conducted in Nigeria and 15 each in Ghana and Senegal. Interview questions focused on three areas: the impact of climate change on the activities of artisanal fisheries and fishers, and efforts at mitigating these impacts; the pattern of adoption and usage of WI by artisanal fishers both coastal and inland; and the ways in which WI products can be developed to suit the circumstances of different fishers. All the 29 fishers who participated during this phase were artisanal marine fishers. The second phase of interviews focused more on inland fishers and began in January 2022 when 30 respondents were recruited from Ghana, Senegal, and Nigeria (Table 1). Like the first phase, these respondents were recruited through snowball sampling. 21 of them were inland fishers and nine were fishmongers. To make the best use of the data collected for this study and to meet the research objectives, all data (first and second phase) were analyzed through "hybrid thematic content analysis" (Nowell et al., 2017; Xu and Zammit, 2020). Identified themes across datasets were threaded together, and the frequencies with which themes occurred were converted to percentages (i.e., of interviews in which they emerged).

4 Results

The results of the fieldwork are divided into three subsections- fishers' perceptions of 1) the impact of climate change on their activities; 2) efforts at mitigating the impact of climate change on them; and 3) the pattern of their adoption and usage of WI and across the case study countries.

4.1 Fishers' perceptions of the impact of climate change on their fishing activities

Although about 40% of the artisanal fishers who participated in this study were not familiar with the phrase "climate change," all the 50 artisanal fishers, the 20 women employed directly in fishing or secondary activities, and the 10 staff from fisheries and meteorological agencies agreed that the rivers, seas, and lakes are changing and that these changes are directly impacting the fishing activities. All 50 respondents directly involved in fishing mentioned rainfall loss and wind and temperature variations as the most important elements of weather and climate that are changing and impacting negatively on their fishing activities. Rainfall is good for fishing: KI-1 said marine artisanal fishers' welcome rainfall (though not with wind): "*if it rains heavily without strong winds, then we would catch plenty fish. . .rain brings fish" (KI-55)*. Similarly, about 65% of inland fishers believe that heavy rainfall is helpful because by increasing the volume of water in dry lakes and rivers, it increases the quantity of fish in them:

> "*When there is excessive rain sometimes leading to flooding, the water from the rain will enter every nook and cranny and our belief is that we are surrounded by water everywhere and where there is water there are fishes. So, with the heavy rainfall, all the fishes hiding are forced to come out. In fact, sometimes when you catch some fishes, you will see rust stain on their back signifying that they have stayed hidden for a long time in wherever they hid themselves. We catch different varieties of fish during this time. . . these fishes have stayed so long in their hiding places*" (KI-10).

However, the pattern of rainfall is changing and becoming less plentiful: "*rainfall in the past was heavy and frequent. . .*

our lakes and rivers are drying; it is very hard to catch a bowl of fish" (KI-17). KI-40 said "*Fish do not like shallow rivers, when the water begin to reduce, the fish know that the water is reducing, so they will look for where to hide and only a handful of them will be available. This makes our catch to reduce.*"

For the marine artisanal fishers, the wind is classed as the most dangerous element of weather and climate that affects their fishing activities: "*wind is very dangerous for our canoes…if it is windy, the sea is rough, it affects every fisherman, it causes accidents*" (KI-1). KI-2 said "*we cannot control the wind and the swells*". KI-19, another marine artisanal fisher, said "*it is very dangerous to go to the sea when it is windy*"; in addition, "*it is hard to catch any fish when it is windy*" (KI-45). Also, rising sea temperature is a problem. Although the fishers do not understand the science, most of them observed that the waters are getting unusually warmer; thus, according to KI-16 (marine artisanal fisher) "*it affects our fishing, we now travel far into the sea to look for fish.*"

Climate change affects not only fishers (marine and inland) but also those involved in secondary activities, including fishmongers and women investors (fish mammies). Indeed, it may affect secondary workers more than fishers: "*we can at least get one or two pieces of fish to eat and then sleep, but where will fish sellers find fish to buy, sell, and feed their family*?" (KI-1, marine artisanal fisherman). KI-33 (a fishmonger) said "*we need government and the authorities to help us…most of us have used up all our capital to feed our children, including monies borrowed from micro-finance banks of which we are paying interest on*". "*What am I going to do? No fish, so I grind maize and my family feeds on it morning, evening, and night*" (KI-31 inland fisherwoman), KI-51); an inland fisherman said "*when we get to the river these days, we spend several hours and catch little, tiny fishes…it was not so in the past*" (KI-51 inland fisherman). For the marine artisanal fishers, climate change has multiplied their problems: "*there is now a big change, fish is scarce, and I go very far to look for them…our fish is migrating, and we need to chase them. I start fishing from 3 a.m.*" (KI-1 fisherman). The operational cost of fishing is higher as compared to the past, so aside from spending more time in the sea, it has financial implications: "*I have been fishing for 35 years now, I did not travel far to catch fish, but nowadays, we do, and this very long-distance fishing consumes so much fuel*" (KI-57 fisherman). Another marine artisanal fisher (KI-18) says "*it is very expensive for us…we travel very far to catch fish*". As the cost of fishing continues to increase, K1-64 explains that it impacts household diets: "*believe me, you can spend so much to go to the sea and return with nothing…I mean when you sell the fish, there will be nothing left to feed your family, not even to buy bread.*" All 50 fishers stated that they need help to mitigate the impacts of climate change on their fishing activities.

4.2 Fishers' perceptions of efforts at mitigating the impact of climate change on them

Across the three case-study countries, open access fishing is the common policy in place to help fishers cope with the impact of climate change: "*we understand this, and this is why they* (artisanal fishers) *are allowed to fish without restriction…it is open access*" (KI-65, staff of fisheries agency). While this open-access fishing is meant to protect artisanal fishers from food insecurity, all the 29 marine capture fishers who participated in this study described this policy as futile, because it does not protect them from industrial fishing: "*industrial fishers practice irregular fishing…they fish from our own space* (inshore areas) *and the quantity of fish that they collect from our sea is affecting our own catch*" (KI-1, Senegalese artisanal fisherman). Likewise, KI-11, an artisanal fisherman from Ghana, says: "*everywhere in our water you will see big boats taking all our fish…what are we going to do*?" KI-16, another fisherman, said industrial fishers "*take all our fish, they* (industrial fishers) *are licensed to land demersal fish, but they catch our pelagic fish.*" However, KI-18, a staff of a fishing agency, pins some of the blame on artisanal fishers themselves:

> "*the fishing behavior of our artisanal fishermen also frustrates the process…they are hard to control, they fish without restrictions, and this is a big problem here, and then they blame the industrial fishermen for their inability to catch fish.*"

4.3 Fishers' perceptions of their adoption of weather information

4.3.1 Marine fishers in Senegal

About 55% of the respondents mentioned that weather information (WI) is currently helping fishermen cope with the impact of climate change. The WI Innovators are from international institutions, and they worked with national meteorological agencies in case-study countries: National Agency of Civil Aviation and Meteorology of Senegal (ANACIM); Ghana Meteorological Agency (GMet); and Nigerian Metrological Agency (NiMet). The Early Adopters include marine artisanal fishers from Senegal using motorized canoes who had earlier contact with Innovators (about 30% of respondents): "*for about six years, we have been getting support from outside organizations to improve our weather forecasting, and we are now sending weather climate information to fishermen for their safety on sea*" (K1-56, from ANACIM). This statement was confirmed by all the Senegalese artisanal marine fishers who participated in this study: "*we have been using these ANACIM* (weather information data) *for about 6–7 years*" (KI-1). ANACIM sends this product directly to their phones (KI-1, 66; 57). Television and radio are other communication channels through which these fishers access WI. KI-1 said, "*the service is much better now, if they* (ANACIM) *say it will rain, then it will.*"

For the Early Adopters, their decision to adopt this innovation is based on the following considerations: perceived relative advantage and observability; the innovation is not complex to understand and is compatible with their values and existing technical knowledge; and they can test this innovation with little investment. On relative advantage and observability, the fishers had previously relied on their traditional ways of reading the weather before fishing: "*by looking at the sea, stars, and sky, fishers can tell whether it is safe to go to the sea for fishing*" (KI-1); "*when the moon is dark, we get fish and when the moon is bright, we do not get fish*" (KI-23). However, according to KI-19, this information is not reliable: "*during those days, my father used to look at the moon and take his decisions, only for us to get halfway into the sea and return because of heavy winds*". In contrast to traditional weather predictions, fishers feel that the innovations in weather services saves them unnecessary journeys and fuel: "*if we hear that there would be storm at noon, we wake up very early to do our fishing*" (KI-2). With WI, these fishers can engage in supplementary livelihoods: "*if the forecast says that the weather will be bad, I will go and do another business*" (KI-3); "*once I hear that the weather is not good for fishing…I look for other things to do, so I can feed my children*" (KI-6). Like fishermen, women fishmongers in Senegal are increasingly using WI to make important decisions: "*I will not take any loan this season, they said there will be heavy wind and so we are not expecting fish*" (KI-37). Finally, most accidents are linked to the use of traditional weather forecasting: "*because these traditionalists* (fishers) *do not listen to ANACIM, and even when you tell them to wear vests, they decline…but things are changing out of 100 fishermen, more than 90 use ANACIM weather products*" (KI-6).

On complexity, compatibility, and trialability, a senior staff member of ANACIM said "*we are continuing to improve our products…for fishers that cannot read and write we normally use different colors of flag, like green, yellow, and red to demonstrate to fishers when it is safe to go to the sea*" (KI-56). Most fishers in Senegal are comfortable using this innovation, which is easy to access: "*personally before going to bed, I already know whether the sea will be rough or not, or whether it will be windy… ANACIM sends all these information*" (KI-1). KI-57 mentioned that phones, television, and the radio as channels through which they receive WI. The spread of WI in Senegal is also through networking: "*we have our Whatsapp group, we send information to our colleagues*" (KI-47). According to KI-48, a woman fishmonger, "*we get information* (WI) *from the fishers.*"

4.3.2 Marine fishers in Ghana and Nigeria

The Early Majority in Ghana are a set of artisanal marine fishers who accepted WI from the GMet (59% of respondents from Ghana): "*we have a database of marine artisanal fishers in Ghana…for those that we have their contact details, we send them WI and to be honest some of them appreciate and are using it*" (KI-13, staff member of fisheries agency). The Early Majority claim that WI is very helpful: "*the weather information that we get works for me…I cannot talk for others, but it should work for them as well*" (KI-59); "*whenever I receive this information on my phone, I plan my activities…if the information says that the weather will be rough, I look for other sources of income to feed my family until the weather changes*" (K1-18, fisherman). KI-66, a fisherman, said WI helps reduce his fishing operational costs:

> "*Before I started getting weather information on my phone, sometimes I made unnecessary journey to the sea and then when there was heavy wind, I had to rush out of the sea without anything to feed my family…I have 7 children, how to feed them becomes a problem*" (KI-70).

KI-67 said, "*all I know is that the traditional methods no longer work for me…I can no longer keep waiting for the moon, there is no fish in our water, the only thing that can stop me from going to the sea is when the forecast says there will be strong winds.*"

The Late Majority, who follow the Early Majority, are mostly marine artisanal fishers from Nigeria and women investors who sponsor fishermen, and they get WI from these fishermen: "*Mr X* (fisherman) *was the first person to talk to me about the weather information*" (KI-49). Women fish mammies benefit from WI: "*if the forecast says the weather will be fine, I look for money to support him* (fisherman), *if they say the weather will be bad, I will not borrow money to give him*" (KI-68).

On complexity, compatibility, and trialability, when compared to Senegal, the spread of WI in Ghana to both the Early and Late Majority is slower for several reasons, including the difficulty of understanding the weather information:

> "*this information is hard for some of our fishers to understand… some of these fishers do not understand English… Ghana is a multilingual country, we have over 50 languages, so how do we translate weather information into all these languages*?" (KI-66, staff member of fisheries agency).

4.3.3 Inland fishers from all three countries

Inland fishers from the three case countries are yet to adopt and use WI. Like other fishers who participated in this study, this set admit that climate change is affecting their fisheries: "*in the past, when I used to go to the river three or four times a day with my mother, we used to catch big fishes that filled our big basins… but now, you will go to the river and labor in vain for long hours, and then return home with only a handful of fish or no fish at all*" (KI-40). However, on relative advantage and observability, all fishers in this category attribute their changing weather patterns to the will of God and they are resigned to their fate: "*if God brings the rain, we thank him*" (KI-79). KI-80 said, "*all of these are the making of God . . . at the right time our rainfall will come and fill our river and like before we will start enjoying abundant fish*". This set of fishers depend on traditional methods for predicting their weather. For example, for rainfall, the signs are dark cloud and excessive heat; but if it becomes windy then "*we would know that it will no longer rain, the wind takes away our rain*" (KI-77). These fishers (76% of inland fishers) believe so strongly in their traditional methods that they distrust modern scientific meteorology. There were a few Late Majority in this category (47% of respondents) who joined this non-WI user group because a radio weather forecast had given them wrong information "*that program will tell us that there will be heavy winds and there would be no heavy wind*" (KI-76). On complexity, compatibility, and trialability, while this set of fishers do not routinely use WI, most of them will try it to test its accuracy: "*if they tell us that it will rain, we really want to see the rain*" (KI-75). Another reason for the low take-up rate of WI by inland fishers is because the fishery agencies focus on the marine sector: "*we send this information only to the marine artisanal fishers that use motorized canoes*" (KI-74 staff member of fisheries agency).

5 Discussion

There are four main questions for discussion in this section: 1) What is the extent of the impact of climate change on West Africa's artisanal fishery sectors and their fishers? 2) Have efforts at mitigating climate change helped fishers? 3) What is the proportion of artisanal fishers who make use of WI? 4) How can more fishers (especially inland) be encouraged to use WI?

On 1), the effect of climate change on artisanal fishers in West Africa, although it is hard to differentiate between the effects of illegal, unreported, and unregulated (IUU) industrial fishing and the effects of climate change on their fisheries, all the respondents in this study agreed that current patterns of rainfall, temperature, and wind are changing and these changes affect their fishing activities and thereby the quality of their lives (Muhala et al., 2021). But the level of vulnerability to climate change is not the same across the artisanal fishing sector (70% of all respondents). Inland fisheries, which also involve women, are more vulnerable than marine fisheries, which are mostly populated by men, because West African countries pay more attention to the marine artisanal fisheries than to the inland fisheries (Funge-Smith and Bennett, 2019; Lynch et al., 2016; Okeke-Ogbuafor et al., 2020; Smith and Basurto, 2019). Consequently, the often "neglected" inland fishers develop a lower adaptive capacity to cope with the impact of climate change (40% of respondents). Poorer than their male counterparts in the marine sector, the female inland fishers who depend on fishing from rivers, lakes, inland valleys, and streams are generally subjected to vague "open access fishing" regulations, which assume that fish is affordable and available to this group of fishers (Okeke-Ogbuafor et al., 2020).

On 2), the efforts at mitigating climate change, unlike, WI, which has immediate benefit to artisanal fishers (see Table 2), marine protected areas, co-management, wealth-creation, and social welfare measures have limited immediate benefits because they were developed to respond to the longer-term issues of poor fisheries management, overfishing, and declining fish stocks, which are currently undermining the livelihoods and incomes of West African artisanal fishers (Food and Agriculture Organization of the United Nations, 2015; Muhala et al., 2021; Okeke-Ogbuafor et al., 2021). While there is some merit in the argument that these four measures, if well-planned and implemented, could eventually help alleviate fishers' poverty, thus reduce their vulnerability and increase their adaptability to cope with the impact of climate change in the long-run, they are unlikely to have any immediate effect in reducing the fishing-dependent culture which currently threatens West Africa's already declining fish stock (Kituyi and Thomson, 2018). Unlike these long-term measures, the immediate effect of the use of WI is helping fishers and those involved in secondary activities assess the weather risks on their fishing activities.

On 3), the proportion of artisanal fishers adopting WI, the focus of the WI fishery agencies in the case countries is marine artisanal fishers and not their inland counterparts (46% of all respondents), so the larger proportion of users of WI come from the marine artisanal sector. This focus on marine artisanal fishers and the user-perceived qualities are particularly evident in Senegal (Rogers, 2003). Senegal has the advantage of time and management structures, which are especially important for the diffusion of innovation. International organizations have had a long engagement with partners in Senegal helping to improve their weather forecasting and communication (Muhala et al., 2021), while also understanding their users' needs. A total of 16 respondents from Senegal reported a significant improvement in the quality of WI that is currently sent to them when compared with the past. Senegal's fishers have gone beyond ANACIM's primary channels of communication to develop subchannels, including the use of WhatsApp groups, and word-of-mouth to convince more fishers and fishmongers employed in the secondary industry to adopt this innovation. The extensive adoption of WI by fishers in Senegal is due to the accuracy of its information and analysis which confers real-time advantages, including risk management during short- and long-term decision making, and this is helping to mitigate the impact of climate change on their fisheries. Ghana's high linguistic diversity slowed down the spread and adoption of weather information (see Section 4.3.2)

TABLE 2 Identified benefits of WI to fishers and those involved in secondary activities.

User	Risk and consequence	Benefit	% of respondents
Marine artisanal	Health and safety	Reduces operational costs: fishers reschedule fishing time	51
	Loss of life, properties, and increasing operational cost		
Fishmongers	Fish is highly perishable	Make rational decisions about whether to buy fish or where to sell quickly	56
	Loss of profit or business capital and impact on household income		
Fishers and fishmongers	Zero catch	Invest in supplementary livelihoods for income and food security	57
	Impact on household income, food security, and nutrition		
Artisanal marine fishers and fishmongers	Declining fish catch	Taking long-term decisions investing in alternative livelihoods	32
	Loss of business capital, inability to pay off or service loans, and impact on household income and food security		
Fish mammies	Loss creditworthiness and repay with high interest	Recalculate the cost of short-term servicing of loans and invest in other businesses	29

Source: data are collected from case countries in 2021 and 2022.

On 4), encouraging artisanal fishers, including inland fishers, to use WI, there is a clear need for more collaborative action between stakeholders. The artisanal fishers are too important to ignore in West Africa, a region with a growing number of malnourished children, and so fishery agencies should pay particular attention to them. More research on this sector (especially inland fisheries) could help us understand how climate change impacts them, and this knowledge would be helpful in customizing WI into a form that will be tailored to meet their needs. While most marine adopters of WI are benefitting from the usage, including using it to plan supplementary and alternative livelihoods, inland fishers are yet to benefit and climate change has continued to impact on their fishing and farming activities.

6 Conclusion

There is evidence that artisanal fishers in West Africa are willing to adopt and use WI. The Early Adopters in Senegal and the Early Majority in Ghana are increasingly using WI for assessing risks and making management decisions related to their fishing practices, which are helping them to enhance their resilience to climate change. With a population of over 213 million people with varying demographic characteristics and over 500 languages, we can speculate that it could take much more time for innovations to spread in Nigeria. Unlike the long-term measures for mitigating the impact of climate change, the use of weather information has immediate benefit for fishers. It is already helping many marine artisanal fishers and those involved in secondary fishing activities in Senegal to take proactive decisions, including investing in supplementary livelihoods with some fishers moving to alternative livelihoods, thus building resilient household incomes. There are two key considerations for the lower rate of adoption and usage of WI in Ghana and Nigeria, especially by inland fishers. First is the lack of coordinated action between stakeholders (researchers, representatives of local communities, Ministry of Fisheries, Meteorological Agency, and inland fishers) to understand the WI needs of inland fishers in order to coassess and codevelop bespoke weather products that offer benefits to this set of fishers. The second reason is cultural: most inland fishers still practice traditional fishing, holding strongly to their culture, and are skeptical about innovations and change. As a result, inland fishers remain most vulnerable to the impacts of climate change, yet this fishing sector is critical for food security, nutrition, and income. West Africa's fisheries, especially the inland sector, are too important to ignore, and to help this sector fully benefit from the use of WI, this study recommends a detailed study into the WI needs of these fishers.

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.

Ethics statement

This research followed the research and ethics guidelines of University of Leeds. Participants provided their consent and were debriefed. The University of Leeds research ethics committee approved this research.

Author contributions

Conceptualization: NO-O, AT, AD, TG, and SS. Method: NO-O. Validation: AT, AD, SS, TG, and NO-O. Formal analysis: NO-O, AD, and AT. Formal writing—original draft preparation: NO-O and TG. Review and editing: all authors reviewed and edited the draft. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Relationship between microclimate and cow behavior and milk yield under low-temperature and high-humidity conditions

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This study aimed to evaluate the relationship between temperature (T), relative humidity (RH), and temperature and humidity index (THI), milk yield (MY), rumination time (RT), and activity (AT) of dairy cows in different parities under low temperature and high humidity (LTHH). In this study, the number of samples each day was determined by all healthy cows in the barn with parity and days in milk (DIM) within 5 and 305, respectively. The box plot method was used for screening and removing outliers of dairy cow indicators after classification according to parity and DIM. To remove the effect of DIM on MY, a bivariate regression model was used to standardize the MY in milk yield index (MYI). The best bivariate regression model based on the lowest Akaike information criterion was used to analyze the relationship between behavioral parameters, MYI, and microclimate indicators for each parity. In the barn with the microclimate at a low temperature above 0°C, high RH was negatively correlated with MYI in primiparous and multiparous cows but positively correlated with AT in primiparous and multiparous cows and RT in multiparous cows ($p<0.05$), so RH was a significant factor related to MYI, RT, and AT of cows. The 2-day lagged daily average T and THI were correlated with MYI in primiparous cows ($p<0.05$). The inflection point value of 71.9 between AT and RH in the multiparity as the upper limit of RH was beneficial for improving comfort and MY in all parity dairy cows. Compared with MYI and RT, AT had a higher R^2 with a microclimate indicator, so it could be used as a better indicator for assessing the LTHH. Comparing the R^2 of multiparous cows to T (R^2=0.0807) and THI (R^2=0.1247), primiparous cows had higher R^2 in MYI to T (R^2=0.2833) and THI (R^2=0.3008). Therefore, primiparous cows were more susceptible to T and THI. The inflection point values for MYI to T and THI were greater in primiparous cows than in multiparous cows, indicating that primiparous cows had a smaller tolerance range to T and THI than multiparous cows. Thus, parity should be considered when studying the relationship between MY, T, and THI under LTHH.

KEYWORDS

low temperature and high humidity, milk yield, rumination time, activity, parity

1. Introduction

There is a growing interest in dairy cow welfare (von Keyserlingk et al., 2013; Tucker et al., 2021), which is closely related to the environment. As a major factor in the indoor barn environment, climate affects the welfare level of dairy cows (Honig et al., 2012; Polsky and von Keyserlingk, 2017). Previous studies have shown that heat stress occurs in cows when the temperature and humidity index (THI) of the environment is above 72 and that milk yield

(MY) decreases by 0.2 kg for a unit increase in THI (Ravagnolo et al., 2000; West, 2003). In heat stress, cows will spend more time standing, less time activity (Cook et al., 2007; Allen et al., 2015; Polsky and von Keyserlingk, 2017), and less time rumination with increasing temperature (T; Blackshaw and Blackshaw, 1994). The comfortable ambient T for dairy cows is between 5 and 15°C (Hahn, 1999; Kadzere et al., 2002). Due to the extremely low T in northeastern China for 6 months, large intensive farms often use fully enclosed housing management to keep warm. However, this management leads to the humidity in the barn being difficult to discharge thus increasing humidity. High humidity conditions weaken the dairy cow's fur insulation, resulting in quicker heat loss (Angrecka and Herbut, 2015). Therefore, T alone is insufficient to assess the effect of housing microclimate on dairy cows (Degen and Young, 1993), and humidity should be considered. Low-temperature and high-humidity (LTHH) microclimate in the barn may cause cows to exceed their comfort zone, thus negatively impacting welfare.

Animal behavior can reflect the condition of the environment, and this behavioral performance helps evaluate the level of animal welfare (Cook et al., 2005; Godyn et al., 2013; Hoffmann et al., 2020). There is evidence that dairy cows adjust their productivity and behavior to microclimate conditions (Angrecka and Herbut, 2016; de Sousa et al., 2021). The lying time of dairy cows can reflect their welfare level to some extent (Tucker et al., 2021), and therefore has been used as an indicator to evaluate cow welfare in several studies (Fisher et al., 2003; Tucker et al., 2003; Schütz and Cox, 2014). Wet surfaces reduce lying time (Tucker et al., 2007; Schütz et al., 2019), thus, this may result in a corresponding change in activity time (AT) for dairy cows housed in winter. The rumination time (RT) is mainly related to diet composition (Beauchemin, 2018). However, the reduction in RT may also be related to the stress that the dairy cow is experiencing (Paudyal, 2021). The MY can be interpreted to be a direct welfare indicator (Polsky and von Keyserlingk, 2017). Therefore, MY, RT, and AT changes can reflect dairy cows' climatic environment and welfare level. The smart collar and milking robot accurately monitor dairy cows' daily RT, AT, and MY, making obtaining behavioral indicators non-invasive and non-stressful (Schirmann et al., 2009; Burfeind et al., 2011).

The temperature and humidity index is used to assess changes in the T and humidity of the environment and is commonly used in studies of heat stress in dairy cows (Bernabucci et al., 2014; Menta et al., 2022). Also, Li et al. (2021) used it to describe the climate's humidity and coldness in a free-stall barn (indoor). Angrecka and Herbut (2015) used the wind chill temperature (WCT) index to measure the effect of cold stress on dairy cows in a free-stall barn (indoor). However, T and humidity are important factors for the microclimate of a fully enclosed barn in cold conditions (Buonomano et al., 2017).

To our knowledge, little information is available evaluating the effect of LTHH conditions on MY and behavioral indicators of lactating dairy cows. This study aimed to evaluate the relationship between T, humidity, and THI and MY, RT, and AT of dairy cows in different parities under LTHH conditions to understand the effects of LTHH on dairy cow welfare and to provide a reference for comfortable management of LTHH environments and early development of automatic early warning systems. We hypothesized that dairy cows' MY, RT, and AT are related to T, humidity, and THI, but different parities respond differently to T, humidity, and THI.

2. Materials and methods

2.1. Farm

The experiment was performed under an experimental license from Northeast Agricultural University, Harbin, China. All experimental procedures were conducted in accordance with the principles and responsibilities outlined in the university's guidelines for animal research. This study was conducted on a commercial farm in Heihe City in northeastern China (49°0′6 ″N, 126°2′24 ″E), with a cold-temperate continental monsoon climate. The barn was fully enclosed with a half-bell tower roof. The middle of the barn was a feeding path and there were four pens in the barn.

2.2. Animals and management

A total of 854 healthy Holstein cows were used for the study. Each day, the number of samples included in the study was determined by all healthy cows in the barn with parity and DIM within 5 and 305, respectively. The average parity was 3 ± 1 (mean ± SD). The dairy cows were housed in a free-stall barn with sand bedding and milked two times daily (0600 and 1800 h). Dairy cows were fed a TMR to meet or exceed dietary nutritional requirements (NRC, 2001) and drank freely at all times.

2.3. Sensors and dataset

A fully automated temperature and humidity recorder (YDBS, China) was used to record the temperature and RH in the barn. Three temperature and humidity recorders were evenly distributed and installed in the barn, approximately 1.5 m high from the ground. Each recorder measured and recorded data once every 2 h (a total of 12 data records from 0000 to 2400 h every day). The recording was from 1 January 2021 to 30 April 2021. The formula reported by Kendall et al. (2008) was used to calculate the THI:

$$THI = (1.8*T+32)-(0.55-0.0055*RH)*(1.8*T-26)$$

Where T (°C) is the temperature and RH (%) is the relative humidity. This formula was chosen because it has been used previously in animal trials conducted in a continental climate (Schüller et al., 2014; Shock et al., 2016). T, RH, and THI recorded by three recorders every day were averaged to obtain the daily average of T, RH, and THI.

All dairy cows enrolled in the study were fitted with a smart collar sensor (SCR, Israel) measuring activity with a 3-axis accelerometer and rumination with a microphone and microprocessor. The SCR system was validated by Schirmann et al. (2009) and Ambriz-Vilchis et al. (2015). The SCR recorder calculated and summarized the data every 2 h and finally reported the total AT and RT data from 0 to 24 h every day to SCR DataFlow™ II System software as the daily AT (units/d) and RT (min/d). The recording was from 1 January 2021 to 30 April 2021. The milk hall was equipped with milking machines (SCR, Israel) that can measure the MY of each dairy cow from the milking parlor by infrared and upload data to the SCR DataFlow™ II System. The daily MY of each dairy cow was the sum of two milkings. Then, the daily MY of all cows included in the study every day was averaged as the daily MY. The recording was from 1 January 2021 to 30 April 2021.

2.4. Data processing and statistical analysis

The MY, RT, and AT were acquired from the SCR DataFlow™ II System. Data for T and RH were exported into an Excel spreadsheet (Microsoft Corp., Redmond, WA). The JMP Pro 16 (SAS Institute, NC) is the data processing and statistical analysis software used in this experiment.

The boxplot method can truly represent the data distribution and ensure that the results of identifying outliers were more objective. Dairy cows were grouped according to parity (1–5) and DIM (1–305 days). The boxplot method of JMP Pro 16 was used to mark the outliers of MY, RT, and AT in each group and remove them. The range of outliers defined in the boxplot was less than QL - 1.5 IQR or greater than QU + 1.5 IQR (QL: lower quartile, indicating that a quarter of the observed values in each group are smaller than it; QU: upper quartile, indicating that a quarter of the observed values in each group are larger than it; IQR: interquartile spacing, indicating the difference between the upper quartile QU and the lower quartile QL).

To avoid the influence of DIM and parities on MY, MYI was used to evaluate the MY of each dairy cow. The MY was grouped according to parity and DIM, i.e. MY with the same parity and the same DIM were in the same group, and then the maximum milk yield of the same group was selected as the dependent variable in the bivariate regression model. Models were compared using R^2, and models that best explained the milk variations in DIM were chosen based on the highest R^2 value. The standard MY of the same DIM was calculated according to the fitting function of the best model. The formula of MYI is

$$MYI = \left(DMY - SMY + MMY\right) * 100 / SMY$$

where DMY is daily MY, SMY is standard MY, and MMY is maximum milk yield.

To evaluate the relationship between T, RH, and THI and MYI, AT, and RT, daily average T, RH, and THI corresponded to daily MY, AT, and RT as the input variables of the model. In addition to considering the relationship between the current day and MYI, the relationship between measures 1, 2, and 3 days before the current day and MYI was determined (Collier et al., 1981; West et al., 2003). These relationships were termed the lag effects, which consider the environmental effects that occurred 1, 2, or 3 days before the day in which milk yield was measured by the fit curve of JMP Pro 16 and fitting the following linear mixed-effects model:

$$Y = \beta_0 + \sum_{j=1}^{k} \beta_j THI^j + \varepsilon$$

where Y is a measurement of dependent variables (daily MYI, RT, and AT), k is the order of the polynomial, β_0 is the intercept, β_j represents the estimated coefficients of the fixed effect of daily average T, RH, and THI, and ε represents the random residual effect.

Models were compared using AIC, and models that best explained the day-to-day variations in MYI, RT, and AT were chosen based on the lowest Akaike information criterion (Cook et al., 2005) and then determined whether it was relevant based on the significant threshold level ($p < 0.05$).

3. Results

Since the data (MY, AT, and RT) recorded by the system on 23 April 2021 was considered an outlier, all the data for that day was removed. To make the results representative, we removed the data records corresponding to the daily average T higher than 15°C (21 and 22 April 2022). The distribution of all dairy cows by MYI, RT, and AT is shown in Table 1, and the barn by T, RH, and THI is shown in Table 2 and Figure 1.

3.1. The relationship between MYI and T, RH, and THI

Figure 2 shows that both primiparous and multiparous cows are related to T ($p < 0.0001$ and $p = 0.0083$, respectively; Figures 2A,D, respectively). However, the MY of primiparous cows was related to the 2-d lagged daily average T. The R^2 was lower for multiparous cows ($R^2 = 0.0807$, Figure 2D). MYI of the primiparity decreased as the T increased from 0.6 to 8.6 (Figure 2A). However, the MYI of the multiparity decreased with increasing T from 0.6 to 5.2 (Figure 2D). Thus, the different T ranges indicated a difference in the appropriate T range (from the inflection point value to the upper limit of the comfort zone temperature) for the primiparous and multiparous cows.

Both primiparous and multiparous cows were related to RH ($p = 0.0018$ and $p < 0.0001$, respectively; Figures 2B,E, respectively). MYI tended to decrease with RH increasing when RH was in the range of 77.5 to 88 for primiparity (Figure 2B). However, the relationship between MYI and RH took on a negative linear correlation trend for the multiparity throughout the test period (Figure 2E). Overall, RH had different effects on the MY of primiparous and multiparous cows.

Figure 2 shows that both primiparous and multiparous cows are related to THI ($p < 0.0001$ and $p = 0.0005$ respectively; Figures 2C,F, respectively). However, the MY of primiparous cows was related to the 2-d lagged daily average THI. MYI of the primiparity decreased with increasing THI when THI was 35.4 to 49.8 (Figure 2C). Similarly, the MYI of the multiparity decreased with increasing THI from 35.4 to 42.8 (Figure 2F). Therefore, the different THI ranges indicated a difference in the appropriate THI range for the primiparous and multiparous cows. In conclusion, the MY of the primiparous and multiparous cows responded differently to T, RH, and THI under LTHH conditions.

TABLE 1 Descriptive statistics of the milk yield index, rumination time, and activity in relation to lactation number.

Item	Parity	N[1]	Mean±SE
[2]Milk yield index	Primiparity	20,193	67.65 ± 0.10
	Multiparity	37,262	69.33 ± 0.08
Rumination time, min/days	Primiparity	19,941	540 ± 0.41
	Multiparity	46,781	541 ± 0.29
Activity, units/days	Primiparity	20,073	508 ± 0.40
	Multiparity	46,453	472 ± 0.28

[1]*N* = sample sizes are given under N as the number of records.
[2]MYI = (DMY − SMY + MMY) * 100/SMY. DMY is daily milk yield, SMY is standard milk yield, and MMY is maximum milk yield.

TABLE 2 Descriptive statistics for temperature and relative humidity in relation to month number recorded by fully automated temperature and humidity recorder (1 January 2021 to 30 April 2021) and for temperature–humidity index (THI) calculated from temperature and relative humidity data using Equations (1).

Item	Month	N[1]	Statistic			
			Mean	SD	Minimum	Maximum
Temperature, °C	January	1,116	3.5	1.69	0.6	6.8
	February	1,008	6.7	2.32	1.5	10.6
	March	1,116	9.2	1.81	5.7	12.4
	April	1,080	9.8	3.43	4.0	18.6
RH	January	1,116	82.8	1.50	80.3	88.1
	February	1,008	82.9	1.77	80.5	86.9
	March	1,116	67.7	10.20	51.0	83.6
	April	1,080	47.7	7.14	39.3	69.4
THI	January	1,116	40.1	2.79	35.4	45.6
	February	1,008	45.3	3.89	36.6	51.7
	March	1,116	50.1	2.88	44.0	55.1
	April	1,080	52.0	4.51	44.2	63.1

[1]N = sample sizes are given under N as the number of records.

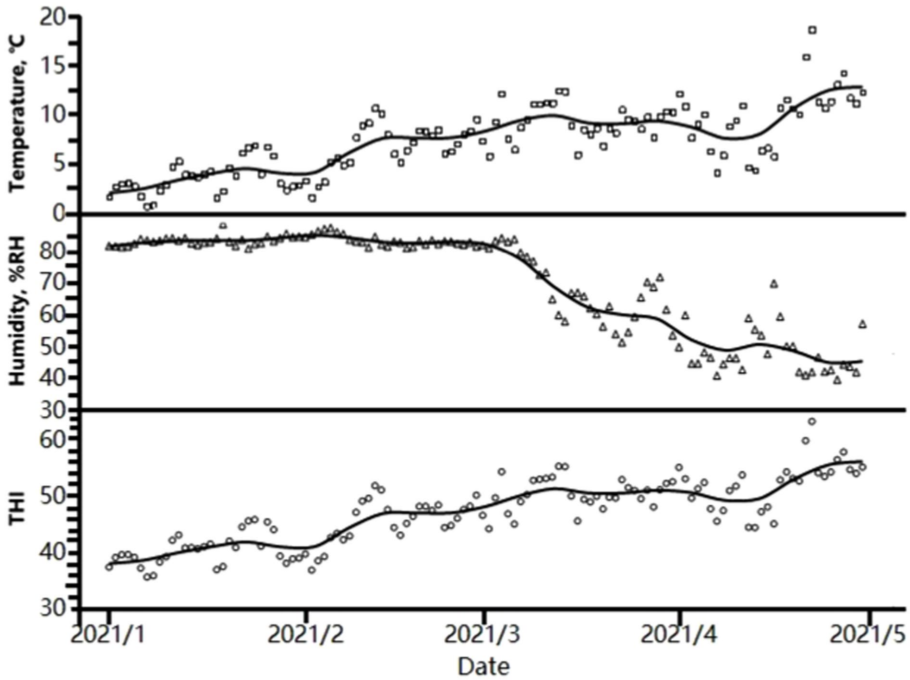

FIGURE 1
Mean daily temperature, relative humidity, and temperature–humidity index (THI) in the barn of the research farm, Heihe, China, during the study period (January 2021–April 2021).

3.2. The relationship between RT and T, RH, and THI

Figure 3 shows that the rumination of primiparous cows was related to T (Figure 3A), RH (Figure 3B), and THI (Figure 3C), with p-values ranging from 0.0754 to 0.1109. For multiparous cows, the RT was not related to T and THI ($p = 0.0877$ and $p = 0.0621$, respectively; Figures 3D,F). However, the rumination time of multiparous cows was related to RH ($p = 0.0021$), and when RH was in the range of 74.9 to 88, the rumination time of multiparous cows increased with increasing RH (Figure 3E).

3.3. The relationship between AT and T, RH, and THI

Figure 4 shows that AT is related to T in both primiparous and multiparous cows ($p < 0.0001$ and $p = 0.0004$, respectively; Figures 4A,D,

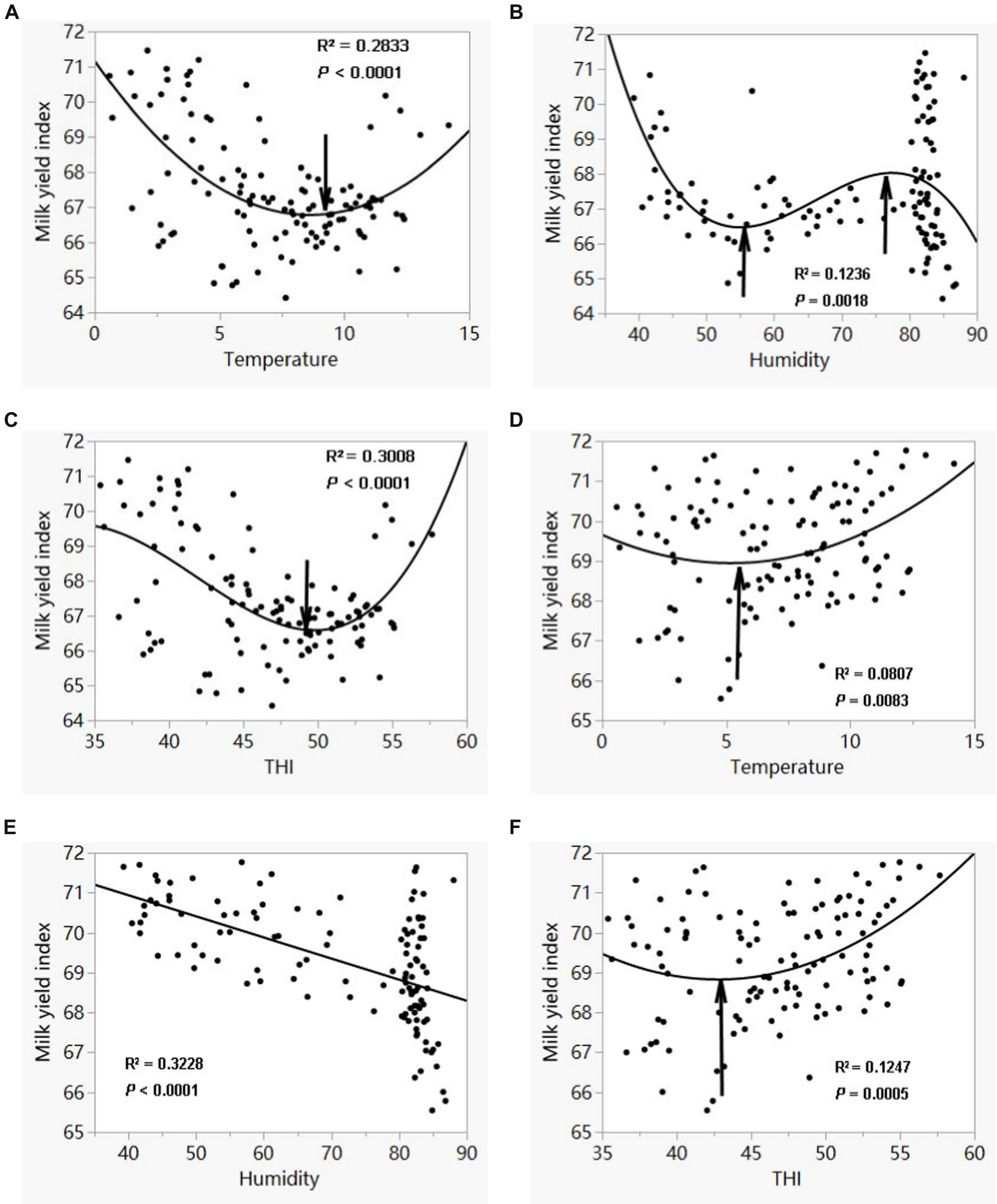

FIGURE 2
The relationship between milk yield index and **(A)** temperature (the 2-day lagged daily average temperature), **(B)** humidity, and **(C)** THI (the 2-day lagged daily average THI) of the primiparous dairy cows. The relationship between milk yield index and **(D)** temperature, **(E)** humidity, and **(F)** THI of the multiparous dairy cows.

respectively) and varied in a similar pattern with T with inflection points of 5.7 and 6.1, respectively, with AT decreasing with increasing T below inflection points.

AT of both primiparous and multiparous cows was related to RH ($p < 0.0001$ and $p < 0.0001$, respectively; Figures 4B,E, respectively) and was more highly correlated with RH ($R^2 = 0.2888$ and $R^2 = 0.3657$, respectively) compared to T and THI. The RH change pattern was similar for the primiparous and multiparous cows, with RH inflection points of 76.9 and 71.9, respectively, and the AT increased with increasing RH above inflection points.

Both primiparous and multiparous cows were related to THI ($p < 0.0001$ and $p < 0.0001$, respectively; Figures 4C,F, respectively). AT of the primiparity decreased with increasing THI at THI below 44 (Figure 4C). Similarly, AT of the multiparity decreased with increasing THI at THI below 44.5 (Figure 4F). In summary, AT of the primiparity and multiparity responded similarly to T, RH, and THI under LTHH conditions.

4. Discussion

According to West (2003), a thermoneutral zone ranging between −0.5 and +20°C is acceptable for dairy cows. Although our results showed that the average daily T in the barn was above 0°C, MY, RT, and AT still varied with T, RH, and THI under LTHH conditions. This indicates that

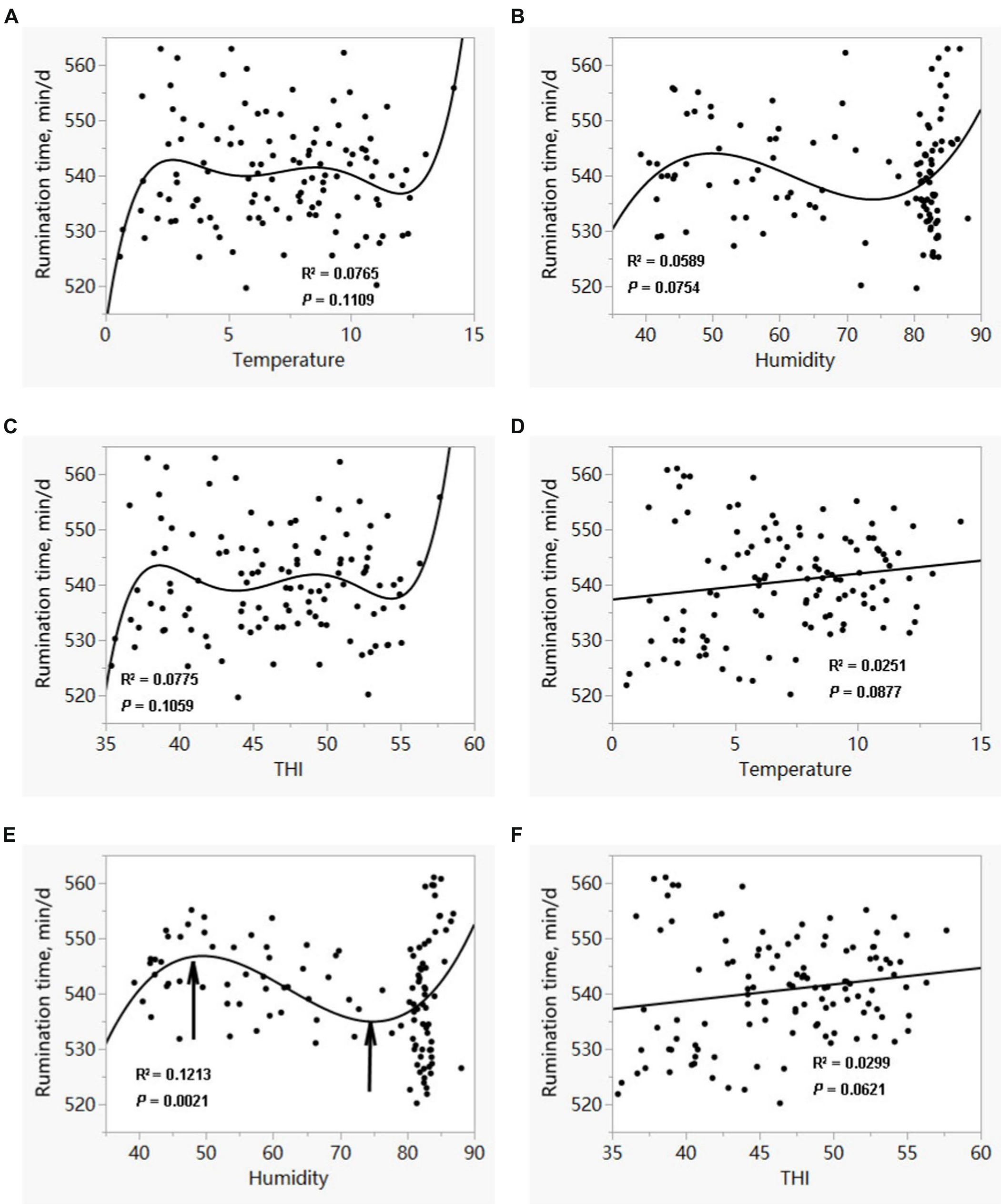

FIGURE 3
The relationship between rumination time and **(A)** temperature, **(B)** humidity, and **(C)** THI of the primiparous dairy cows. The relationship between milk yield index and **(D)** temperature, **(E)** humidity, and **(F)** THI of the multiparous dairy cows.

high humidity at low T was an important environmental factor affecting dairy cows' MYI, RT, and AT. In addition, our results showed that the difference in inflection point values of MYI in T and THI between primiparity and multiparity was large and that the trend with RH was different for different parities. This suggested that different parities of dairy cows had different ranges of adaptation to T, humidity, and THI. Therefore, the same T, RH, and THI levels were not used to assess the response of dairy cows of different parities to LTHH (Hammami et al., 2013), and the parity was a factor that cannot be ignored when assessing the effect of cold and high humidity on dairy cows. Although our results showed that the R^2 values (from 0.0807 to 0.1848) of the models assessing MYI with RH in primiparous cows, MYI with T and THI in multiparous cows, AT with T in primiparous and multiparous cows, and AT with THI in multiparous cows were small, the R^2 value of the model by Stone et al. (2017) assessing the correlation between THI and cow lying time was 0.01 and they concluded that THI was related to lying time. This shows that the level of R^2 value cannot be used to determine whether there is a correlation or not, but rather the *p*-value is used to determine the correlation, so our results assessing the correlation between T, RH, THI and MYI, RT, and AT under LTHH conditions are reliable.

4.1. The relationship between MYI and T, RH, and THI

The findings of this study showed that MYI of both primiparity and multiparity was related to T, humidity, and THI, indicating that the microclimate of the barn affects MY (Vaculíková et al., 2017).

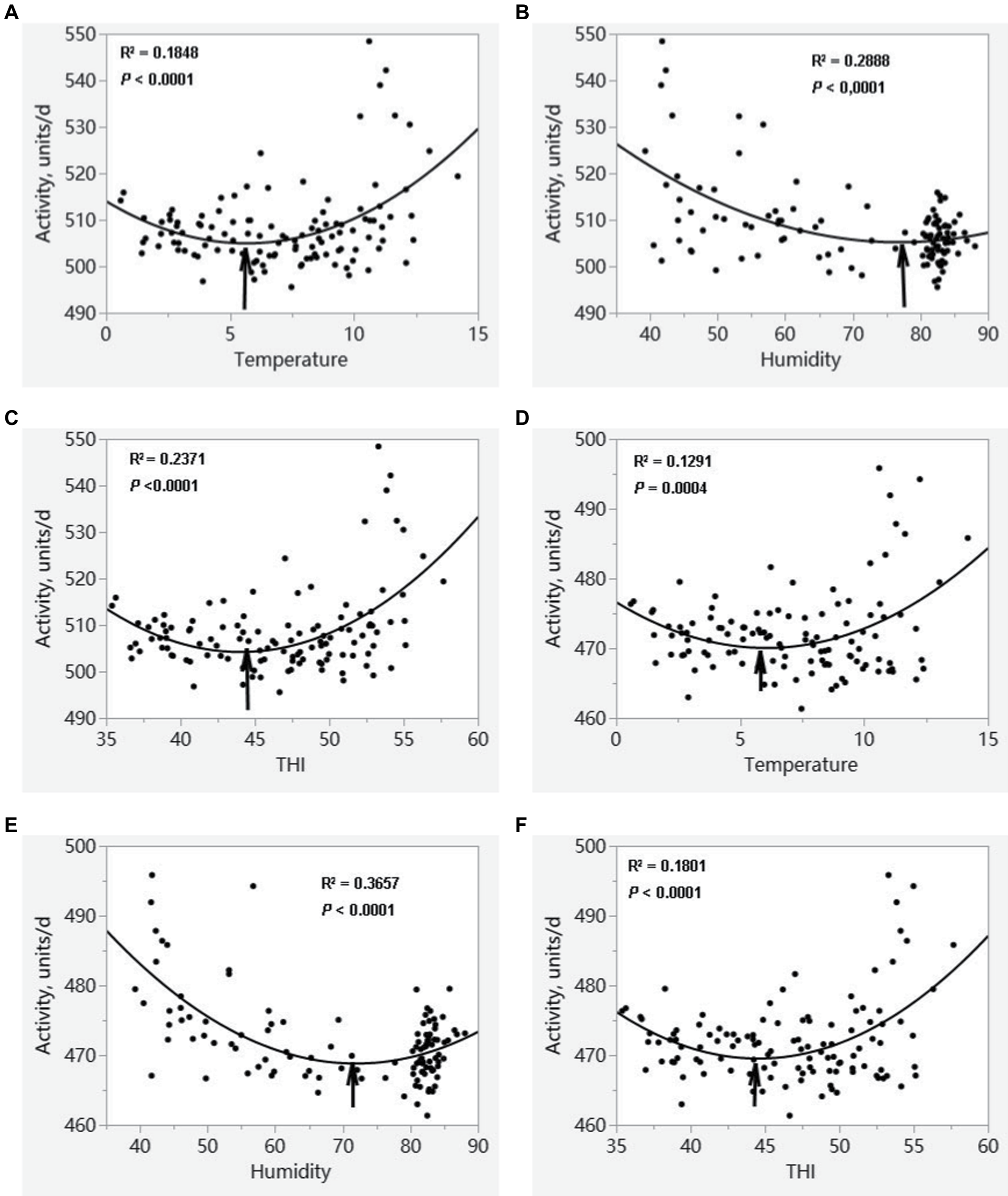

FIGURE 4
The relationship between activity and **(A)** temperature, **(B)** humidity, and **(C)** THI of the primiparous dairy cows. The relationship between milk yield index and **(D)** temperature, **(E)** humidity, and **(F)** THI of the multiparous dairy cows.

However, the MYI of dairy cows in response to T, RH, and THI at LTHH varied from parity to parity. Compared to multiparous dairy cows, primiparous dairy cows had higher R^2 in T and THI, suggesting that T and THI explained more variation in MYI in primiparous dairy cows than in multiparous dairy cows, and therefore primiparous dairy cows were more susceptible to the effects of T and THI. In addition, our results suggested that the inflection point of MY with T for multiparous dairy cows was 6.1, which is similar to the lower critical T of 5, considered by Vtoryi et al. (2018) as the most suitable for cow production. However, the inflection point values of MYI in relation to T and THI for primiparous dairy cows were greater than those for multiparous dairy cows, indicating that the T and THI tolerance range of primiparous cows is less than that of multiparous cows. This difference may be because primiparous dairy cows are still in the growth phase and the energy obtained from the diet must be distributed to growth (Wathes et al., 2007), thus compared to the multiparous dairy cows, the primiparous dairy cows use less energy to maintain body T balance. The MY increased with an increase in lactation (Vijayakumar et al., 2017) and an increase in the number of mammary epithelial cells (Herve et al., 2016). For high-yield dairy cows with the multiparous dairy cows (Lee and Kim, 2006), more metabolic heat is generated during milk synthesis to maintain body T balance (Marumo et al., 2022), so the multiparous dairy cows have a higher tolerance to low T than the primiparous dairy cows. In addition, primiparous cows are lighter than multiparous cows, so the ratio of surface area to volume will be slightly higher, thus predisposing them to heat loss. Interestingly, our study found that the MY of primiparous cows was related to the 2-day lagged daily average temperature and THI, but not to RH on the current day. This delayed effect may be related to a change in feeding or a delayed response to a change in the metabolic or endocrine status of the animal (Collier et al., 1981; West et al., 2003). Changes in RH may rapidly change the endocrine status of the cow thus leading to MY in relation to the daily average RH of the current day. This suggests that in dairy management, we should take immediate action to reduce the loss of MY at the time of climate change, rather than taking action after MY has decreased.

For primiparous cows, MYI decreased with increasing RH at RH greater than 77.5. Interestingly, Sharma et al. (1988) found in their study of heat stress in dairy cows that optimal conditions for MY were maximum T below 19.4°C and minimum RH between 33.4 and 78.2%. This means that in both cold and hot conditions, when the humidity in the barn exceeds about 77, it will have a negative impact on milk yield. However, a negative linear correlation existed between the MYI of multiparous cows and RH. This can be attributed to the fact that at higher RH, dairy cows transfer net energy for heat production to maintain heat balance resulting in lower MY (Brouček et al., 1991; Collier and Gebremedhin, 2015). The MY is a direct reflection of the welfare level of the dairy cow (Polsky and von Keyserlingk, 2017). Our results suggest that higher RH plays a negative role in the welfare of primiparous and prolific cows under LTHH conditions. Thus, it is important for farm managers to control the RH to maximize the productive performance of animals during the period of LTHH (Marumo et al., 2022).

Previous works assessing the effect of cold stress on MY have given conflicting views on the T at which the MY begins to decrease (Young, 1983; Brouček et al., 1991; Kadzere et al., 2002). Our results also suggested that MY was affected in a proportion of dairy cows even when the T was above 0°C. Therefore, the low critical T should be defined with caution after full consideration of the interaction of several climatic factors. In addition, our study showed that the MYI of the multiparous dairy cows at THI below 42.8 decreased with increasing THI, while Hammami et al. (2013) found that MY decreased in assessing the effect of THI on MY with increasing THI when THI is below 62. This may be because their T and humidity data were obtained from a nearby weather station, which does not accurately represent the microclimate in the barn, thus affecting the determination of the inflection point. Barn microclimate would have provided a better understanding of the effect of ambient T and humidity on dairy cow performance (Gauly et al., 2013). In conclusion, microclimate should prevail when assessing the effect of the environment on housed cows, and the role of RH on T should be considered.

4.2. The relationship between RT and T, RH, and THI

Rumination time is commonly used to assess heat stress in dairy cows and exceeding the critical threshold RT that negatively correlates with THI (Soriani et al., 2013; Moretti et al., 2017). However, our results showed that THI and T under LTHH did not correlate with RT, whereas only the RT of multiparous cows correlated with RH and increased with increasing RH. This may further suggest that the physical and chemical composition of the diet and NDF intake were the most important factors influencing RT (Beauchemin, 2018). Therefore, RT cannot be used as an assessment factor for the effect of LTHH.

4.3. The relationship between AT and T, RH, and THI

The high R^2 values of AT with T, RH, and THI, compared to MYI and RT, indicated that AT was a better factor in assessing the influence of LTHH. In addition, comparing T and THI, AT had a high R^2 value with RH, suggesting that humidity strongly correlated with AT under LTHH conditions and was an important factor that could not be ignored in influencing cow AT.

Primiparous and multiparous cows presented similar trends, showing higher AT at lower levels below the inflection point of T and THI and at higher levels above the inflection point of RH. Higher AT levels indicate that cows spend more time exposed to wet surfaces, leading to paws that absorb moisture and become soft, raising the risk of lameness (Borderas et al., 2004). Keeping track of changes in cows, AT provides insight into the levels of T, RH, and THI in the barn and can be useful in preventing the occurrence of lameness (Tolkamp et al., 2010), which is beneficial to the welfare of the dairy cow. In addition, higher AT levels mean that cows tend to spend less time lying down, thus reducing their comfort. This phenomenon can be explained by the fact that active cows generate more heat to maintain body T than lying cows (Tucker et al., 2007). However, we need to investigate further the variation of active and lying time with T and humidity, which will help us fully understand cows' behavioral changes under LTHH conditions.

5. Conclusion

In the barn with the microclimate at low T above 0°C, RH correlates with MYI and AT in primiparous cows and RT in multiparous cows, so RH is a significant factor related to MYI, RT, and AT in cows. In addition, the inflection point value of 71.9 between AT and RH in the multiparous cows as the upper limit of ambient RH is beneficial for improving comfort and maintaining good performance in all parity dairy cows. AT was a better factor in assessing the impact of LTHH than MYI and RT. The vulnerability of MY to T and THI, as well as the smaller range of tolerance to T and THI in primiparous cows compared to multiparous cows, suggests that parity should be considered when studying the relationship between MY and T and THI under LTHH conditions.

Data availability statement

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

Ethics statement

The animal study was reviewed and approved by Northeast Agricultural University. Written informed consent was obtained from the owners for the participation of their animals in this study.

Author contributions

JS and YS conceptualized and designed the study. JS conducted animal trials, analyzed some of the data, and drafted the original manuscript. QY, XW, and YW analyzed some of the data. YS and YZ reviewed and provided critical comments on the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Model emulators for the assessment of regional impacts and risks of climate change: A case study of rainfed maize production in Mexico

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The collection of publicly available databases about climate change and its impacts on natural and human systems is unprecedented and ever-growing. However, the requirements of information can vary widely among users depending on their region, socioenvironmental context, and interests. Moreover, in the current era of active mitigation and adaptation policies, information needs are frequently not satisfied even by these massive and variated collections of databases. The development and use of emulators can help closing this information gap by allowing users to approximate the output from complex models and create user-defined experiments, without being technically or computational demanding on the user. Here, a simple emulator of the EPIC biophysical crop model is presented which is able to adequately reproduce the changes in rainfed maize and to create projections for user-defined scenarios. Moreover, it allows to produce risk measures that are not available with the original model. The proposed methodology is illustrated with a case study of rainfed maize production in Mexico for a reference emissions scenario (SSP370) and two user-defined international mitigation policy scenarios. These scenarios represent 1) current international mitigation commitments and 2) a scenario in which China withdraws from international mitigation efforts. Results showed that, under the reference scenario, climate change could have widespread consequences on rainfed production all over the country with decreases in yields reaching up to 80% in the southeast and northeast of the country. These impacts can be partially modulated by the moderately ambitious mitigation commitments assumed in recent international agreements if all countries comply. However, a potential withdraw of China from these efforts would significantly reduce any benefits from international mitigation. Under all scenarios, changes in productivity impose increasing risks for already vulnerable populations and considerable economic costs at the state and national levels. These results suggest the urgent need for critical planning for adaptation in the agricultural sector of the country.

KEYWORDS

climate change, agriculture, emulator, risk, integrated assesment

1 Introduction

Climate change poses a serious risk to agriculture worldwide potentially compromising food security both globally and locally (Altieri and Nicholls, 2017). All domesticated crops, and particularly cereals, have been adapted to constrained climatic requirements that rely on predictable and recurrent climatic patterns. Deviations from these conditions have differential impacts on agricultural production around the world. It is expected that negative changes will be more evident in tropical regions where temperature is already close to the high temperature thresholds for suitable cereals production (Rosenzweig et al., 2014; Betts et al., 2018). Hazards of an altered climate on agriculture include the rise in global temperatures (Betts et al., 2018), the increment in frequency of extreme climatic events (Lesk et al., 2016; Cook et al., 2018) and a shift in precipitation seasonality (Zaveri et al., 2020). To understand and prevent the worst potential impacts of climate change on agriculture, a plethora of investigations have been conducted at different geographical scales from global to subnational (Ziska et al., 2012; Deryng et al., 2014; Rosenzweig et al., 2014; Lesk et al., 2016; Kukal and Irmak, 2018; Agovino et al., 2019; Jägermeyr et al., 2021; Kogo et al., 2021). Nevertheless, the availability of these main sources of information (satellites, censuses, surveys and models) and the spatial and temporal resolutions of these data products are not matching. In addition, these resources are frequently beyond of the computational abilities of different types of users which include policymakers (Kim et al., 2021). As a result, there is an urgent need to close the gap between the generation of sound scientific information, and its application in decision making to manage climate risks for global food systems facing climate change.

At least three approaches have been adopted to address the evaluation of climate change impacts on agriculture: empirical studies on observed climate variability and change and crop production; field experiments, and; process-based computational models. The first consists on case-studies of observed anomalous climatic events to exemplify the potential impact if similar conditions were to happen in the future. This type of approach is also used to extrapolate the impacts on crops under future climate conditions (Estrada et al., 2012; Iizumi and Ramankutty, 2015). This methodology has the advantage of being applicable at any spatial scale, thus potentially generating direct information for the decision makers. However, it usually involves using statistical models to extrapolate the effects of climate conditions beyond the range of observations in which the model was calibrated. In addition, climatic events as analogs of future climate conditions can offer little insight about how crops can respond to persistent climate conditions (Dell et al., 2014). A second approach is the employment of field trials, such as rain-exclusion and warming experiments (Robertson and Hamilton, 2015), which evaluate how crop yields could change in locally constructed future climatic conditions. Although they offer greater insights on potential response in face of future scenarios, their spatial extrapolation is limited to similar local conditions. Also, these studies are usually costly, limited to case studies and not feasible at the national or regional scales. The final approach has been the construction of computational models based on the processes that govern the agricultural systems and their relationships with climate. Despite limitations of their own (Rosenzweig et al., 2014), including that potential yields in general do not reflect the observed yields, this approach has enough flexibility to provide information at multiple spatiotemporal scales, including past events and future climatic scenarios.

Several global agricultural models have been developed in the last decades for generating climate change impact projections. The Environmental Policy Integrated Climate (EPIC-TAMU) is an open model which originally estimated the effects of soil erosion on crop productivity (Williams et al., 1984, 1989). The major components of this model are weather simulation, hydrology, erosion-sedimentation, nutrient cycling, pesticide fate, crop growth, soil temperature, tillage, economics, and plant environment control. Although EPIC operates on a daily step, it is capable of simulating hundreds of years (Williams et al., 2015). The EPIC-IIASA global gridded crop model (Balkovič et al., 2014) is not an open model, based on the EPIC-TAMU version 081. It assesses the impacts on yields, water availability, and soil degradation in the main global agricultural systems with different management such as cropping, fertilization, irrigation practices, and organic options under future climate change conditions. The EPIC-IIASA model estimates plant growth and yield based on temperature and soil moisture (Balkovič et al., 2014). Another popular and open model is the pDSSAT which comprises an assortment of survey-based and geospatial data sources (Elliott et al., 2014), and field-scale crop models, including those based in the Decision Support System for Agrotechnology Transfer (DSSAT) framework (CROPGRO103 and CERES (Crop Environment Resource Synthesis (Jones et al., 2003) (referred to as pDSSAT). The pDSSAT model simulates food, fiber and biomass production systems at high spatial resolution and continental or global extents (Müller et al., 2019). The Lund-Postdam-Jena managed Land model (LPJLmL) originated from the LPJ-Dynamic Global Vegetation Model (Sitch et al., 2003) and it is associated with biogeochemical processes (mainly carbon cycling) (Bondeau et al., 2007). The LPJLmL model simulates the growth and geographical distribution of natural plant and crop functional types. There are other alternative crop models such as WOFOST that is a simulation model for analyzing the growth and production of field crops under a wide range of weather and soil limiting conditions (Diepen et al., 1989), the CLM-Crop (Levis et al., 2012), ORCHIDEE-CROP, and PEGASUS (Deryng et al., 2011).

Considering the wide variety of crop models, some international efforts have been developed to compare their projections such as the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) (https://www.isimip.org/) and the Agricultural Model Intercomparison and Improvement Project (AgMIP) (https://agmip.org/). Their main goal is to facilitate the evaluation and improvement of the models. They also aim to improving the estimates of the biophysical and socio-economic impacts of climate, to provide knowledge for enhancing technological capabilities, and to tackle food security, and poverty at local to global scales.

How countries adapt to climate change impacts and prevent further risks possess critical questions about the countries' capacity to produce climate knowledge on a relevant scale for local decision-makers. This is a key aspect of the climate services discussions (Vaughan and Dessai, 2014; Soares and Buontempo, 2019) and the analysis of how to bridge climate policy and the science interface (Lemos et al., 2012; Tang and Dessai, 2012; Knutti, 2019). Unequal climate knowledge infrastructures have been identified as one of the key dimensions to better understanding how climate information is locally produced, circulated, selected, and used by policymakers in different development sectors (Edwards, 2010; Mahony and Hulme, 2016). This geographical imbalance can be modulated by how countries customize the information from all parts of the world and integrate it to their processes. Here, novel modelling approaches are proposed to help different regions customize and use model output and data. At the same time, this approach can help build stronger technical capacities and provide adequate information for decision making.

The increasing availability of crop projection databases from leading modelling groups allows proposing simple model emulators based on statistical techniques (Blanc, 2017; Estrada et al., 2020). These emulators have low technical and computing requirements and aim helping a variety of users who have no access to biophysical crop models, but that have information needs that may go beyond publicly available datasets. The requirements of information can vary widely among users and include tailor-made, user-defined policy or reference climate change scenarios to address specific information needs. The low-computational and technical costs of emulators also facilitate the use of simulation and resampling methods that allow generating probabilistic scenarios and estimating various risk measures to facilitate communication of results and help decision-making processes. Examples of such risk measures include the social and economic time of emergence, and multivariate risk indices (Hawkins and Sutton, 2012; Estrada and Botzen, 2021; Estrada et al., 2021; Ignjacevic et al., 2021).

Limited access to complex models and technical and computational challenges are much more common for policy makers and stakeholders in developing countries (Blicharska et al., 2017). In these regions, the development of alternative modelling approaches and tools, such as emulators, can be of high scientific and policy relevance. For instance, biophysical crop models require high levels of expertise and programming to use and adapt in a way that they can address relevant national, subnational and local needs. Due to the lack of modelling alternatives, policymakers in these countries are frequently left with model runs created for other users' needs that do not respond to their specific demands. However, the usefulness and benefits of emulators of complex models are not limited to cases in which technical or computational resources are scarce or not available. A variety of emulators, such as MAGICC (Meinshausen et al., 2011), are used in high-impact publications on climate change (Fawcett et al., 2015; IPCC, 2021) and play a central role in integrated assessment modelling (Tol and Fankhauser, 1998; van Vuuren et al., 2011; Nordhaus, 2013; Meinshausen et al., 2020; Estrada and Botzen, 2021).

The main objective of this work is to offer a simplified mathematical framework to produce emulators that can approximate complex climate change impact assessment models for agriculture. These emulators can extend the original models' results to a wide range of user-defined intervention/inaction greenhouse gas emissions scenarios. They can also be extended to a probabilistic setting in which a variety of risk measures can be developed to address the user's information needs. In specific, emulators of the EPIC model based on the simulations that are freely available in the AgMIP7 database are developed. Some performance metrics and a test to evaluate their performance are proposed. This builds upon concepts such as "weather typing" (Hay et al., 1991), "time-shift approach" (Herger et al., 2015) and "time sampling" (James et al., 2017), developed for climate simulations and for downscaling. These concepts have been applied to interpolate impact projections for the Network for Greening the Financial System (NGFS)[1]. Here we extend previous work to a formal mathematical model and provide metrics and tests for evaluating its performance.

The proposed methodology is illustrated with a case study of rainfed maize production in Mexico, which has a particular cultural and socioeconomic importance for the country. Although the contribution of agricultural activities accounts for 3.4% of the Mexican GDP (INEGI, 2020), there are ~6 million people who depend directly on this sector (SIAP, 2019) and up to 26.9 million people considering their relatives (INEGI, 2021). Farmers in Mexico have been cataloged as of the most vulnerable to climate change because of a mosaic of conditions (Monterroso et al., 2014; Murray-Tortarolo et al., 2018; Donatti et al., 2019), and their incomes are highly dependent on crop yields. The vast majority of agricultural land is rainfed (69.7%) (SIAP, 2021), and conducted in small patches of land (usually <2ha) (Ibarrola-Rivas et al., 2020), with traditional management practices (e.g., milpa). The proposed emulators are used to estimate the changes in yields at the grid ($0.5^\circ \times 0.5^\circ$) and state levels for three emissions scenarios that are not available in the AgMIP7 database. These scenarios explore the benefits of strict compliance of the Nationally Determined Contributions (NDC) and what consequences would arise if a large emitter would drop out of the NDC and the Paris Agreement. In the current context of the cancellations of the US-China talks by China, a modified NDC scenario in which China decides not to participate in the NDC efforts is selected for the analysis. The economic costs and benefits of such scenarios are evaluated, and two risk measures are used to identify the regions that are more exposed to climate change impacts on rainfed maize production.

The remainder of this article is structured as it follows. Section 2 presents the data and methods used. It develops the modelling framework for constructing the emulators and presents an approach to evaluate the emulators' adequacy and accuracy. Section 3 presents and discusses model evaluation and the projected changes in yields and their implications for rainfed maize production in Mexico. Section 4 summarizes the results and concludes.

1 https://climate-impact-explorer.climateanalytics.org/methodology/

2 Data and methods

2.1 Model description

A simple methodology for constructing crop model emulators is presented. The proposed emulators can closely reproduce the outcome of complex models and address information needs that cannot be covered with the simulations that are publicly available. This methodology is illustrated using the EPIC crop model projections that are available in the AgMIP7 database. The emulator is based on a simple non-parametric modeling strategy described in the following paragraphs.

The evolution of crop yields y_t can be represented by means of a signal plus noise model, such as:

$$y_{i,j,t} = S_{i,j,t} + \varepsilon_{i,j,t} \tag{1}$$

$$\hat{S}_{i,j,t} = f(H) + \eta_{i,j,t} \tag{2}$$

where $S_{i,j,t}$ is the true, unobserved systematic component of $y_{i,j,t}$ which can be approximated by a general function $f(H)$ of a set of information H, and i, j are geographical coordinates (latitude and longitude). $\hat{S}_{i,j,t}$ is the resulting approximation of $S_{i,j,t}$. The noise term $\varepsilon_{i,j,t} = \eta_{i,j,t} + u_{i,j,t}$ has two components, one related to bias and the other to non-systematic variation. $\eta_{i,j,t} = S_{i,j,t} - \hat{S}_{i,j,t}$ is an error term which absorbs the influence on the systematic part of $y_{i,j,t}$ of all other factors not included in H. In addition, $\varepsilon_{i,j,t}$ includes $u_{i,j,t}$ which is a zero mean, stationary noise that accommodates the non-systematic effects of other factors, such as some short-term variability in climate variables. Note that the error term $\eta_{i,j,t}$ can become a non-stationary process if $\hat{S}_{i,j,t}$ has systematic biases due to the omission of important determinants in H. If no biases are present in $\hat{S}_{i,j,t}$, $\eta_{i,j,t}$ is a zero mean, stationary variable (i.e., $\eta_{i,j,t} \sim I(0)$).

The first step in the methodology is to construct an information set H that contains a library of simulations from the biophysical model and the corresponding global temperature change, both for a range of emissions scenarios, such as those in the Representative Concentration Pathways (RCP):

$$H = \{L, T^g\} \tag{3}$$

where $L = l_1, l_2, \ldots, l_k$ and each l_k is a three-dimensional matrix (latitude, longitude, time) of yield projections for a particular crop, production system and emissions scenario. T^g is a vector $T^g = \left\{T_1^g, T_2^g, \ldots, T_k^g\right\}$ of annual global temperature change for a total of k different emissions scenarios, each one covering a horizon of n years and that are expressed with respect to a reference period (e.g., pre-industrial times).

The second step consists of indexing the information contained in L with respect to the associated changes in annual global temperature T^g and proposing the following specification for the systematic component of $\hat{y}_{i,j,t}$:

$$\hat{S}_{i,j,t} = E\left[y_{i,jt} \mid \theta_t\right] = \frac{1}{M_t}\sum_{m \in \theta_t}^{M_t} y_{i,j,m} \tag{4}$$

$$\hat{\varepsilon}_{i,j,t} = y_{i,j,t} - \hat{y}_{i,j,t} = \hat{\eta}_{i,j,t} + \hat{u}_{i,j,t} \tag{5}$$

where θ_t is a subset of L such that $\theta_t = \left\{T_t^g - \omega \le T_t^g \le T_t^g + \omega\right\}$ and ω is a parameter that defines a rolling window around T_t^g. Eq. 4 consists in calculating the average of yield maps across the elements of θ_t which satisfy the condition of being associated with a global temperature change in the range of $T_t^g \pm \omega$, regardless of the date of occurrence and/or the emissions scenario they belong to. Averaging over this range of values has the effect of minimizing the effects of factors that are not common across the elements of θ_t and reinforcing those that are common. In particular, $\hat{S}_{i,j,t}$ would preserve the effects over yields of changes in external forcing, as well as other determinants (e.g., soil properties, fertilizers, among others), and dilute the effects of those that are different (e.g., natural variability, differences in regional forcing). As such, by analyzing the error term $\hat{\varepsilon}_{i,j,t}$ it can be inferred if the proposed model has important biases $\hat{\eta}_{i,j,t}$ and thus if information set H provides a representative sample to adequately emulate the outcome $y_{i,j,t}$. The existence of important biases in $\hat{y}_{i,jt}$ can be evaluated by testing if $\hat{\varepsilon}_{i,j,t} \sim I(0)$. Since $\hat{y}_{i,j,t}$ is an average, a centered running mean of $y_{i,j,t}$ is used to calculate $\hat{\varepsilon}_t$ and to compute in-sample and out-of-sample forecast evaluation measures (RMSE, nRMSE). This running mean is closer to what $\hat{y}_{i,j,t}$ represents and minimizes the effects of natural variability.

Some relevant properties and limitations of the proposed methodology include:

- There are no assumptions about the functional form relating the effects of changes in climate over yields.
- Spatial patterns produced by the original biophysical crop model are preserved. Noise is introduced to these patterns by the mismatch between $\hat{S}_{i,j,t}$ and $S_{i,j,t}$, as well as by $u_{i,j,t}$. However, if $\hat{\varepsilon}_{i,j,t} \sim I(0)$ any mismatch is transitory, and no systematic biases are present.
- As with many other models, projections beyond the range of values used for calibration are likely not valid.
- The proposed methodology is not appropriate for scenarios which involve large changes in spatial climate patterns (i.e., spatial stationarity of changes does not hold, see below) such as those that correspond to climatic catastrophes (e.g., thermohaline circulation collapse).
- At each time t the emulator in Eqs 4, 5 constructs a library of realizations that represents the response of the biophysical climate models to similar levels of warming. These collections of realizations can be used to approximate the empirical distributions of crop yields conditional on the level of warming T^g at time t, through resampling and simulation methods as illustrated in the following section. This allows to explore, for example, the probabilities of exceeding thresholds and other risk measures.

Finally, note that T^g provides a succinct representation of changes in climate as it implicitly offers an approximation of how temperature and precipitation vary at a spatially explicit scale. A variety of studies has provided strong evidence in favor of stationarity in the spatial patterns of change in variables such as monthly and annual temperatures (mean, maximum and minimum), as well as in precipitation (Tebaldi and Arblaster, 2014). This implies that changes in temperature and precipitation at the grid cell are proportional to changes in annual global temperature:

$$v_{i,j,t} = T_t^g P_{i,j}^v + \xi_{i,j,t} \tag{6}$$

where $v_{i,j,t}$ is the change in variable v, $P^v_{i,j}$ is a matrix of scaling values that are fixed in time but that vary across space. The scaling pattern $P^v_{i,j}$ represents the response of the climate system in variable v to changes in external forcing, while $\xi_{i,j,t}$ is a noise term that includes the effects of natural variability. This means that while changes in the climate variable v (or in multiple climate variables $V = \{v_1, v_2, \ldots, v_p\}$) are heterogeneous in space, they all scale linearly with T^g at a fixed proportion. Thus, $S_{i,j,t} = f(V, \cdot) \propto f(T^g, \cdot)$. In consequence, the proposed methodology requires the assumption of spatial stationarity to hold.

2.2 Computation of risk measures estimates

A relevant application of the proposed methodology is to provide risk measures that are currently not available from the original biophysical crop models. The library of realizations in the information set H, in combination with resampling methods, can be used to approximate the empirical distribution of crop yields conditional on the level of warming T^g at time t. Specifically, for each time step t, the set of realizations in H are resampled with replacement n times and the resulting four-dimensional matrix (latitude, longitude, time, resampled realizations) can be used to approximate the probability of exceedance of a risk threshold defined by the user (Estrada et al., 2020; Estrada and Botzen, 2021). A risk threshold based on the percent change in yields is defined by the user and the probabilities of exceedance are computed from the four-dimensional matrix of yields. A Boolean function is used to assign the value 1 to the entries in the four-dimensional matrix that exceed the chosen threshold and 0 otherwise. The average value of the resulting matrix is calculated to approximate the probability of exceedance per grid cell and time step. Once the probabilities of exceedance have been computed, the date of exceedance can be estimated by selecting a probability threshold at which the occurrence of exceedance is declared.

2.3 Calculation of economic losses

For calculating the economic losses, the following steps were carried out. First, because modelled and observed yields are not directly comparable (Rosenzweig et al., 2014) the change in modelled yields is applied to observed yields as follows (see Estrada et al., 2022):

$$Y_{fut} = Y^{obs}_{ref}\left(1 + \frac{Y^{mod}_{fut} - Y^{mod}_{ref}}{Y^{mod}_{ref}}\right)$$

where Y_{fut} is the future yield, Y^{obs}_{ref} is the observed yield in the reference period, Y^{mod}_{ref} is the yield from the biophysical model emulator in the reference period and Y^{mod}_{fut} is the yield calculated from the model emulator for the future period. Second, the change in yields (Y^{obs}_{ref}-Y_{fut}) is obtained and multiplied by the number of hectares in each state devoted to the production of the crop to provide an estimate of the tons of crop lost due to climate change. Third, the estimated annual loss in production is multiplied by the price per ton of the crop in each state. Finally, the present value of losses is calculated with a user-defined discount rate.

2.4 Evaluating the adequacy and accuracy of models based on different information sets H

As mentioned in the previous subsection, the adequacy of the information set H used to calculate Eq. 5 can be evaluated by analyzing the properties of the error term $\hat{\varepsilon}_{i,j,t}$. If differences between $S_{i,j,t}$ and $\hat{S}_{i,j,t}$ are transitory then $\hat{\varepsilon}_{i,j,t} \sim I(0)$, while if they are persistent, they will make the error term non-stationary. The Augmented Dickey-Fuller (ADF) test is commonly used to distinguish between stationary and non-stationary variables (Dickey and Fuller, 1979; Said and Dickey, 1984), which involves estimating the following regression for any time series x_t:

$$\Delta x_t = \delta x_{t-1} + \sum\nolimits_{j=1}^{J} \beta_j \Delta x_{t-j} + e_t$$

where $\sum_{j=1}^{J} \beta_j \Delta x_{t-j}$ are additional terms to correct for autocorrelation. Under the null hypothesis $\delta = 0$ and x_t contains a unit root, and the alternative is that it is stationary around zero. It is important to note that 1) the power of the ADF test goes to zero when a deterministic trend is omitted, 2) when an intercept is not included, the power is adversely affected and decreases with the magnitude of the omitted constant and, 3) in the case of structural changes in the trend function, the δ will be biased towards zero (the non-rejection of the null). A such, when applied to $\hat{\varepsilon}_{i,j,t}$, the null hypothesis of the ADF would likely not be rejected if a persistent bias is present in $\hat{S}_{i,j,t}$, regardless of the non-stationarity being caused by the presence of a unit root, an omitted trend/intercept or the existence of structural breaks (Perron, 1989).

To evaluate the accuracy of the projections obtained using different H sets, the root mean square error (RMSE) and the normalized RMSE (nRMSE) are calculated using the mean of the yield of the original model for the projected period. These metrics also help to assess how much additional realizations of the biophysical crop contribute to improve the emulator's projections.

2.5 Data description and sources

The proposed methodology is illustrated using the output from the EPIC crop model for rainfed maize (Williams et al., 1984, 1989) forced with the climate projections of the HadGEM2-ES climate model under the RCP8.5, RCP6.0, RCP4.5 and RCP2.6 emissions scenarios.[2] This information constitutes the L component of the information set H. All data was obtained from the AgMIP7 dataset using the Geoshare AgMIP Tool (Villoria et al., 2016). The geographical domain chosen for this study is Mexico, and the period is 2005–2100. For the T^g component, the ensemble average of annual mean global temperature projections from the

2 These emissions scenarios are named after the radiative forcing they would produce by the end of the present century, ranging from 8.5 W/m^2 to 2.6 W/m^2. They can also be interpreted as a very high emissions trajectory (RCP8.5), two scenarios that are similar to what current policies would achieve (RCP6.0) and to what strict fulfilment of Nationally Determined Contributions (NDC) would produce (RCP4.5), and a stringent international mitigation scenario that is consistent with the Paris Agreement goals of keeping global temperature increase well below 2°C by 2100.

HadGEM2-ES climate model were computed for each of the four RCP scenarios. Four simulations were available for the RCP2.6, RCP4.5 and RCP8.5, while only three for the RCP6.0. All HadGEM2-ES output was downloaded from the KNMI's Climate Explorer tool (https://climexp.knmi.nl/). To illustrate the usefulness of the proposed emulators, the ensemble average (one member per model) of the Coupled Model Intercomparison Project phase 6 (CMIP6) dataset for the SSP370 were obtained, which was also obtained from the KNMI's Climate Explorer tool, and two simulations from the CLIMRISK (Estrada and Botzen, 2021) and MAGICC6 (Meinshausen et al., 2011) models. These two simulations represent 1) the strict compliance of the Nationally Determined Contributions (NDC) of all countries and 2) the NDC scenario but with China dropping out from this international effort (NDCnoCHINA). Observed yields, cultivated area and prices for rainfed maize were obtained for the period 2000–2010 from SIACON[3].

3 Results and discussion

3.1 Evaluation of adequacy and accuracy of the proposed emulators

The adequacy and accuracy of different emulators based on all possible combinations of RCP simulations to integrate the information set H was evaluated. Supplementary Tables S1–S4 in the Supplementary Material show the RMSE, nRMSE and the significance of the ADF test statistic. Bold figures denote which emulators provide no evidence of non-stationarities in $\hat{\varepsilon}_{i,j,t}$ and produce the lowest errors. When H is composed of only one RCP scenario, the RCP8.5 is the only one that produces stationary residuals. This emulator has an out-of-sample RMSE (averaged over all simulations except those included in H; in this case, the RCP8.5 is excluded) of 0.89 t/ha and a nRMSE of 13.6%.[4] The nRMSE is reduced by about 30% when the RCP4.5 is added to H, and the errors are also stationary. Including the RCP8.5, RCP4.5 and RCP6.0 in H decreases the average out-of-sample nRMSE by about 4% and produces stationary errors. The average out-of-sample RMSE is 0.64 t/ha and a nRMSE of 9%. When H includes all four RCPs, errors are stationary, the average in sample RMSE is 0.44 t/ha and the average nRMSE is 7%. Supplementary Figures S1–S9 in the Supplementary Material compare the original yield projections obtained from the EPIC model and those produced with the proposed methodology. These figures show the spatial patterns of the nRMSE and the temporal evolution of the yield projections from the EPIC model and the proposed emulators for a randomly chosen grid cell.

The results in Supplementary Tables S1–S4 in the Supplementary Material show that: 1) the errors produced by the proposed emulators are relatively small, as the RMSE is in general below 1 t/ha in comparison with the average yield for the area of study (about 6 t/ha); 2). Due to the fact that the RCP8.5 expands over a wider range of global temperature change, it is the scenario that adds more information to the set H. In contrast, the RCP2.6 adds the least because all other RCP scenarios provide information for changes in yields in a range of global temperature change that encompasses that of the RCP2.6; 3) the out-of-sample RMSE values averaged over the different RCPs decreases as more RCP scenarios are added to the set H, suggesting that the emulator becomes better at producing projections that are not in the training set.

Furthermore, most of the combinations of RCP in H that include the RCP8.5 produce stationary errors at each grid cell, for all RCP that are evaluated. This suggests that differences between $S_{i,j,t}$ and $\hat{S}_{i,j,t}$ are indeed transitory and that RCP-specific differences such as in regional forcing and other factors do not produce a systematic bias in the emulator's projections.

3.2 An illustration of the proposed emulators for generating user-defined scenarios

The usefulness of the proposed methodology is illustrated by projecting rainfed maize yields under three emissions scenarios that are not considered in AgMIP7. Furthermore, risk estimates that are not directly available using current biophysical crop models are provided. The emissions scenarios that were selected are: the SSP370 used in the CMIP6, and that is similar to a "business-as-usual" scenario; 2) a strict compliance NDC scenario and; 3) the NDCnoCHINA scenario which consists of the NDC scenario but excluding China's participation (Estrada and Botzen, 2021).

3.2.1 Climate change impacts on rainfed maize yields

Results of the simulations of rainfed maize yields for the selected emissions scenarios are presented in Supplementary Figure S10 included in the Supplementary Material. This figure shows the changes in yields (%) with respect to 1980–2010 for the SSP370, NDC and NDCnoCHINA emissions scenarios for the time horizons 2055 and 2085. The SSP370 scenario implies large reductions in rainfed maize in Mexico by mid-century. These reductions are highly heterogeneous in space and particularly large for part of the northeast and most of the southeast of Mexico. This is also the case for the south-center region of the US, where the yield changes can exceed −40%. The reductions in yields become much larger and widespread near the end of the century, reaching over 70% in the southeast and northeast of Mexico (and in the southeast of the US), and close to 40%–50% in some regions of the Pacific coast where some of the largest producers of rainfed maize are located.

Aggregating yield changes at the state level (Figure 1) shows that under the SSP370 all states, with the exception of the Baja California peninsula, would experience important decreases in rainfed maize yields during this century. The largest reductions occur in Nuevo Leon reaching close to 50% during the 2050s and about 80% at the end of the century, followed by those in Campeche which exceed 40% by mid-century and 60% by the 2080s. Other states with decreases in yields exceeding 50% by the end of the century are

3 SIACON is a query system for agricultural information created by the Mexican government. SIACON is available at https://www.gob.mx/siap/documentos/siacon-ng-161430

4 Note that there is no consensus about what an acceptable range RMSE or nRMSE values is. This measure is intended to compare the accuracy of alternative models in relative terms (Blanc, 2017; Estrada et al., 2020).

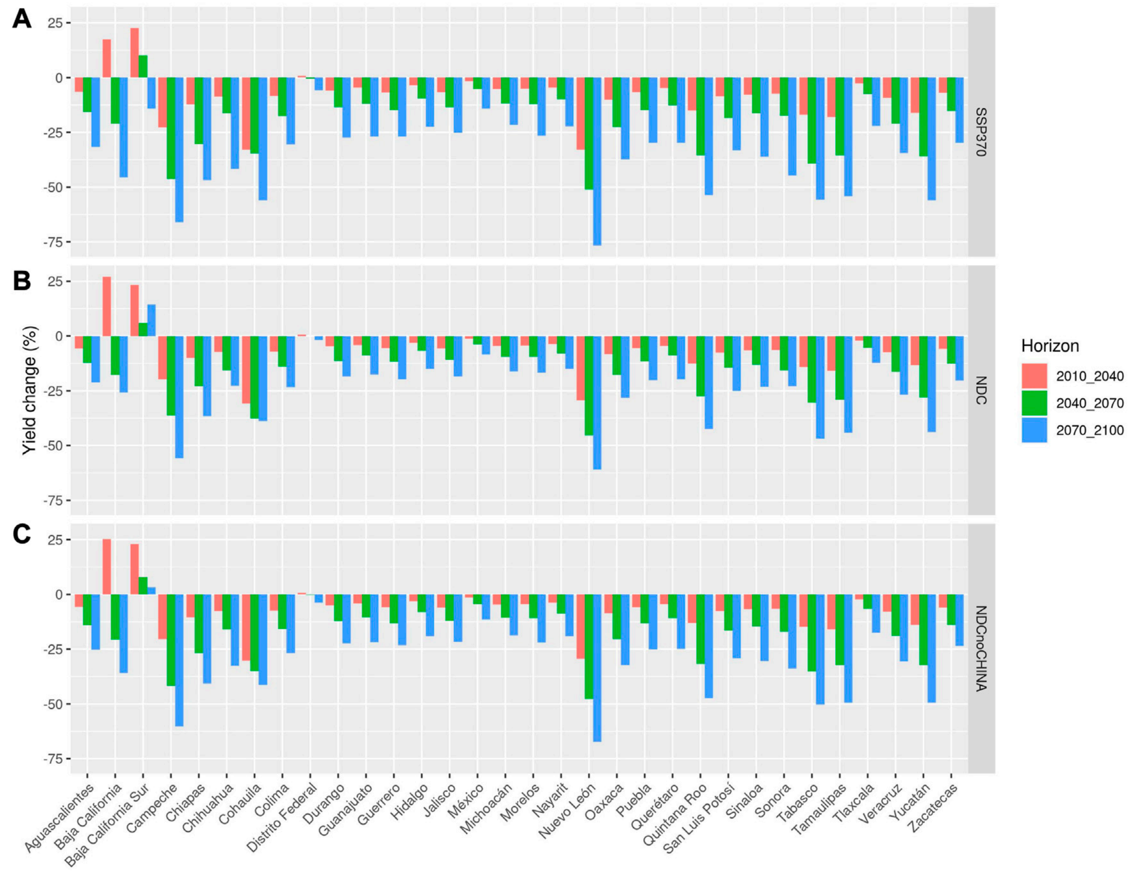

FIGURE 1
Percent changes per state in rainfed yields under the SSP370, NDC and NDCnoCHINA scenarios for three time horizons. Panel **(A)** shows the percent change in yields under theSSP370 scenario while Panels **(B,C)** show those for the NDC and NDCnoCHINA scenarios. Projections for 2010–2040 are shown in red, in green for 2040–2070, and in blue for 2070–2100. The Y-axis depicts the percent changes in maize yields and the X-axis shows the state names.

Coahuila, Quintana Roo, Tabasco, Tamaulipas, and Yucatán. States such as Chiapas, Guerrero, and Oaxaca, which are characterized by high levels of poverty and small-scale producers that depend on rainfed maize production for subsistence, would also experience large reductions in yields. For these states, the expected reductions in yields are about 30%–45% by the end of the century and 15%–30% in the following 3 decades. The largest producers of rainfed maize in the country (e.g., Mexico, Jalisco, and Nayarit) would see reductions between 5% and 15% by the 2050s, and 15% and 25% at the end of the century. Figures 2A, 3A show these results as maps for the short (2025) and medium (2055) time horizons, respectively.

If an international mitigation effort consistent with the NDC commitments would be implemented, a significant fraction of these reductions in yields could be avoided. Figure 1B shows the yield changes obtained for the NDC scenario and reveals that there would be important benefits for most states if such an international mitigation effort would be implemented in comparison with a “business-as-usual” type of scenario (SSP370; Figures 2B, 3B). Thirteen states would avoid losing at least 10% of their current yields by the end of the century, and seven states would avoid reductions in yields of 5% or more by the 2050s. However, if China, one of key actors for limiting greenhouse gas emissions, would decide not to participate in the NDC effort these benefits would be significantly reduced (Figures 1D, 2C, 3C). In comparison with the SSP370, implementing the NDCnoCHINA scenario would more than halve the benefits that would be obtained under the full compliance of all participant countries (NDC): only three states would avoid reductions of at least 10% by the 2080s and no state would see benefits exceeding 5% by mid-century.

3.2.2 Risk measures estimates for rainfed maize in Mexico

In this subsection, the library of realizations in the information set H is used in combination with resampling methods to approximate the empirical distribution of crop yields conditional on the level of warming T^g at time t. Specifically, for each time step, the set of realizations in H are resampled with replacement 10,000 times and the resulting four-dimensional matrix (latitude, longitude, time, resampled realizations) is used to approximate the probability of exceedance of a risk threshold defined by the user. For the results presented below, a 30% reduction in yields is chosen as the user-defined risk threshold and the probability threshold is set at 50%. In other words, it is required that at least 50% of the realizations exceed the risk threshold defined by the user to

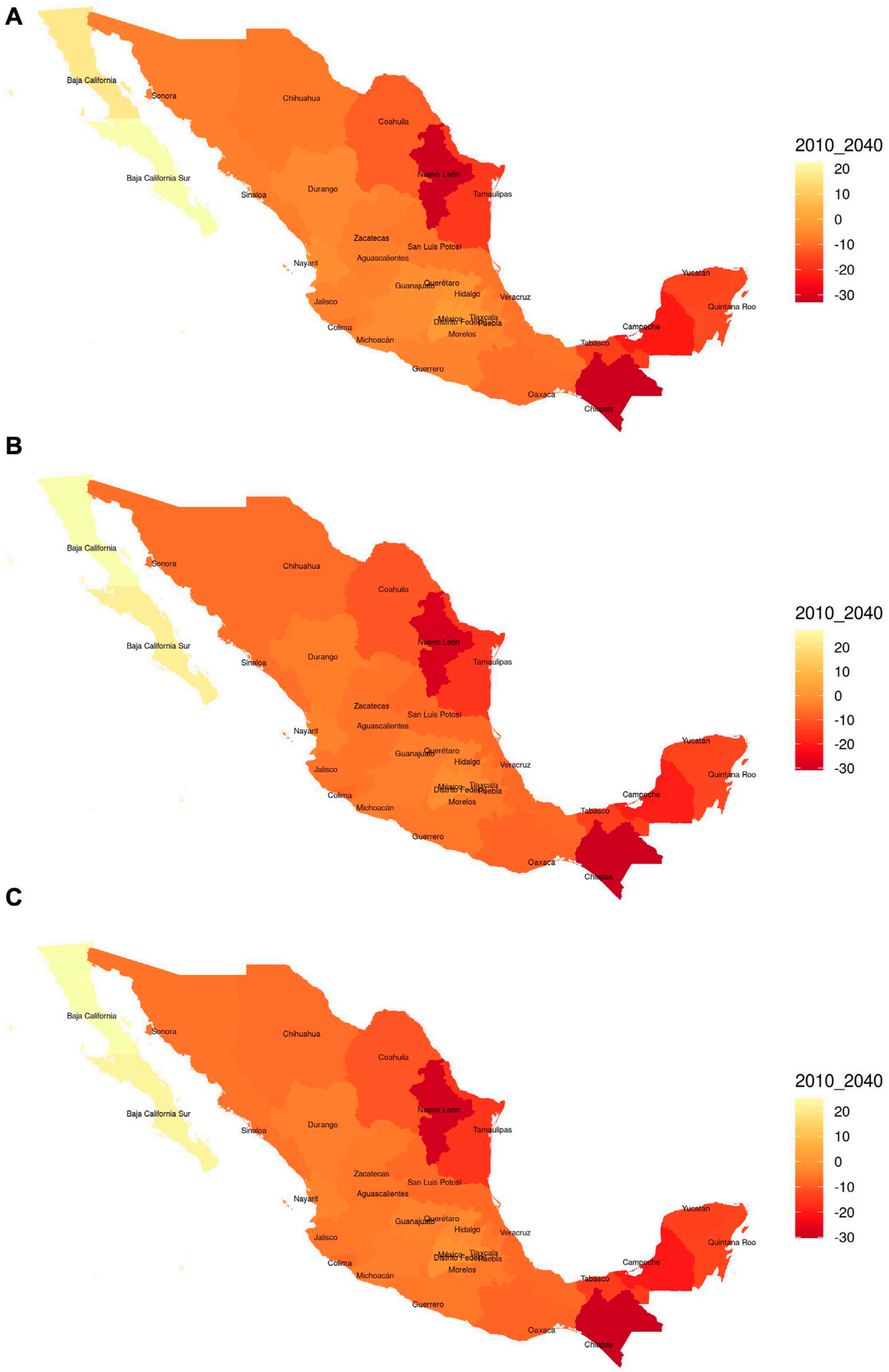

FIGURE 2
Maps of percent changes in rainfed yields under the SSP370, NDC and NDCnoCHINA scenarios for the short time horizon (2010–2040). Panel **(A)** shows the percent change in yields under theSSP370 scenario while Panels **(B,C)** show those for the NDC and NDCnoCHINA scenarios. Figures axes are latitude (Y-axis) and longitude (X-axis).

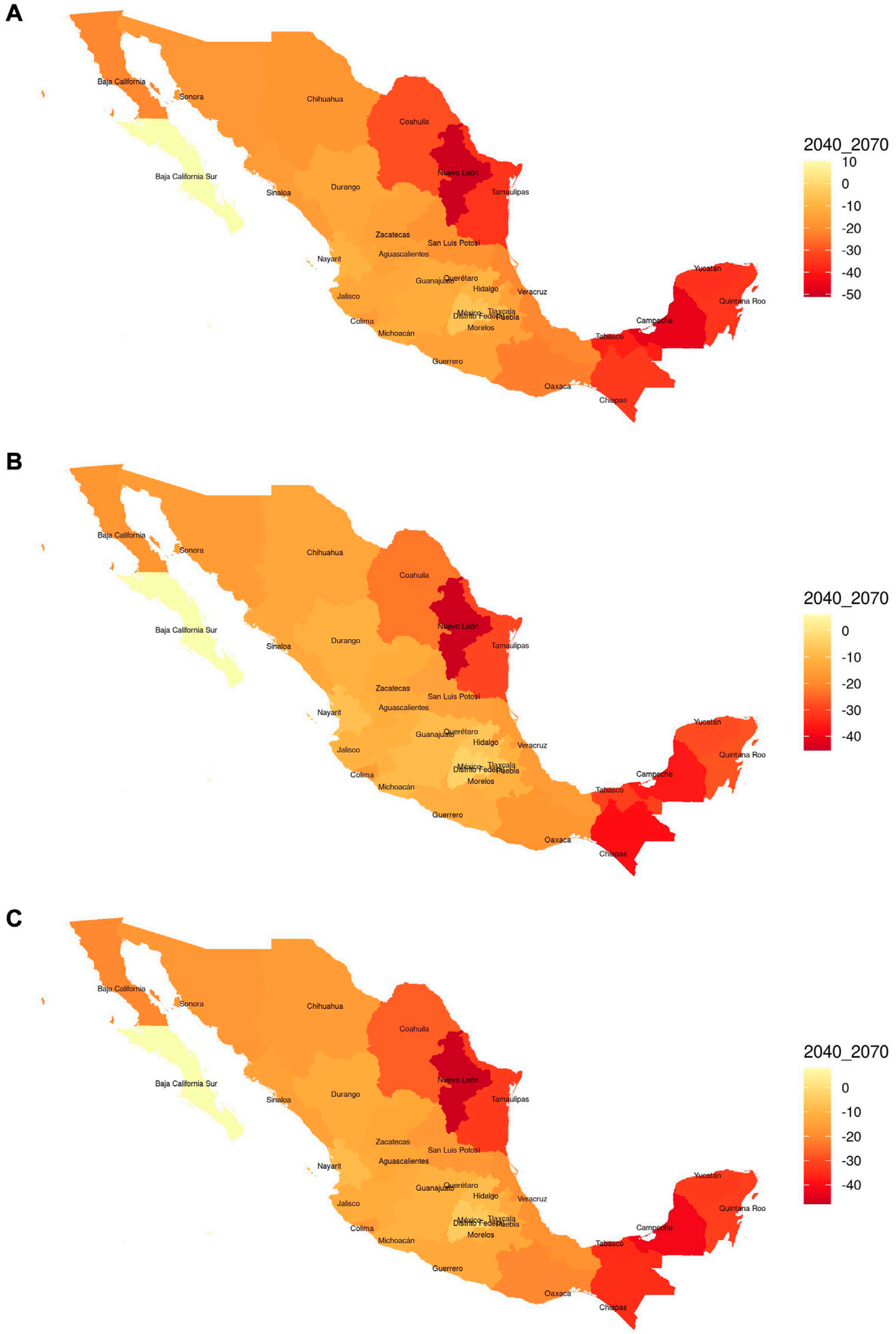

FIGURE 3
Maps of percent changes in rainfed yields under the SSP370, NDC and NDCnoCHINA scenarios for the medium time horizon (2040–2070). Panel **(A)** shows the percent change in yields under theSSP370 scenario while Panels **(B,C)** show those for the NDC and NDCnoCHINA scenarios. Figures axes are latitude (Y-axis) and longitude (X-axis).

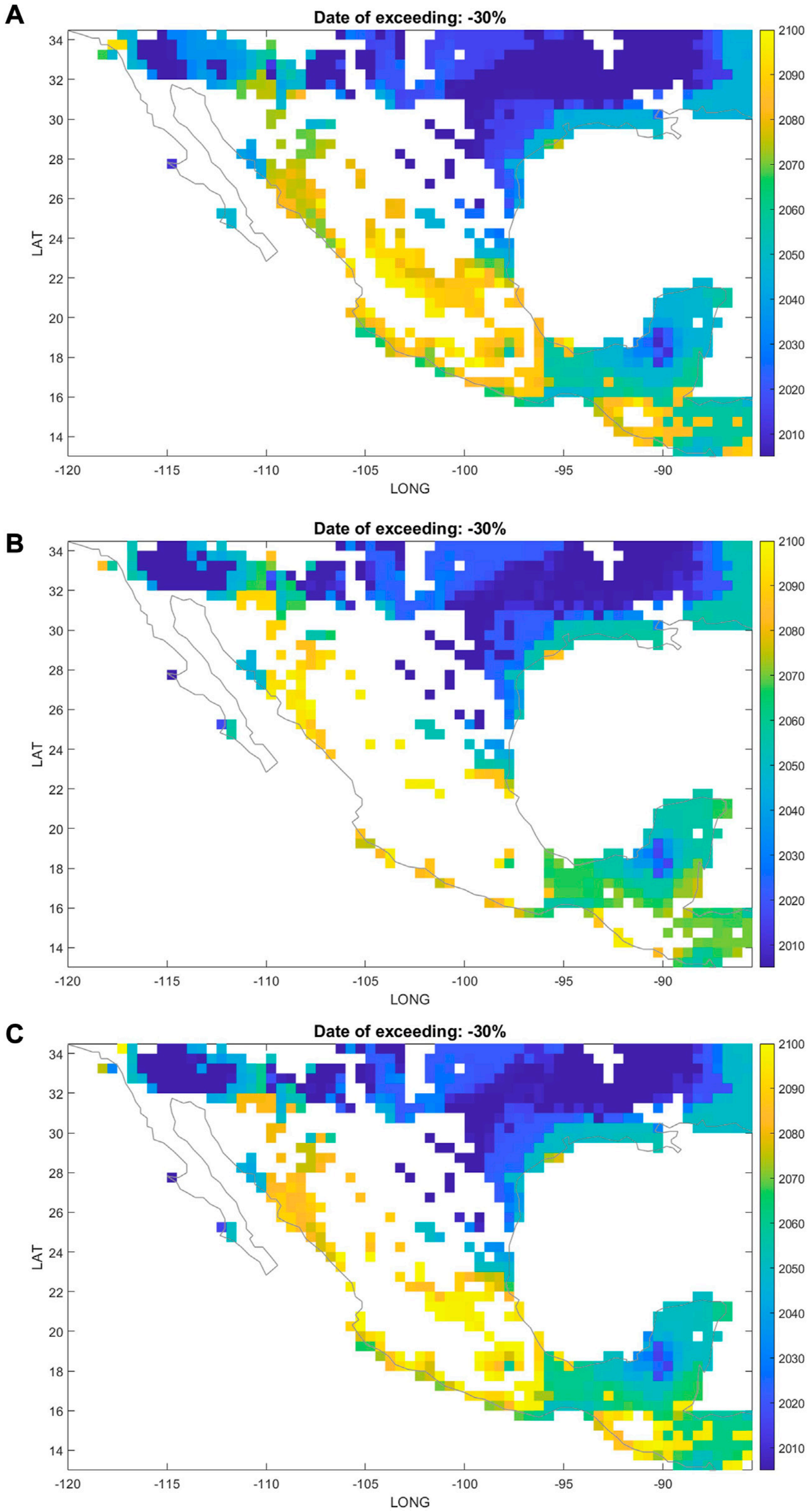

FIGURE 4
Dates of exceedance of reductions of at least 30% in rainfed maize. Panel **(A)** shows the dates of exceedance for the SSP370, while Panels **(B,C)** present the estimated dates for the NDC and NDCnoCHINA scenarios. Figures axes are latitude (Y-axis) and longitude (X-axis). Units are calendar years.

TABLE 1 Present values of the cumulative costs of climate change, of the cumulative benefits of international mitigation over this century and of the costs of China dropping out from international mitigation efforts.

	SSP370	NDC	NDCnoCHINA
Present value of the costs of climate change	$129,773.60	$104,610.17	$113,206.41
Present value of the benefits of mitigation	—	$25,163.43	$16,567.19
Present value of the costs of China dropping out	—	—	$8,596.25

Figures are in 2012 million pesos.

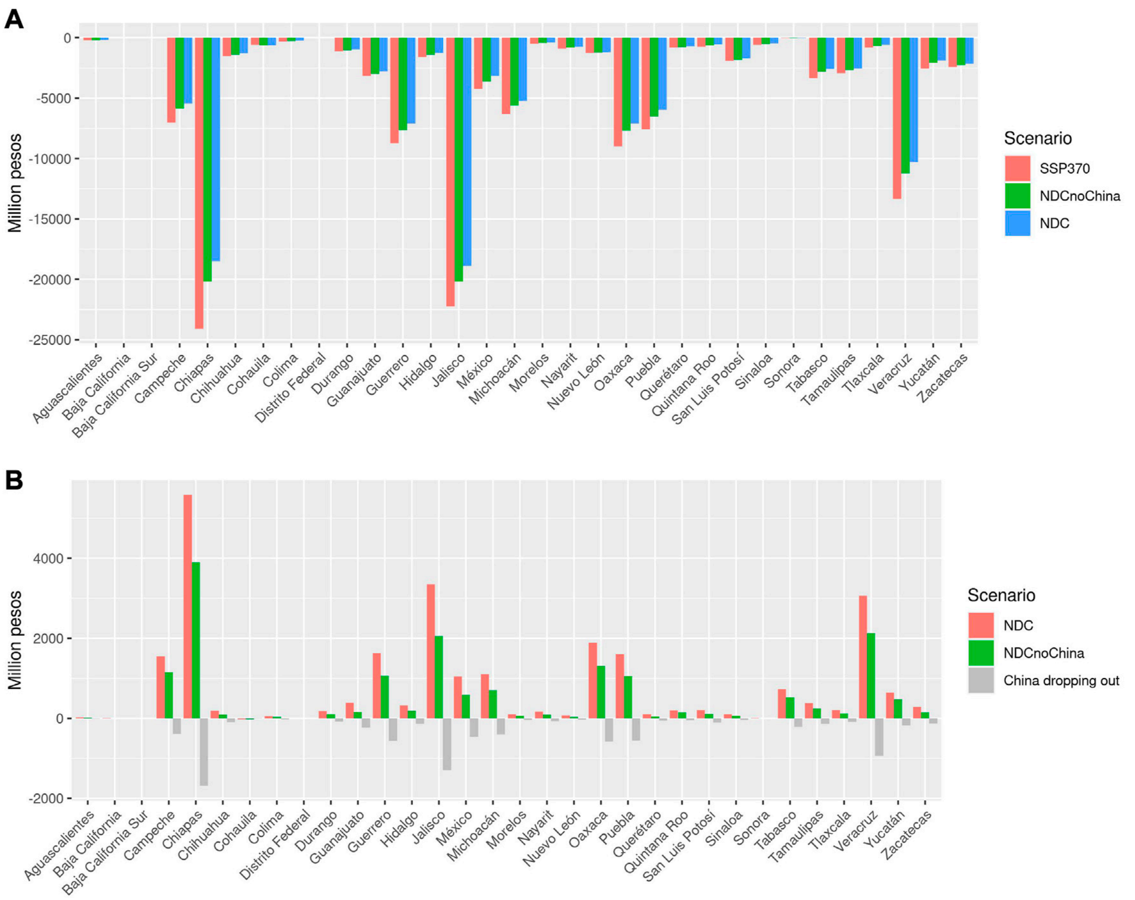

FIGURE 5
Present value of the cumulative costs of climate change over this century in rainfed maize production and of the cumulative benefits of international mitigation. Panel **(A)** shows the present value of the costs of reductions in rainfed yields for the SSP370 (red), NDC (blue) and NDCnoCHINA (green) scenarios. Panel **(B)** shows the benefits of implementing the NDC (red) and the NDCnoCHINA (green) with respect to the SSP370 scenario. The present value of the costs of China dropping out of the NDC mitigation effort are show in grey. The Y-axis depicts the calculated present values, and the X-axis shows the state names. Quantities are expressed in million pesos.

declare that the risk threshold has been exceeded. Once the threshold has been declared as exceeded, the date when this first occurs is retrieved. These risk measures can help decision-makers developing critical path planning for adaptation in which dates of exceedance provide a time frame for designing and implementing a sequence of adaptation activities.

Animated Supplementary Figures S12–S14 in the Supplementary Material show the evolution of the probabilities of exceeding 30% reductions in rainfed maize yields for the SSP370, NDC and NDCnoCHINA scenarios for the period 2005–2100. Under the SSP370 (Supplementary Figure S12), the probabilities of exceedance increase rapidly in the second part of the century reaching values above 80% in the southeast region of the country and all along the Pacific coast. In contrast, for most of the central region these probabilities remain below 60%. Although the NDC is not a very ambitious international mitigation effort, the probabilities of exceeding the selected risk threshold for rainfed maize yields are much lower for most of the country. The exceptions are the states located in the southeast of the country, as well as in Nuevo Leon, Coahuila, Tamaulipas, and Veracruz.

Figure 4 shows the dates of exceedance for each of three scenarios considered. Under the SSP370 scenario (Figure 4A), most of the area devoted to rainfed maize production in Mexico would likely experience reductions of 30% in yields during this century. During the present decade, states such as Nuevo Leon and Coahuila would reach this risk threshold, as well as some parts of Campeche. In the 2030s, Tamaulipas, parts of Sonora and the rest of Campeche would exceed decreases in yields above 30%. The rest of the southeast of Mexico would exceed 30% decreases in yields during the 2040–2060 period, and a large fraction of the remaining area devoted to this crop would exceed the threshold as early as the 2070s. Strict compliance with the NDCs would not be enough to delay exceeding the risk threshold for Nuevo Leon, Coahuila, Tamaulipas or Campeche (Figure 4B). Nevertheless, it would provide about 10 extra years for adaptation in parts of the southeast of Mexico, and about 20 years in Nayarit, Sinaloa and, Sonora. Furthermore, such mitigation scenario would push the date for exceeding the risk threshold into the next century for most of the central part of Mexico.

If China dropped out of the NDCs (NDCnoCHINA), most regions in Mexico would still experience some benefits in terms of delaying the date of exceedance of the risk threshold (Figure 4C). These areas include the southeast of the country, where the dates for exceedance would be like those obtained in the NDC scenario. For most of the Pacific coast there would be a delay of 10–15 years in comparison with the SSP370 scenario. The central part of the country would also experience about a 20-year delay for reaching the risk threshold of with respect to the SSP370 scenario. These delays would provide additional time for designing and implementing adaptation strategies to minimize the impacts of climate change on this crop and for addressing the challenges of the population that depends on it.

3.2.3 Estimates of the economic costs of climate change for rainfed maize in Mexico

In this section, estimates of the economic costs of climate change at the national and state levels are provided. For this purpose, the official statistics about yields, crop area and prices collected over the period 2000–2010 by the Ministry of Agriculture and Rural Development of Mexico are used, as well as the projections of changes in yields obtained for the SSP370, NDC and NDCnoCHINA scenarios.

To represent the reference yields and area devoted to rainfed maize, the state average values of these variables during the 2000–2010 period are used. For each scenario, the future yields are obtained multiplying one plus the projected changes (%) by the observed average yield of each state. Assuming the rainfed maize area remains constant for the rest of this century, the losses/gains from climate change in rainfed production are calculated as the difference between future and reference yields in each state, multiplied by the rainfed maize area in each state. The resulting quantity of tons are multiplied by the state-level price to approximate the costs or benefits of climate change for this crop under a particular emissions scenario. For the results in this subsection, state prices in 2012 pesos and a 4% discount rate are used for calculating present values.

At the national level, the present value of the cumulative losses in rainfed maize yields over this century amounts to $130,000 million pesos, which is comparable to three times the value of rainfed production of Mexico in 2012 (Table 1). These losses are highly heterogeneous at the state level with Chiapas, Jalisco, Veracruz, Oaxaca, and Guerrero account for about 60% of the total national losses (Figure 5A). In comparison with the SSP370, the present value of the cumulative benefits over this century of the NDC scenario (Figure 5B) would be about $25,000 million pesos, with the largest benefits in Chiapas ($5,600 million), Jalisco ($3,300 million) and Veracruz ($3,000 million). The decision of China to drop out of the NDC agreement would represent a loss of $8,600 million pesos for Mexico in rainfed maize production in comparison with the strict implementation of the NDC. About 46% of these lost benefits would occur in Chiapas, Jalisco and Veracruz (Figure 5B).

4 Conclusion

The amount of data about climate change and its impacts on natural and human systems that is available for decision-makers and researchers all over the world is unprecedented and ever-growing. Moreover, a large fraction of these databases is publicly available through international efforts of the climate change modelling community. However, the information needs are highly dynamic in an era of active mitigation and adaptation policies and are very heterogeneous among users. As such, information needs can hardly be satisfied even by such impressive and variated collections of databases. This is particularly true in the case of complex models for which runs are typically available for a limited number of scenarios (e.g., RCP, SSP) and experiments. Limited access to these models and lack of technical and computational capacities to run them constitute significant barriers for a variety of users and preclude them from creating tailor-made scenarios to address their specific information needs.

This information gap can be addressed through the development of emulators which can approximate the output from complex models using simple methods that are not technically demanding on the user, nor costly in computational terms. Moreover, such methods can be easily implemented and made publicly available. In this paper, a simple emulator of the EPIC model applied to rainfed maize is presented. It is shown that it can adequately reproduce the output of this complex biophysical crop model and to create projections for user-defined scenarios, as well as risk measures that are not available with the original model.

The proposed emulator is illustrated with an application for rainfed maize production in Mexico under three scenarios that are not available in the AgMIP7 database: the SSP370 and two user-defined scenarios that represent the strict compliance of the NDC commitments and a hypothetical case in which China drops out of this international mitigation effort. It is shown that under the baseline scenario (SSP370), rainfed maize yields could decrease at least 40% for 11 states of the country and up to 60%–80% in some regions by the end of the century. These results are consistent with the range of yield reductions reported in Estrada et al. (2022), which analyzes yield changes of the EPIC model under the RCP8.5 and RCP2.6 scenarios for rainfed maize in Mexico. The probabilities of exceeding a user-defined risk threshold of −30% reduction in rainfed maize yields are estimated and the areas with higher risks are identified. Using the estimated probabilities, the dates of exceedance of this risk threshold are calculated and reveal that regions such as Nuevo Leon, Coahuila and Campeche would reach this threshold in the current decade, and that most of the southeast of the country would do so in the period 2040–2060. Most of the remaining area devoted to this crop would exceed the risk threshold later this century. It is shown that under the NDC scenario, yield reductions and risks significantly decrease for most of the country but that there are some regions in which such an effort has no effect delaying the date for exceeding the selected risk threshold (i.e., Nuevo Leon, Coahuila and Campeche). Results also show that if China decided not to participate in the NDC effort, some benefits would still be attained but most regions of the country would face significantly higher risk and yield reductions.

The present value of the cumulative costs of climate change over this century under these three scenarios is also provided. Under an inaction scenario (SSP370) the present value of the losses in rainfed maize yields amounts to $130,000 million pesos, with much of these losses occurring in Chiapas, Jalisco, Veracruz, Oaxaca, and Guerrero. As expected, these losses are lower than those reported by Estrada et al. (2022) for a higher emissions scenario (RCP8.5). However, these estimates are consistent with what could be expected for the SSP370, and a similar geographical distribution of losses is shown. The strict implementation of the NDC would represent about $25,000 million pesos of avoided damages in rainfed maize production for Mexico, while the hypothetical decision of China to drop out of the NDC would impose losses for about $8,600 million pesos in rainfed maize production for Mexico. Overall, the results show that climate change could have widespread consequences on rainfed production all over the country, with increasing risks for already vulnerable populations and large economic costs at the state and national levels. Moreover, the proposed methodology allows to estimate dates for exceedance of critical thresholds that can help stakeholders to develop timely adaptation plans and to prioritize regions of higher concern. Note that this methodology can also be used to assess the effects of some adaptation measures, such as converting production from rainfed to irrigated in places where water availability allows for. The development of this type of simple emulators that can produce policy-relevant information could provide helpful assistance for government adaptation and risk reduction policies aimed to minimize the expected negative effects of climate change in different sectors.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://agmip.org/, https://climexp.knmi.nl/, https://www.gob.mx/siap/documentos/siacon-ng-161430.

Author contributions

FE, WB developed the idea. FE, JV, and OC-B processed and analysed the data. FE, GM, AM, JV and TDL wrote the paper. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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China's environmental "fee-to-tax" and foreign direct investment—An empirical study based on intensity difference-in-differences

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To protect and improve the environment, reduce pollutant emissions, and promote ecological civilization, China implemented "the Environmental Protection Law of the People's Republic of China" on 1 January 2018. However, what is the impact of strict environmental regulation on foreign direct investment (FDI)? The study uses the data from 287 cities in 30 of China's provinces between 2003 and 2019 and constructs an intensity difference-in-difference model to test the impact of China's environmental "fee-to-tax" on FDI. Empirical results show that environmental "fee-to-tax" significantly boosts FDI. The "pollution halo" hypothesis is confirmed, and the findings hold up through robustness tests. In addition, the heterogeneity test found that environmental "fee-to-tax" mainly promoted FDI in the eastern and central regions but not significantly in the western regions. Further expansion found that environmental "fee-to-tax" can effectively reduce the emission of pollutants. The results provide important policy implications for deepening the environmental protection tax reform and optimizing FDI.

KEYWORDS

China's environmental "Fee-to-Tax", FDI, pollution halo, Porter hypothesis, intensity difference-in-differences

1 Introduction

Since the reform and opening-up, China's market has established a good foundation for the entry of foreign direct investment (FDI). According to the data published by the National Bureau of Statistics[1], the amount of FDI utilized in China increased from 0.92 billion dollars in 1983 to 144.37 billion dollars in 2020. The role of soaring FDI entry in promoting China's economic growth cannot be ignored (Li et al., 2021; Tawiah et al., 2021), but the problems of over-investment and massive energy consumption are increasingly exposed. Furthermore, with the accelerated economic globalization and trade liberalization, FDI is an indicator of economic globalization, and although, to a large extent, economic globalization positively drives energy efficiency (Liu et al., 2023), FDI is also an essential source of carbon emissions (Shahbaz et al., 2018a). Developed countries focus more on the return of capital to the

1 https://data.stats.gov.cn/easyquery.htm?cn=C01.

outward investing countries and ignore the possible environmental problems in developing countries (Zugravu-Soilita, 2017), resulting in issues such as energy shortage and environmental pollution in China (Zhang et al., 2020), which have a significant impact on the local environment. Khan and Ozturk (2020) found that FDI increases local carbon dioxide, manufacturing emission pollution, and China's urban $PM_{2.5}$ pollution (Cheng et al., 2020). Caetano et al. (2022) found that FDI may increase pollution by increasing overall energy consumption rather than shifting polluting industries. Therefore, appropriate environmental rules are necessary for the sustainable use of physical resources and clean energy to achieve the green growth agenda. Environmental protection taxes can reduce the consumption of natural resources and energy, magnify the consumption of renewable energy, reduce carbon emissions, and promote green development. Therefore, selecting and designing appropriate environmental regulation policies can improve the quality of FDI and effectively alleviate energy consumption and environmental pollution problems. A reasonable ecological system is an indispensable guide to building a harmonious and healthy green economic system and promoting the high-quality development of the national economy.

FDI has a meaningful impact on China's fossil energy consumption, natural resources, and ecological environment (Tan et al., 2021). With the development of the concept of ecological civilization construction in China, environmental problems have been given more and more attention by the Chinese government. Environmental problems affect residents' health and wellbeing and significantly hinder national technological progress and economic development (Rehman et al., 2021). Therefore, coordinating environmental protection and economic growth, effectively utilizing foreign capital, continuously optimizing China's energy structure, rationally utilizing and exploiting natural resources, and realizing green environmental development are crucial to promoting China's technological innovation and high-quality economic development (Jiang et al., 2022). Since carbon emissions are the main product of fossil energy consumption, FDI plays a vital role in energy consumption, economic growth, technological innovation (Chen et al., 2022), and pollutant emissions. Salim et al. (2017) suggested that the Chinese government supports inward FDI in the tertiary and energy sectors and strengthens local absorptive capacities to fully internalize FDI-related knowledge spillovers in energy conservation.

This study uses the data of 287 prefecture-level cities in 30 provinces and cities from 2003 to 2019 to construct an intensity difference-in-difference method to test the environmental "fee-to-tax" effect on FDI. In determining the empirical impact of environmental protection tax implementation on FDI, it is crucial to deal with the potential endogeneity of environmental regulation using instrumental variables (Millimet and Roy, 2015) or difference-in-difference (DID) (Hanna, 2011; Chung, 2014). To overcome the problems caused by endogenous environmental regulation variables and unobservable factors in the empirical analysis, we use the 2018 environmental protection tax reform as a quasi-natural experiment. Compared to previous studies, the main contributions of this study are as follows.

First, the innovative method adopted in my research: In the measurement of environmental regulation, the qualitative scoring method, single indicator method, and comprehensive indicator method are often used, such as the use of a broad environmental protection tax as an agent explanatory variable; taxes of environmental nature, such as resource taxes, consumption taxes, vehicle taxes, and vehicle purchase taxes; or the use of comprehensive indicators to measure environmental regulation. All of the abovementioned methods have been gradually optimized in the treatment of environmental regulation. However, it is still difficult to effectively reflect the net effect of environmental protection tax, and the research has obvious endogenous problems. Second, the research object is innovation: Since the environmental protection tax implementation was not long ago, most of the research identification uses the discharge fees from 2003 to 2017 as the research. Few scholars used the environmental protection tax policy in 2018 as the subject of a natural experimental study on the relationship between environmental regulation and FDI. Therefore, this paper adopts the intensity difference-in-difference method to identify the differences in the intensity of environmental regulation in cities and effectively identify the impact of an environmental protection tax on FDI. Third, we re-examine the "pollution haven" hypothesis and the "pollution halo" hypothesis effects of environmental "fee-to-tax" in China and explore the differences in the impact of the environmental "fee-to-tax." It can provide policy guidance and enrich the existing research for effectively clarifying the macro effects of environmental "fee-to-tax" on FDI.

The rest of the article is structured as follows: Section 2 is the background of environmental protection tax policy reform and literature review; Section 3 introduces the data sources, variable selection, and model construction; Section 4 conducts baseline regression, mechanism analysis, the parallel trend test, the heterogeneity test, the robustness test, and the placebo test; Section 5 is the expanded analysis, testing the relationship between environmental "fee-to-tax" and pollutant emission; and Section 6 is the conclusion and policy implications.

2 Policy background and literature review

2.1 Policy background

China's environmental protection tax system can be traced back to the late 1970s and early 1980s and has undergone the following stages of development: the piloting and formation stage. In 1979, "the Environmental Protection Law (piloting)" was promulgated, which formed the rudiments of the environmental protection tax; second, the development and fulfillment stage. "The Interim Measures for Compensated Use of Special Funds for Pollution Control," promulgated in 1988, and "the Notice on Collection of Sewage Discharge Fees," promulgated in 1993, are important measures taken by the state to control pollution, protect and improve the environment, and promote ecological civilization construction. The third is the full implementation stage. In 2003, the State Council promulgated "the administrative regulations on pollution discharge fee levy," which implemented the original overweight charge instead of a discharge fee and overweight in parallel, has been clear about the discharge capital budget management, the clarity of the waste gas, and the wastewater discharge standard; since 2003, provinces have been adjusting their discharge fee levy standards one after another. By 2016, all 31 provinces in China had adjusted the standards for discharge fees. Fourth is the stage of the environmental protection tax levy. At the government level, the pollutant discharge charge system has problems such as poor standardization of management processes and insufficiently innovative supervisory methods. On the enterprise side, problems included poor auditing of law enforcement plans, poor implementation of the ledger system, and a lack of disclosure of pollution data (Ren et al., 2022). To further promote the green development of the industry, China's green technology innovations should be promoted. On 25 December 2016, "the Environmental Protection Tax Law of the People's Republic of China" was passed and became effective on 1 January 2018. With this, China ended nearly 40 years of the "discharge fee" levy system, and the environmental protection tax system entered the stage of history. Before 2018, it was a "pollution charge system," and in 2018, it was changed to an "environmental protection tax system." Therefore, this study takes the environmental protection tax policy reform in 2018 to discuss the impact of the "pollution charge system" to the "environmental protection tax system" (referred to as the environmental "fee-to-tax") on FDI.

The "pollutant discharge charge system" and the "environmental protection tax system" levy taxes on the pollution within the scope of air, water, solid, and noise pollutants directly discharged to the environment. The "pollution charge system" is collected in the form of a "fee," and the "environmental protection tax system" is collected in the form of a "tax." Therefore, the environmental protection tax law implementation is significantly different from the discharge fee system in terms of the institutional design at many levels. First: Different legal statuses: The penalty form of the discharge fee system is an administrative penalty. At the same time, the environmental protection tax law incorporates the payment of environmental protection tax into the legal principle of taxation so that enterprises are punished by law when there is theft or omission of environmental protection tax. As a result, implementing environmental protection taxes is subject to stricter government supervision and public monitoring. Second: Different tax deductions: For example, if the concentration value of taxable air or water pollutants is less than 30% of the national and local pollutant emission standards, the environmental protection tax is reduced by 75%. If it is less than 50% of the emission standards, the environmental protection tax is reduced by 50%. Third: Different levies and management: The environmental protection tax law will no longer be levied by administrative methods but by the taxation department for levy and the environmental protection department for monitoring and control using the levy and management model of "enterprise declaration, taxation collection, environmental protection coordination, and information sharing."[2] The design of the tax system of "more emission, more payment, less emission, less payment, no emission, no payment" guides emission enterprises to enhance environmental awareness, increase treatment, accelerate the transformation and upgrading, promote the construction of ecological civilization, and help enterprises develop with high quality.

2.2 Literature review

There are mainly two views on the impact of environmental regulation on FDI. The first view is the "pollution haven" hypothesis (Baek, 2016; Shahbaz et al., 2018b; Luo et al., 2022). Another idea is the "pollution halo" hypothesis (Wang et al., 2019; Yu and Xu, 2019; Mert and Caglar, 2020; Pan et al., 2020), which is based on the "Porter hypothesis" proposed by Porter and van der Linder (1995).

The "pollution heaven" hypothesis was first proposed by Walter and Ugelow (1979) and further developed by Copeland and Taylor (1994) in combination with the North–South trade model. The hypothesis states that under open economy conditions, free trade results in the continuous migration of highly polluting industries from developed to developing countries. Foreign companies prefer to invest in low-cost areas with looser environmental regulations. As a result, FDI eventually transfers heavily polluting industries to countries with low environmental regulation and obtains corresponding benefits from the government (Alfredon, 2015; Aziz, 2018; Vo, 2020; Duana and Jiang, 2021), making tax environmental regulation a preferred destination for FDI (Dong et al., 2021). In addition, foreign-invested enterprises invest a lot of low-end intensive products in developing countries, which hinders local technological progress to a certain extent, thus locking developing countries at the lower end of the global value chain (Feng et al., 2019). Strict environmental regulation can enhance the inhibitory effect of FDI on green innovation (Xu et al., 2021). As a result, countries and regions compete to lose environmental regulations and choose lower environmental standards (Hakimi and Hamdi, 2016). Naughton (2014) found that host country regulation reduces the return on monetary capital and triggers capital outflows to regions with lower environmental regulatory standards and that strict environmental regulation hinders the overseas investment expansion of pollution-intensive industries (Cai et al., 2016). Some energy-intensive and polluting MNCs exit the market due to high local environmental regulations (Yang and Song, 2019).

In contrast, the "pollution halo" hypothesis states that for developing countries, FDI inflows can bring advanced technologies that the motherland can imitate to drive technological innovation, reduction of pollutant discharge, and economic growth (Dada and Abanikanda, 2021; Jiang et al., 2021). Furthermore, according to the "Porter hypothesis" (Porter and van der Linder, 1995), strict environmental protection can stimulate innovation, offset environmental costs, and give manufacturers a competitive advantage. Therefore, strict environmental regulations can promote enterprises to invest in technology and actively explore ways to cope with stricter environmental regulations, such as improving productivity (i.e., the weak Porter hypothesis) and technological reform (i.e., the strong Porter hypothesis), to realize "innovation compensation" (Porter, 1991; Porter and Van der Linde, 1995; Albrizio et al., 2017; Naqvi and Stockhammer, 2018). Using

2 In addition to the aforementioned three differences, there are significant differences in the basis of tax calculation, content of tax collection, subject of tax collection, and other methods. For details, please refer to "the Implementation Regulations of the Environmental Protection Tax Law of the People's Republic of China."

transnational data from 34 host countries and 115 countries in Asia from 2001 to 2012, Bashir and Khan (2019) found that stronger environmental regulatory policies can promote the development of new energy and technology-intensive industries and attract FDI from developed countries. In addition, strict environmental regulations can increase domestic production, attract foreign multinationals, and increase FDI (Kim and Rhee, 2019) because foreign-invested enterprises have sufficient funds and advanced technologies. Moreover, their compliance costs with environmental regulations are relatively low. At the same time, strengthening environmental policies in the host country brings higher costs to local companies than to multinational companies, reducing local companies' market competitiveness and improving the core competitiveness of foreign-invested enterprises. Therefore, strengthening the environmental protection tax can still increase FDI (Dijkstra et al., 2011; Yu and Li, 2020).

3 Research design

3.1 Data sources

The article selects 287[3] cities in 30[4] provinces in China from 2003 to 2019 to analyze the impact of the environmental "fee-to-tax" reform on FDI based on panel data. The main reason for choosing 2003 as the study's starting point is that the "Regulations on the Collection and Use of Discharge Fee" were implemented on 1 July 2003. All of the data are obtained from the EPS database.

3.2 Variable selection

3.2.1 Explained variable

Drawing on Cai et al. (2016), the article adopts the actual FDI flow utilized by cities to reflect the level of FDI and takes the logarithm of the FDI used to express it.

3.2.2 Explanatory variables

The environmental protection tax was officially implemented on 1 January 2018. Since the environmental protection tax has different levy standards in each city, which leads to differences in the size of the environmental regulation impact of the implementation of the environmental protection tax on the cities, the study takes the change in the sulfur dioxide tax rate as the object. It sets the policy dummy variable, setting cities larger than the median environmental protection tax rate as 1 and 0 otherwise. Furthermore, it sets the years after 2017 as 1 and 0 otherwise. Finally, the intensity interaction term was obtained by multiplying the policy dummy and the time dummy, reflecting the net effect of environmental protection tax policy implementation on FDI.

3.2.3 Control variables

There are more factors affecting FDI. If we do not add control variables for them, it leads to bias due to omitting critical explanatory variables and affects the empirical results. According to Cai et al. (2016), this study mainly selects the following control variables: to ensure that the empirical results are more accurate, the following variables were selected for control: when the higher local GDP indicates the fact that the cities have more economic strength and are more capable of attracting FDI, the *per capita* GDP is selected for control; the industrial structure is also one of the critical indicators of regional development; the level of industrial structure is controlled; the openness of the region affects the aggressiveness of FDI enterprises; when the openness is higher, it can naturally attract more FDI; and the article chose the proportion of total imports and exports to GDP to indicate the openness. Local taxation will increase the tax burden of enterprises, and a higher tax burden will affect profit, as reflected by the proportion of local general budgetary revenue in GDP. The urban population can provide sufficient labor for FDI enterprises. When the people and population density of the cities are more extensive, it indicates a better local economic development. The resident population and population density of the cities are selected to control and aim for the local income level and financial development level, which are expressed by the average wage of employees and the loans of various balances of financial institutions at the end of the year as a percentage of GDP, respectively. In Table 1, we can see the variable names, symbols, and calculation methods.

Table 2 reflects the descriptive statistics of each variable with the observed mean, standard deviation, and minimum and maximal variables. We can see that the maximum of the logarithm of FDI is 14.152 and the minimum is 2.996, with standard deviations of 1.935, indicating that the distribution of FDI in the cities has a gap. The mean value of the policy dummy variable is 0.422, indicating that half of the cities are included in the experimental group, which also ensures the adequacy of experimental subjects.

3.3 Model setting

We establish an intensity difference-in-difference model to examine the impact of environmental "fee-to-tax" on FDI. The intensity difference-in-differences model is an econometric regression method similar to difference-in-difference. In the difference-in-difference model, we divide the sample into an experimental group and a control group according to whether they were shocked by the policy. However, all samples were affected by the environmental protection tax reform, making it impossible to construct an experimental group and a control group according to whether they were shocked by the policy. Therefore, according to Chen (2017), we divided it into experimental and control groups based on intensity. It should be noted that this study uses intensity difference-in-differences and median to distinguish between the experimental and control groups for the following reasons. First, the median environmental protection tax rate in this study is 1.8. Second, most cities

3 Currently, there are 333 prefecture-level city administrative regions in China; the number of prefecture-level cities is 293; and the prefecture-level cities with more serious missing data are deleted.

4 There are 31 provinces (autonomous regions and municipalities) in mainland China, where the data do not include Chinese Hong Kong, Chinese Macao, and Chinese Taiwan. Due to the more serious data deficiency in the Tibet Autonomous Region, Chinese scholars generally do not include data from the Tibet Autonomous Region in their empirical studies.

TABLE 1 Variable names, symbols, and calculation methods.

Variable name	Symbol	Calculation method
Foreign direct investment	LnFDI	Log of the actual utilization of FDI
Time dummy variable	Time	After 2017 as 1; otherwise, 0
Policy dummy variable	Treat	Larger than the median environmental protection tax rate as 1; otherwise, 0
Intensity interaction term	Intensity DID	Time dummy variable*Policy dummy variable
Gross domestic product *per capita*	Lnpgdp	Regional GDP *per capita* in logarithm
Industry structure	Ind	Primary industry ratio 1 + secondary industry ratio 2 + tertiary industry ratio 3
Openness	Open	Total imports and exports to the GDP ratio
Tax burden	Tax	Fiscal revenue to the GDP ratio
Population	Lnrk	Log of resident population
Population density	Lnrkmd	Log of population density
Average wage	Lnpwage	Average wage of employees
Financial development	Financial	Balance of loans from financial institutions as a percentage of GDP at the end of the year

TABLE 2 Descriptive statistics.

Variable	Obs.	Mean	Std. dev.	Min	Max
LnFDI	4,605	9.643	1.935	2.996	14.152
Time	4,879	0.118	0.322	0.000	1.000
Treat	4,879	0.422	0.494	0.000	1.000
Intensity DID	4,879	0.050	0.217	0.000	1.000
Lnpgdp	4,878	10.21	0.831	7.712	12.456
Ind	4,823	2.244	0.146	1.847	2.749
Open	4,532	0.195	0.331	0.001	2.859
Tax	4,879	0.067	0.028	0.02	0.204
Lnrk	4,876	5.850	0.672	3.748	7.791
Lnrkmd	4,825	7.868	0.855	4.407	9.534
Lnpwage	4,832	10.384	0.626	8.797	11.772
Financial	4,849	0.864	0.500	0.180	4.027

increase the environmental protection tax rate based on 1.26 and raise the standard by more than 1.8. For example, taking sulfur dioxide as an example, Liaoning Province still adopted the standard of 1.26 Yuan/kg, Hunan Province raised it from 1.26 Yuan/kg to 2.48 Yuan/kg, and Tianjin still adopted the standard of 6.3 Yuan/kg. Therefore, the empirical strategy of this study not only ensures the advantage of traditional difference-in-differences but also ensures that cities with higher standards fall into the control group. Furthermore, we set cities larger than the median of the environmental protection tax as the experimental group and cities smaller than the median of the levy standard as the control group, so grouping based on the intensity difference-in-difference method is relative rather than absolute. Based on the intensity difference-in-difference design requirements, the following intensity difference-in-difference model is used to test the impact of environmental "fee-to-tax" on FDI:

$$Y_{it} = \alpha_0 + \beta_1 intensitydid_{it} + \sum_{j+1}^{n} \beta_j control_{it} + year_t + city_i + \varepsilon_{it},$$

where Y_{it} is the explained variable, which represents FDI. $intensitydid_{it}$ is the explanatory variable and represents the interaction term of the time dummy and policy dummy variables. The interaction coefficient β_1 measures the impact of environmental "fee-to-tax" on FDI and is the core variable index coefficient concerned. To further ensure the accuracy and validity of the empirical results and to mitigate the endogeneity of the results due to the omission of significant explanatory variables, the study controls a series of control variables, of which $contral_{it}$ reflects the control variables added to the model, as shown in the variable selection in this section. $year_t$ is the year-fixed effect, which is used to control for macroeconomic factors and policy changes that can affect all cities in a given year. $city_i$ is the city fixed effect, which is used to remove the effects of factors that do not change over time (over a short period), such as the location of the city and cultural factors, and ε_{it} is the error.

4 Empirical results

4.1 Baseline regression

Table 3 reports the results of the baseline regression of environmental "fee-to-tax" for FDI. Models (1)–(4) represent the two-way fixed effects without control variables, random effects with control variables, fixed effects, and two-way fixed effects, respectively. The final results are presented in model (4). In the latter, we use a two-way fixed effects model with the inclusion of control variables for analyses. The results of model (4) show that the impact of environmental "fee-to-tax" on FDI is positive and passes the 1% significance level test, indicating that the environmental "fee-

TABLE 3 Baseline regression.

Model	Model (1)	Model (2)	Model (3)	Model (4)
Intensity DID	0.6916***(0.1235)	0.1128* (0.0655)	0.4433*** (0.1166)	0.4564*** (0.1191)
Lnpgdp		1.4302*** (0.1706)	1.5699*** (0.1181)	1.3799*** (0.2011)
Ind		0.7254* (0.4217)	0.7490* (0.4184)	0.5856 (0.5092)
Open		0.4205*** (0.1491)	0.3882*** (0.1329)	0.2823* (0.1478)
Tax		10.5456*** (1.7459)	7.9935*** (1.7377)	7.5618*** (1.8533)
Lnrk		0.6821*** (0.2444)	1.2640*** (0.0808)	0.8888*** (0.2669)
Lnrkmd		0.1070*** (0.3333)	0.0829** (0.0368)	0.0891** (0.0385)
Lnpwage		−0.6076*** (0.1892)	0.1705 (0.2158)	0.4623** (0.2334)
Financial		−0.4871*** (0.1173)	−0.1943** (0.0887)	−0.1866* (0.1084)
City fixed	Yes	Yes	No	Yes
Time fixed	Yes	No	Yes	Yes
R^2	0.034	0.694	0.732	0.711
N	4,605	4,202	4,202	4,202

*, **, and ***, respectively, represent the significance levels of 10%, 5%, and 1%. The values in parentheses are standard errors. Clustering standards estimate the model regression at the city level, and the results of the control variables were reported in the baseline regression but not the other results.

TABLE 4 Mechanism analysis.

Model	Model (1)	Model (1)
Variable	Green innovation	LnFDI
Intensity DID	0.0115** (0.0054)	0.3122**(0.1465)
Green innovation		0.1241** (0.0583)
Control variables	Yes	Yes
City fixed	Yes	Yes
Time fixed	Yes	Yes
R^2	0.5698	0.6588
N	4,163	4,163

*, **, and ***, respectively, represent the significance levels of 10%, 5%, and 1%. The values in parentheses are standard errors; clustering standards estimate the model regression in the cities.

to-tax" policy does not expel FDI from the country. On the contrary, it can promote the growth of FDI.

4.2 Mechanism analysis

In the baseline regression, we have confirmed that the environmental "fee-to-tax" does not lead to the withdrawal of FDI. On the contrary, it increases traumatic FDI, and the "pollution halo" effect is confirmed. Therefore, we used the mediation model (Muller et al., 2005; Yuan and MacKinnon, 2009; Zhang and Kong, 2021) to test the effect of the "pollution halo" and analyze whether environmental "fee-to-tax" significantly increases enterprise R&D. We use the proportion of green invention patents to all invention patents to measure the level of green innovation in cities. According to the "Porter hypothesis," proper environmental regulation can promote green innovation. Fahad et al. (2020) found that environmental regulation attracted more foreign capital investment, the influx of capital further promoted technological progress (Zeng and Zhou, 2021), and there was a positive interaction between technological innovation and FDI. According to model (1) in Table 4, the environmental "fee-to-tax" significantly promotes green innovation. According to model (2), the environmental "fee-to-tax" interaction and green innovation terms can significantly promote FDI. Therefore, the study finds that the environmental "fee-to-tax" can increase FDI, and the "pollution halo" effect is verified.

4.3 Parallel trend test

We adopt a quasi-natural experiment approach to study the impact of environmental "fee-to-tax" on FDI. We must ensure that our research subjects satisfy the assumption of parallel trends. If they do not meet the

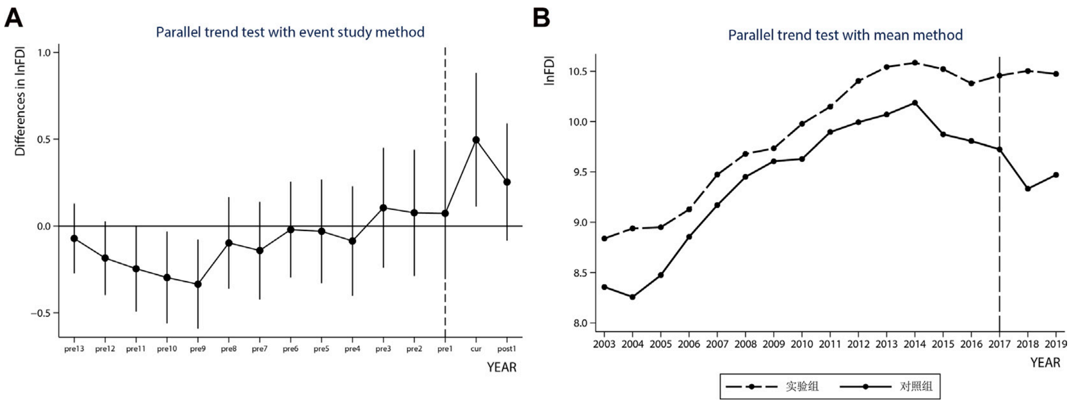

FIGURE 1
Parallel trend test.

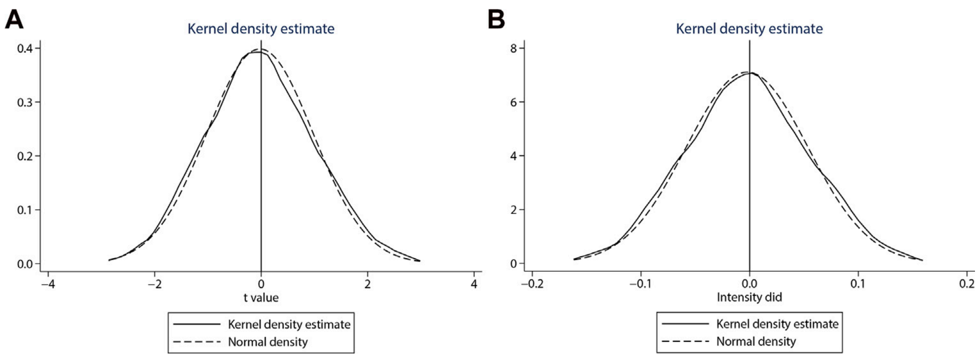

FIGURE 2
Placebo test.

assumption of parallel trends, they lead to unreliable results. Our research subjects should maintain the same trend when there is no policy shock, and the research subjects should change when there is a policy shock. In model (4) of Table 3, the environmental "fee-to-tax" significantly drives FDI, which means that to verify the conclusion here, we need to ensure that the trend of FDI is consistent until 2018; after 2017, the level of FDI in the experimental group should be significantly higher than the trend of the control group.

In Figure 1A, we can see the parallel trend with the mean method of FDI. The trend of the experimental group in FDI and the control group remained the same before 2018, when the policy was implemented, but after 2017, it showed a significant difference; FDI in the experimental group was significantly higher than that of the control group. The parallel trend test graph is drawn using the mean method to determine whether the common trend test may be crude, and we further adopt the event study method for the parallel trend test, whose results are more accurate and scientific, where Figure 1B indicates the parallel trend test with the event study method of FDI, pre1–pre13 represent the previous policies, cur represents the current policy, and post1 represents the first issue after the policy. Before 2018, FDI fluctuated around 0; its 95% confidence interval contains 0. In 2018 and after 2018, FDI showed a significant increase, and its 95% confidence interval is significantly different from 0, indicating that FDI showed a significant increase after implementing the policy. However, a part of the interval containing 0 in 2019 still passed the 5% significance level test.

4.4 Heterogeneity test

China is a vast country with a severe development imbalance between regions, and there may be significant differences in the shock effects on FDI. Therefore, we explore the differences in the influence of environmental "fee-to-tax" FDI from three perspectives: east, central, and west China[5]. Models (1)–(3) in Table 5 represent

5 See https://data.stats.gov.cn/easyquery.htm?cn=E0103: the three zones of the areas.

TABLE 5 Heterogeneity test.

Model	Model (1)	Model (2)	Model (3)
Area	East	Middle	West
Intensity DID	0.4879*** (0.1626)	0.5575** (0.2186)	0.1062 (0.2528)
Control variables	Yes	Yes	Yes
City fixed	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
R^2	0.769	0.726	0.253
N	1,372	1733	1,097

*, **, and ***, respectively, represent the significance levels of 10%, 5%, and 1%. The values in parentheses are standard errors; clustering standards estimate the model regression in the cities.

the impact of environmental “fee-to-tax” on FDI in east, central, and west China, respectively. We find that the environmental “fee-to-tax” has a significant positive effect on FDI in the eastern and central regions, passing the 1% and 5% significance level tests, but it is not significant in the western region.

On the whole, the environmental “fee-to-tax” did not trigger the withdrawal of FDI, and the hypothesis of the “pollution halo” was verified, indicating that the environmental “fee-to-tax” reform significantly promoted technological innovation of foreign-invested enterprises and improved market competitiveness. As the eastern region is a developed coastal area, its superior geographical location has local natural advantages for the location of foreign-invested enterprises. In addition, the eastern region has a high level of economic development, good resource conditions, and greater urban openness. This region can provide sufficient technology demand and labor supply for foreign-invested enterprises. Therefore, environmental regulation can continuously strengthen technology spillover, and a good market environment can also provide a recasting power for FDI in the eastern region. In recent years, Southeast Asian countries have introduced many preferential policies to attract foreign investment in land, tax revenue, foreign exchange, and other aspects and formed great competition with our country in undertaking the international industrial transfer. Compared with the adjacent Southeast Asian countries, the western region does not have a competitive advantage in attracting foreign investment through preferential tax policies. For a long time, in the western region, the preferential tax policy and no corresponding adjustments according to the international and domestic situations changed before the formulation of the narrow scope of the national encouraging directory, and infrastructure and technical conditions in the western regions were relatively scarce. There is little attraction for FDI. Environmental “fee-to-tax” cannot promote the performance of FDI in western China through the technology spillover effect. The central region’s economic development, market conditions, and technological level are between the eastern and western regions. The central region provides a stable market for FDI and relatively suitable environmental standards for enterprises. Therefore, the environmental “fee-to-tax” plays a significant role in FDI in the central region.

4.5 Robustness tests

We use a series of methods to test the empirical results to ensure that they are robust. Since the financial crisis outbreak turned the economy into a depression to ensure that the empirical results were not affected by economic cycle shocks, the financial crisis occurred in 2008. The main impact was in 2009. Therefore, model (1) in Table 5 excludes the policy year of 2008 and adds the 2009 dummy variable. The impact generated by the financial crisis is not short-term. China has launched its currency policy and released four trillion dollars to stimulate the economy; therefore, the outbreak of the financial crisis will have an impact on economic growth and FDI. Model (2) identifies the sample interval as after 2008; the 287 prefecture-level cities include municipalities, provincial capitals, and vice-ministerial-level cities, which are of a higher administrative level and have better economic resources and a better market environment to attract FDI. Model (3) deletes municipalities, provincial capitals, and vice-ministerial-level cities; the level of FDI in the previous period is more related to the level of FDI in the current period. Model (4) controls for the lagged period of FDI data in the model for control; the implementation of the environmental protection tax levy standard is not random and plays a leading role in demonstration. The areas with high levy standards are generally those with better economic development. Therefore, non-randomization of the grouping can lead to biased policy results. The PSM approach can reduce these biases and the influence of confounding variables so that the experimental and control groups can be compared more reasonably. Therefore, we use the propensity score matching–difference-in-difference (PSM–DID) method to continue the analysis. Using the logit regression method to determine the matching variables based on 1:1 matching (one-to-one matching) removes the unmatched cities for intensity difference-in-difference regression analysis. Model (5) reflects the study based on the PSM–DID method in our empirical research.

We use the method to cluster at the city level. The higher the clustering level, the weaker the implied hypothesis. However, suppose the empirical results after defining the clustering level at the provincial level are still significant. In that case, it indicates that the empirical results are trustworthy. Model (6) uses the clustering method at the provincial level, and the change in the clustering level does not change the regression coefficient. However, only the standard error, the magnitude of the baseline regression

TABLE 6 Robustness test.

Model	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
Robustness test	Deletes 2008, and adds the 2009 dummy variable	After the financial crisis	Deletes municipalities, provincial capitals, and deputy provincial capital cities	Lags one period of FDI	PSM-DID	Province of clustering	Time dummy variable interacts with the intensity variable
Intensity DID	0.4311*** (0.1180)	0.3261*** (0.1038)	0.4223*** (0.1264)	0.2507*** (0.0835)	0.3379* (0.1715)	0.4564* (0.2507)	0.1087*** (0.0029)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.713	0.695	0.648	0.934	0.623	0.711	0.7124
N	3,932	2,863	3,741	4,114	1873	4,202	4,202

*, **, and ***, respectively, represent the significance levels of 10%, 5%, and 1%. The values in parentheses are standard errors; clustering standards estimate the model regression in the cities, except for model (6). The regression adopts clustering standards to estimate the province; the others are all estimated by clustering standards in the cities.

coefficient of model (6) in Table 6, is consistent with model (4) in Table 3. The identification method of this paper is to use the median environmental protection tax rate to distinguish the experimental group from the control group and construct the intensity difference-in-differences model. Therefore, model (7) directly interacts with the time dummy variable and the environmental protection tax rate to obtain a new intensity difference-in-differences interaction term. From the robustness regression results of models (1)–(7) in Table 6, we find that the impact of environmental "fee-to-tax" on the FDI remains significantly positive and passes the significance test at 10% and smaller. A series of robustness tests reveal that the empirical results are consistent with those of the baseline regressions and that there are no significant fluctuations in the coefficient changes, indicating that the empirical evidence is very robust and valid and that the empirical results are credible.

4.6 Policy uniqueness test

During the sample period of this study, China announced a series of policies to improve the environment. To accurately and effectively identify the increase in FDI due to the environmental protection tax policy in 2018, the article excludes the interference of other policies to increase the robustness of the results. If, after controlling for other policies, the effect of the environmental "tax reform" on FDI becomes insignificant, then there is at least a reason to doubt the effect of the environmental "tax reform" on FDI; conversely, the results' reliability is enhanced. Although discharge fees were levied during 2003–2017, the levy standards for discharge fees have continued to be adjusted by cities. Taking the sulfur dioxide levy as an example, the levy standard in Beijing was increased from 0.63 RMB/pollution equivalent to 10 RMB/pollution equivalent during the period; Tianjin also experienced the following adjustments: 0.42 RMB/pollution equivalent, 0.63 RMB/pollution equivalent, 0.96 RMB/pollution equivalent, 1.26 RMB/pollution equivalent, 2.52 RMB/pollution equivalent, and 5.04 RMB/pollution equivalent. However, the adjustment of discharge fees was completed in 2015 in all cities. Thus, to exclude the error caused by the increase of the emission levy standard, which affects FDI, model (1) in Table 7 excludes this policy interference by shortening the time years, so the time interval years are set to 2016–2019. The carbon trading policy is also essential for optimizing the energy structure, promoting technological innovation, reducing pollution, and facilitating the entry and exit of FDI. In October 2011, the National Development and Reform Commission issued "the Notice on the Pilot Work of Carbon Emission Trading," which approved the pilot work of carbon trading in seven provinces and cities, including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen. Excluding the carbon trading policy, cities implementing carbon trading policies are removed from the model (2). The empirical regression results of models (1)–(2) in Table 7 show that the environmental "fee-to-tax" still significantly promotes FDI, indicating that the environmental "fee-to-tax" policy indeed causes the increase in FDI.

4.7 Placebo test

In addition to being affected by policy shocks and relevant variables, we need to eliminate the possibility that the empirical results are a randomized conclusion. First, the experimental and control groups are randomly assigned to construct new grouping dummy variables. Second, intensity difference-in-difference regression is re-run to obtain t-values and interaction term coefficients for the interaction terms of the policy variables. Finally, the aforementioned steps are repeated 500 times to observe the distribution of t-values and interaction term coefficients. From Figure 2, we found that the t-value (A) and interaction term coefficient (B) of the placebo test showed a normal distribution with a mean close to 0, and the accurate estimate of 0.4564 obtained by the benchmark regression model (4) in Table 3 was significantly different from the value obtained by the placebo test, indicating that the empirical results were not random.

TABLE 7 Policy uniqueness test.

Model	Model (1)	Model (2)
Policy	Discharge fee policy	Carbon trading policy
Intensity DID	0.3671*** (0.1203)	0.5266** (0.1211)
Control variables	Yes	Yes
City fixed	Yes	Yes
Time fixed	Yes	Yes
R^2	0.571	0.674
N	996	3,938

*, **, and ***, respectively, represent the significance levels of 10%, 5%, and 1%. The values in parentheses are standard errors; clustering standards estimate the model regression in the cities.

TABLE 8 Expand analysis.

Model	Model (1)
Expand analysis	Discharge of pollutants
Intensity DID	−0.0114*** (0.0038)
Control variables	Yes
City fixed	Yes
Time fixed	Yes
R^2	0.6135
N	4,154

*, **, and, ***, respectively, represent the significance levels of 10%, 5%, and 1%. The values in parentheses are standard errors; clustering standards estimate the model regression in the cities.

4.8 Expand analysis

The environmental protection tax has an important impact on reducing pollutant emissions and promoting environmental protection. Therefore, this study explores the impact of environmental "fee-to-tax" on pollutant emissions. In Table 8, we select industrial waste water, waste gas, and dust to construct a comprehensive index to reflect pollutant emissions by entropy. The larger the value, the more pollutants are discharged. The results show that the environmental "fee-to-tax" is conducive to reducing the emission of pollutants and can achieve the effect of pollution control, which has passed the significance level test of 1%, and that environmental protection tax plays a vital role in reducing the emission of pollutants. Therefore, we can actively promote the implementation of the environmental protection tax, which is not only conducive to the promotion of high-quality development through FDI but also conducive to the use of low-carbon technologies to reduce pollutant emissions (Edziah et al., 2022).

5 Conclusion and policy implications

Using the data from 287 cities in 30 provinces in China, this paper constructs an intensity difference-in-difference model to examine the impact of the environmental "fee-to-tax" on FDI and finds the following conclusions: first, empirical results show that the environmental "fee-to-tax" significantly boosts FDI, and the findings hold up through a series of robustness tests. The "pollution halo" hypothesis is confirmed by the latest environmental policy. Second, the heterogeneity test found that the environmental "fee-to-tax" mainly promoted FDI in the east and central regions but not significantly in the western regions. Third, further research found that the environmental "fee-to-tax" can effectively reduce the emission of pollutants. The main limitation of this study is that it cannot accurately depict the behaviors of enterprises under strict environmental regulations at the company. Therefore, in the following research, we can analyze the impact of environmental "fee-to-tax" on the investment of foreign-invested enterprises, such as the company's investment scale and the number of foreign-invested enterprises. Further analysis of environmental "fee-to-tax" significantly increases the innovation of foreign-invested enterprises and explores the impact of environmental "fee-to-tax" on firm heterogeneity. Due to the differences in environmental protection tax rate standards between regions, company registration data are used to analyze whether environmental "fee-to-tax" be transferred internally between regions in China.

Based on the research, this paper puts forward the following suggestions: the first is implementing and strengthening environmental protection tax policies and exploring more reasonable environmental protection tax regulations and giving full play to the policy effect of "treating pollution with taxes and increasing efficiency." The second is the government should strengthen its support for green innovation activities of foreign-invested enterprises to reduce the risk of R&D and innovation. The third is expanding the degree of openness to attract high-quality foreign-invested enterprises. The fourth is the government can make a negative list of FDI, include more polluting industries in the negative list, and guide FDI to clean industries. The fifth is paying attention to FDI regional differences and promoting FDI regional synergistic development. Finally, innovation support for foreign-invested enterprises in the east and central regions should be strengthened, tax incentives should be increased, and environmental subsidies should be provided for foreign-invested enterprises in the West.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.epsnet.com.cn/index.html#/Index.

Author contributions

JH: Conceptualization, Formal analysis, Software, Validation, Data curation, Writing—original draft and review. YL: Methodology, Formal analysis, Funding acquisition.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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