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Topography-dependent paradox: how extreme climate and the digital economy affect food security differently across terrains

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Introduction: The increasing frequency of extreme weather events poses significant challenges to global food security, while the rapid development of the digital economy offers new pathways for mitigation.

Methods: This study constructs a Household Food Insecurity Experience Scale and a Digital Economy Indicator System based on survey data from 1,066 households in Sichuan Province, China, collected in 2024. Using publicly available extreme weather data from official websites, the research examines the impact of extreme weather on farmers' food security across different terrains and explores the moderating role of the digital economy.

Results: Contrary to conventional understanding, an increase in the extreme weather index was found to enhance household food security, with the effect varying by topography. In plain areas, where extreme weather events occur more frequently, households exhibited higher food security indices compared to non-plain areas. Specifically, a one-unit increase in the extreme weather index raised the food security index by 28.2% in plain areas but reduced it by 9.7% in non-plain areas. This divergence stems from differences in food access mechanisms shaped by terrain. In plains, extreme weather increased households' reliance on external food purchases without significantly compromising self-sufficiency. In contrast, in non-plain areas, extreme weather substantially weakened self-sufficiency, while complex terrain further restricted access to external food supplies. Moreover, the digital economy effectively mitigated the negative impact of extreme weather on food security in topographically disadvantaged regions. Under its moderating influence, a one-unit increase in the extreme weather index amplified the food security improvement in plain areas from 28.2 to 68.9%, while in non-plain areas, extreme weather no longer exerted a significant effect. The underlying mechanism lies in the digital economy's ability to enhance agricultural insurance participation, food production efficiency, and household income, collectively offsetting extreme weather's adverse effects through increased earnings, reduced production costs, and better risk management.

Conclusion: This study highlights the terrain-dependent effects of extreme weather on household food security and the moderating role of the digital economy. The findings provide valuable insights for policymakers and stakeholders to strategically leverage digital economy practices in narrowing regional disparities in food security.

KEYWORDS

extreme climate, food security, digital economy, different topographies, food sources

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1 Introduction

Food security is a central issue related to human wellbeing, global stability, and sustainable development. Despite efforts by the international community to address global food security challenges, the issue remains pervasive. In the post-pandemic era, although global food supply chains and international trade are gradually recovering, multiple factors—such as imbalances in global food supply and distribution and geopolitical conflicts—have increasingly complicated the global food trade environment. Consequently, some low- and middle-income countries continue to face food crises (Devereux et al., 2020; Hellegers, 2022). Food security refers to ensuring that all people, at all times, have physical and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life. This concept encompasses four core dimensions: food availability (adequate production), access (economic and physical means to obtain food), stability (resilience against supply disruptions), and utilization (nutritional adequacy and food safety). To quantitatively assess food insecurity levels, the Food and Agriculture Organization (FAO) developed the Household Food Insecurity Experience Scale (HFIES), which classifies food insecurity severity through direct surveys on households' difficulties in acquiring food. Furthermore, the multidimensional nature of food security is evaluated using dietary diversity scores and food group consumption frequencies to comprehensively measure dietary quality and nutrient adequacy. In recent years, academic research on food security has become increasingly in-depth. Existing studies have examined how factors such as urban–rural development (Liu and Zhou, 2021), climate change (Lee et al., 2024), and government interventions (Cordonnier et al., 2024) impact food security from an external perspective, and how land use (Molotoks et al., 2021) and risk aversion (de Raymond et al., 2021) influence it from an internal perspective. Although existing research has explored food security from multiple perspectives, it tends to focus more on systemic and structural factors, while giving less attention to the direct impact of climate change, particularly extreme weather, on food security. Extreme weather has, in fact, become a significant risk factor affecting food production efficiency and farmers' livelihoods (Hasegawa et al., 2021; Rising et al., 2022). This study's food security indicator system therefore incorporates comprehensive considerations of both food insecurity and dietary diversity.

Digital economy represents an emerging economic form that utilizes digitalized knowledge and information as core production factors, leverages modern information networks as its carrier, and achieves efficiency improvements and economic structure optimization through the deep integration of information technologies with the real economy. Within the agricultural sector, its core components comprise digital infrastructure, digital production technologies, digitalized distribution and sales systems, and digital financial services—elements which have informed the construction of our digital economy indicator framework for this study. With the rapid development of the digital economy, digital technologies have profoundly transformed farmers' production processes and lifestyles. The digital economy has deeply penetrated every aspect of food production. How, then, does the digital economy alleviate the impact of climate change on farmers' food security? First, the digital economy leverages precision agriculture technologies to help farmers optimize production decisions, reducing uncertainties caused by climate change (Yao and Fu, 2023). Second, digital management enhances the efficiency of the agricultural supply chain, mitigating the impact of extreme weather on market supply and demand (Kumar et al., 2023). Additionally, digital finance and insurance services provide farmers with risk protection, alleviating the economic pressures caused by natural disasters (Gao et al., 2024). Through knowledge dissemination via digital platforms, farmers can access the latest agricultural technologies and coping strategies, enhancing their ability to cope with extreme weather.

Although existing studies have examined the relationships between extreme weather, the digital economy, and household food security from various perspectives, significant research gaps remain. First, current research predominantly focuses on the impact of long-term climate change on agricultural production, overlooking the direct and immediate shocks of extreme weather events on household food security. It also fails to adequately reveal the role of the digital economy in mitigating sudden climate disasters and safeguarding food security. Second, topographic heterogeneity has not been effectively incorporated into analyses. Given topography's substantial influence on climatic conditions, the frequency and impact mechanisms of extreme weather likely differ significantly across terrains. However, relevant studies lack in-depth comparisons of how extreme weather affects household food security under varying topographic conditions. Third, empirical evidence at the micro-level is relatively scarce. Existing research primarily relies on macro-level or regional aggregate statistics, lacking analysis based on household-level microdata. This limitation constrains a nuanced understanding of how the digital economy alleviates extreme weather shocks and ensures food security at the individual level. Consequently, addressing these gaps, this study frames its core research questions as: How do extreme weather events affect grain production? How does this effect vary across different terrains? Can the digital economy mitigate the impact of extreme weather events on household food security, and if so, how?

To answer these questions, utilizing the latest 2024 survey data from 1,066 farming households in Sichuan Province, this study aims to: (1) uncover the impact and mechanisms of extreme weather events on household food security across diverse terrains, and (2) examine the moderating effect of digital economic development on this impact under different topographic conditions. Leveraging detailed microdata and novel digital economy metrics, we characterize extreme weather events and digital economy levels, ensuring our analysis captures the diversity of individual households' contexts.

This paper contributes to the literature in three primary ways. First, employing household-level data, we deepen the research on climate shocks and food security from a micro-perspective, addressing a blind spot in prior macro-level studies. We specifically examine differences in extreme weather impacts across mountainous, hilly, and plain areas, revealing regional characteristics of climate shocks. Second, our study introduces significant content innovation: by incorporating the digital economy variable, we test how digitalization aids households in coping with extreme weather—to our knowledge, this represents one of the first empirical efforts examining the role of the digital economy in mitigating extreme weather shocks on food security among farming households in developing regions. Third, we refine the measurement system for the digital economy: constructing indicators via the Technology Acceptance Model (TAM), we comprehensively account for farmers' acceptance and perceived utility/usability of digital technologies, making the digital economy index more relevant to the practical needs of rural settings in low- and middle-income countries.

Collectively, these contributions enhance our understanding of how extreme weather, topographic heterogeneity, and digital development jointly influence household food security, providing new insights for enhancing agricultural risk resilience. In summary, this paper systematically analyzes the combined effects of extreme weather, topographic variation, and the digital economy on household food security using micro-survey data. It not only proposes solutions to multiple shortcomings in the existing literature but also provides valuable empirical evidence to inform related theoretical research and policy formulation.

2 Theoretical analysis

2.1 Extreme climate and farmers' food security

Agricultural production is fundamentally an intertwined process of natural reproduction and economic reproduction. Climatic factors, as core natural variables, disrupt crop physiological cycles and the efficiency of production factor allocation through nonlinear pathways. Weather extremes directly destabilize the stable growth environment for crops by altering the spatiotemporal distribution of light, temperature, water, and heat resources. This triggers a cascade of effects including intensified pest and disease outbreaks, suppression of photosynthesis, and disruption of pollination processes (Lobell and Gourdji, 2012). These disturbances manifest as yield fluctuations at the micro level while escalating into regional food supply imbalances at the macro level. Within the theoretical framework of agricultural production functions, the impact of climatic shocks on output can be deconstructed into two primary pathways: technical efficiency loss and resource utilization distortion (Aragon et al., 2021). On one hand, anomalous precipitation or temperatures deviating from optimal crop growth thresholds cause soil moisture imbalances and nutrient depletion, reducing the marginal output elasticity of land (Shirley et al., 2020) drought-induced irrigation water scarcity directly reduces grai. On the other hand, catastrophic events compel farmers to adjust their strategies for factor inputs. Topographic heterogeneity plays a critical role in this process—plains areas, with their advantages in contiguous cultivation and mechanization adaptability, can buffer climatic shocks through scale economies. Conversely, hilly and mountainous regions, constrained by fragmented landholdings and ecological fragility, experience amplified effects of climatic disturbances through exacerbated soil erosion and microhabitat degradation. Consequently, theoretical models must simultaneously capture the direct biophysical effects of climatic variables and their interactive effects with topographic features to precisely quantify the net impact of extreme weather on food security.

Crop production is the result of the interaction between socioeconomic and natural factors. Therefore, when examining the impact of climate factor changes on food security, the primary consideration is how climate factors affect crop yields and agricultural production efficiency. During the derivation of the production function, it is first necessary to separate the economic yield of food crops to obtain the yield determined solely by natural factors under climate variables, thus identifying the "fluctuating yield" influenced by climate. Therefore, the total yield of food crops is defined as Equation (1):

$$Y = Y_i + Y_c + \varepsilon \tag{1}$$

In the above formula, Y represents the total grain yield in a given region, Y_i denotes the economic yield resulting from social factors in that region, Y_c signifies the fluctuating yield affected by climate, and ε represents the random error.

To accurately investigate the fluctuating yield impacted by climate, this study applies the Cobb–Douglas production function to calculate socioeconomic yield and thus assess the influence of various socioeconomic factors on yield as Equation (2):

$$Y_i = K_1^{\alpha_1} K_2^{\alpha_2} \tag{2}$$

Here, K_1 and K_2 represent two primary socioeconomic factors under simplified expressions, α_1 and α_2 are the corresponding elasticity coefficients of these factors, satisfying $\alpha_1 + \alpha_2 = 1$, which aligns with the assumption of constant returns to scale. Under constant factor inputs, grain production efficiency can be represented as the ratio of actual grain output to optimal output. Within a fixed period, if the optimal yield from arable land remains constant, production efficiency can thus represent actual grain output in calculations.

The stochastic frontier approach (SFA) model, introduced in 1977, has since undergone extensive research and development, gaining widespread attention for its application in measuring resource use efficiency and analyzing utilization patterns. Analyzing grain production reveals that primary constraints on output include arable land conditions and capital investment. This paper constructs a stochastic frontier production function (SFA) to calculate grain production efficiency. This paper constructs a stochastic frontier production function to calculate grain production expressed as Equation (3):

$$\ln\left(Y_i\right) = \ln\left(f\left(K_1, K_2\right)\right) + v - u \tag{3}$$

Here, v represents a random error term following a normal distribution $N\left(0, \sigma_v^2\right)$, u is a random variable assumed to be non-negative due to technical inefficiency, following a truncated normal distribution $N^+\left(0, \sigma_u^2\right)$. In the specified model, agricultural production efficiency (APE) with regard to socioeconomic factors can be defined as Equation (4):

$$APE = \frac{Y_i}{\exp\left(\ln\left(f\left(K_1, K_2\right)\right) + v\right)} \tag{4}$$

To introduce the impact of climate factors on yield variability Y_c, this paper selects typical climate variables C, including precipitation P, temperature T, and humidity H, to examine the impact of extreme weather on agricultural production efficiency, assuming that

$$Y_c = g\left(C\right) = g\left(T, P, H\right) \tag{5}$$

In Equation (5), $g\left(\cdot\right)$ represents a function of climate variables. At this point, Y_c is a function of *T, P and H*, as these climate variables influence the variability of crop yields. To incorporate the impact of climate factors on production efficiency into the model, climate variables C are introduced as additional input variables, assuming that the production function becomes Equation (6):

$$\ln(Y) = \ln(f(K_1, K_2)) + \ln(g(C)) + v - u \tag{6}$$

At this point, $\ln(g(C))$ reflects the direct impact of climate factors on crop yield. Following the previous assumption, let $g(C) = T^{\beta_1} \cdot P^{\beta_2} \cdot H^{\beta_3}$, where β_1, β_2 and β_3 are elasticity coefficients representing the influence of temperature, precipitation, and humidity on crop yield, respectively. In summary, the production function is expressed as Equation (7):

$$\begin{aligned} \ln(Y) = {} & \alpha_1 \ln(K_1) + \alpha_2 \ln(K_2) + \beta_1 \ln(T) + \\ & \beta_2 \ln(P) + \beta_3 \ln(H) + v - u \end{aligned} \tag{7}$$

At this point, in terms of total output, agricultural production efficiency (APE) can be redefined as Equation (8):

$$APE = \frac{Y}{\exp\begin{pmatrix} \alpha_1 \ln(K_1) + \alpha_2 \ln(K_2) + \beta_1 \ln(T) + \\ \beta_2 \ln(P) + \beta_3 \ln(H) + v \end{pmatrix}} \tag{8}$$

To explain the impact of major socioeconomic factors on agricultural production efficiency under extreme weather conditions, this paper introduces a terrain impact coefficient G to differentiate the productive effects of various terrains. Intuitively, plains are more suitable for mechanized operations, making them more favorable for cultivation compared to hilly or mountainous areas. Thus, we assume that if the terrain is conducive to cultivation $G = G_1 > 1$, indicating that this terrain enhances agricultural production efficiency. Conversely $G = G_2 < 1$ suggests that such terrain conditions constrain output and production efficiency. Based on the original production model, this paper defines the adjusted crop yield Y as Equation (9):

$$Y = G \cdot f(K_1, K_2) \cdot g(C) \cdot e^{v-u} \tag{9}$$

At this point, agricultural production efficiency is expressed as Equation (10):

$$APE = \frac{G \cdot f(K_1, K_2) \cdot g(C) \cdot e^{v-u}}{\exp\begin{pmatrix} \alpha_1 \ln(K_1) + \alpha_2 \ln(K_2) + \beta_1 \ln(T) + \\ \beta_2 \ln(P) + \beta_3 \ln(H) + v \end{pmatrix}} \tag{10}$$

If $G = G_1 > 1$: Under these terrain conditions, favorable natural factors such as soil quality, moisture, and slope enhance crop growth, increasing yield per unit area and production efficiency. $G_1 > 1$ represents a positive impact of terrain on output. The opposite holds for unfavorable terrain. The terrain coefficient G directly multiplies the original output, either amplifying or reducing the final crop yield. Thus, terrain conditions alter the efficiency value, with favorable terrain increasing efficiency and unfavorable terrain reducing it.

2.2 The mediating role of food sources

Food security is fundamentally a function of supply stability and access reliability. Extreme weather indirectly threatens food security by disrupting the dual pathways through which rural households obtain food—subsistence production and market procurement. Subsistence production, serving as the first line of defense against risk, sees its output elasticity significantly suppressed by climate shocks: drought-induced irrigation water scarcity directly reduces grain setting rates, while waterlogging from heavy rainfall accelerates root rot and grain mold, leading to contraction in household grain reserves (Wheeler and von Braun, 2013). As the subsistence production gap widens, households increasingly rely on market procurement to meet consumption needs. However, extreme weather simultaneously distorts the agricultural supply chain—floods damaging transport networks increase logistics costs, while high temperatures accelerate the spoilage of perishables, exacerbating supply losses. This manifests as heightened market price volatility and supply uncertainty. These dual pressures create a negative cycle of "subsistence decline–market failure": weakened self-sufficiency forces greater market dependence, while market failure increases the cost and risk of food access. Theoretical models must specifically identify the differing substitution elasticities of these two mediating pathways. In plains with developed infrastructure, market mechanisms can partially offset production losses; in high-transaction-cost mountainous areas, however, the combined effect of diminished subsistence output and obstructed procurement causes a sharp decline in food security levels. Consequently, the mode of food sourcing acts as the critical nexus transmitting climate shocks to food security outcomes, with transmission efficiency profoundly constrained by regional market development and logistical resilience.

To quantify the complementary relationship between self-sufficient food production and external market purchases in ensuring food security, this paper develops a corresponding mediation effect model. Self-sufficiency in production and external market purchases are treated as two key variables affecting food security, with consideration given to the impact of extreme weather on both. The specific modeling approach is as follows:

Food security level is represented y, y a function of the quantity of food produced for self-sufficiency Q_1 and the quantity purchased from external markets Q_2, both influenced by extreme weather C. The mediation effect model can be constructed as Equation (11):

$$y = \varphi + \tau_1 Q_1 + \tau_2 Q_2 + \gamma C + \delta(Q_1 \cdot C) + \theta(Q_2 \cdot C) + \epsilon \tag{11}$$

Here, Q_1 denotes the quantity of food produced by farmers for self-sufficiency, which can reduce dependency on the external market. Q_2 represents the quantity of food purchased from the external market, which can supplement supply when self-sufficient production is insufficient. C (as previously defined) represents the variable for extreme weather intensity. φ is a constant term representing the baseline level of food security. τ_1 and τ_2 are the direct impact coefficients of self-sufficient production Q_1 and external market purchases Q_2 on food security level. γ is the direct impact coefficient of extreme weather on food security. δ is the coefficient of the interaction term $Q_1 \times C$, measuring the compensatory effect of self-sufficient production on food security under extreme weather. θ is the coefficient of the interaction term $Q_2 \times C$, indicating the effect of extreme weather on dependency on external markets. ϵ is the error term, capturing unexplained random fluctuations within the model.

In this framework, the impact coefficient τ_1 of Q_1 on y indicates how an increase in self-sufficient production enhances food security. If $\tau_1 > 0$, it suggests that increasing the self-sufficient production Q_1 helps to improve food security levels, as self-sufficiency can stabilize food supply. The impact coefficient τ_2 of Q_2 on y represents the supplementary effect of external market purchases. If $\tau_2 > 0$, external market purchases Q_2 can supplement supply, mitigating shortages and strengthening food security. Additionally, extreme weather C impacts food security through the direct coefficient γ; If $\gamma < 0$, extreme weather has a negative effect on food security. The interaction terms $Q_1 \times C$ and $Q_2 \times C$ examine the mediating roles of self-sufficient production and external market purchases on food security under extreme weather conditions. If $\delta > 0$, it suggests that self-sufficient production can mitigate the impact of extreme weather on food security, reducing dependence on the external market. Conversely, if $\theta < 0$, it implies that external market purchases may be adversely affected by extreme weather, thereby reducing food security levels.

2.3 The moderating role of the digital economy

Digital economy mitigates the negative impact of extreme weather on food security through four-dimensional restructuring. Digital acceptance determines the breadth of farmers' application of digital tools, with high-adoption groups proactively leveraging digital technologies to avoid planting risks and reduce production-side vulnerabilities. Digital finance innovates risk-dispersing instruments, converting physical losses into actuarial payouts to alleviate post-disaster capital constraints hindering grain reproduction. Digital production technologies optimize resource allocation by dynamically adjusting water, fertilizer, and pesticide inputs in real time, thereby suppressing yield volatility (Yu et al., 2025). Digital infrastructure underpins this ecosystem: logistics big data platforms dynamically route shipments around disaster-affected routes, while e-commerce markets bridge information gaps by connecting oversupplied regions with cross-regional demand (Giacalone, 2025). Crucially, these four dimensions synergistically form an "early warning-buffer-adaptation-recovery" cycle. Digital economy not only shortens the time lag between climate shocks and responsive decision-making but also reduces climate sensitivity per unit output through precision resource allocation. Theoretical models must elucidate how digital economy reshapes the response function of "climate shock-food security" by reducing information asymmetry, enhancing factor mobility, and strengthening risk dispersion capabilities—fundamentally shifting the marginal effect curve of climate impacts downward through reduced systemic vulnerability and heightened adaptive capacity.

To further analyze the moderating effect of the digital economy on the relationship between food security and extreme weather, this paper introduces the moderating variable T to build an econometric model. The digital economy can mitigate the negative impact of extreme weather on food security by enhancing information transmission efficiency, optimizing supply chain management, and promoting precision agriculture. Extending the discussion above, the econometric model introduces a digital economy moderation variable, where food security level y has a direct relationship with Q, and extreme weather C and the digital economy T have a moderating effect on y. The model is constructed as Equation (12):

$$y = \varphi + \tau Q + \gamma C + \vartheta \left(T \cdot C\right) + \epsilon \tag{12}$$

In addition to the variables defined in the previous model, Q represents the total quantity of food (regardless of source), and τ is the direct impact coefficient of the total food quantity Q on food security. ϑ is the interaction coefficient between extreme weather and the digital economy, measuring the moderating effect of the digital economy on food security under extreme weather conditions.

If $\tau > 0$, this indicates that increasing the food supply Q can directly enhance food security levels. The interaction term $T \times C$ has a coefficient ϑ, representing the moderating effect of the digital economy on food security under extreme weather conditions. If $\vartheta > 0$ this suggests that the digital economy can exert a positive moderating effect on food security during extreme weather. Advances in the digital economy, such as supply chain optimization, market information transmission, and precision agriculture technology, can mitigate the negative impact of extreme weather on food security.

3 Data source, indicator selection and model construction

3.1 Data source

The data for this study primarily come from two sources: first, micro-level survey data from farmers. This survey was led by the research team in collaboration with the Rural Revitalization Institute of Sichuan Open University, focusing on agricultural production, the digital economy, and land use. The survey was conducted among farmers in Sichuan Province in the summer of 2024. Based on the geographical characteristics, the research team divided Sichuan Province into five regions: Eastern Sichuan, Western Sichuan, Southern Sichuan, Northern Sichuan, and Central Sichuan. Two prefecture-level cities were randomly selected from each region. Employing a combined stratified and random sampling approach, five distinct villages were chosen per city based on two criteria: proximity to urban centers (categorized as near-village [<5 km], medium-distance village [5–10 km], and remote village [>10 km]) and economic development level (high, medium, low) determined by tertile-based pairing of village-level GDP. Using official rosters provided by village committees, 25 farming households were then randomly sampled per village for in-person household surveys. A total of 1,250 farmer questionnaires were collected in this survey. After excluding irrelevant, incomplete, or invalid responses and conducting several follow-up phone interviews, 1,066 valid questionnaires were obtained, yielding an effective response rate of 85.28%. Sichuan Province is located in the southwest interior of China, spanning the first and second steps of the Chinese mainland's topography, characterized by significant elevation differences, with higher elevations in the west and lower elevations in the east. The region features diverse and complex terrain, including plateaus, mountains, hills, and plains. Given the varied natural resource endowments, the development of the digital economy and the manifestation of extreme weather exhibit significant heterogeneity, making this study both forward-looking and highly representative. The second source is climate data. The extreme weather indicators used in this study were obtained and further processed from the China Meteorological Science Data Center and the U.S. National Oceanic and Atmospheric Administration (Figure 1).

3.2 Indicator selection

3.2.1 Extreme weather

This study uses extreme low temperatures days (LTD), extreme high temperatures days (HTD), extreme rainfall days (ERD), and extreme drought days (EDD) as indicators of the Climate Physical Risk Index (CPRI) for empirical analysis (Lesk et al., 2016; Ummenhofer and Meehl, 2017). To obtain extreme weather data, this study first gathers ground-level climate data from each county in the survey region, including maximum temperature, minimum temperature, rainfall, and relative humidity. If data for a specific county is unavailable, data from neighboring counties or the nearest city is used as a substitute. Additionally, given the complex terrain and significant climate variability in the study area, a relative threshold method is applied to identify extreme weather events. Specifically, daily average temperatures from 2023 are sorted in ascending order, with the 90th and 10th percentiles used as the thresholds for extreme high and low temperatures, respectively. For rainfall, precipitation values greater than 0 are sorted in ascending order, and the 95th percentile is set as the threshold for extreme rainfall. Relative humidity is also sorted in ascending order, with the 5th percentile serving as the threshold for extreme drought. The min-max normalization method is then applied to process the data, calculating the number of days for each type of extreme weather during the year, and the average is used to form the Climate Physical Risk Index (Guo et al., 2024). Table 1 presents the extreme weather conditions in the counties within the study area, showing a higher probability of extreme high temperatures and extreme drought.

3.2.2 Food security

This study examines food security from the perspective of farming households. Therefore, it uses the Household Food Insecurity Experience Scale (HFIES) developed by the Food and Agriculture Organization of the United Nations (FAO) to assess the level of food insecurity faced by farming households (Akim et al., 2024). Specifically, farming households are asked eight binary questions related to food insecurity, with "yes" coded as 1 and "no" coded as 0. The higher the score, the more severe the food insecurity experienced by the household. Considering the multidimensional nature of food security, the study further measures the Household Dietary Diversity (HDD) score by examining the types of food consumed by households over the past 7 days. Each type of food is assigned a score, and the weighted sum of nutritional density is used to calculate the Food Consumption Score. The nine food groups and their respective weights are as follows: dairy products, 4; animal protein, 4; legumes, 3; staple foods, 2; vegetables, 1; fruits, 1; fats, 0.5; sugar, 0.5 (Cordonnier et al., 2024). Finally, these variables are incorporated into the food security indicator system, and the final score is calculated using the entropy method. Table 2 reports the food security status of the surveyed households, indicating relatively good food security in the study region.

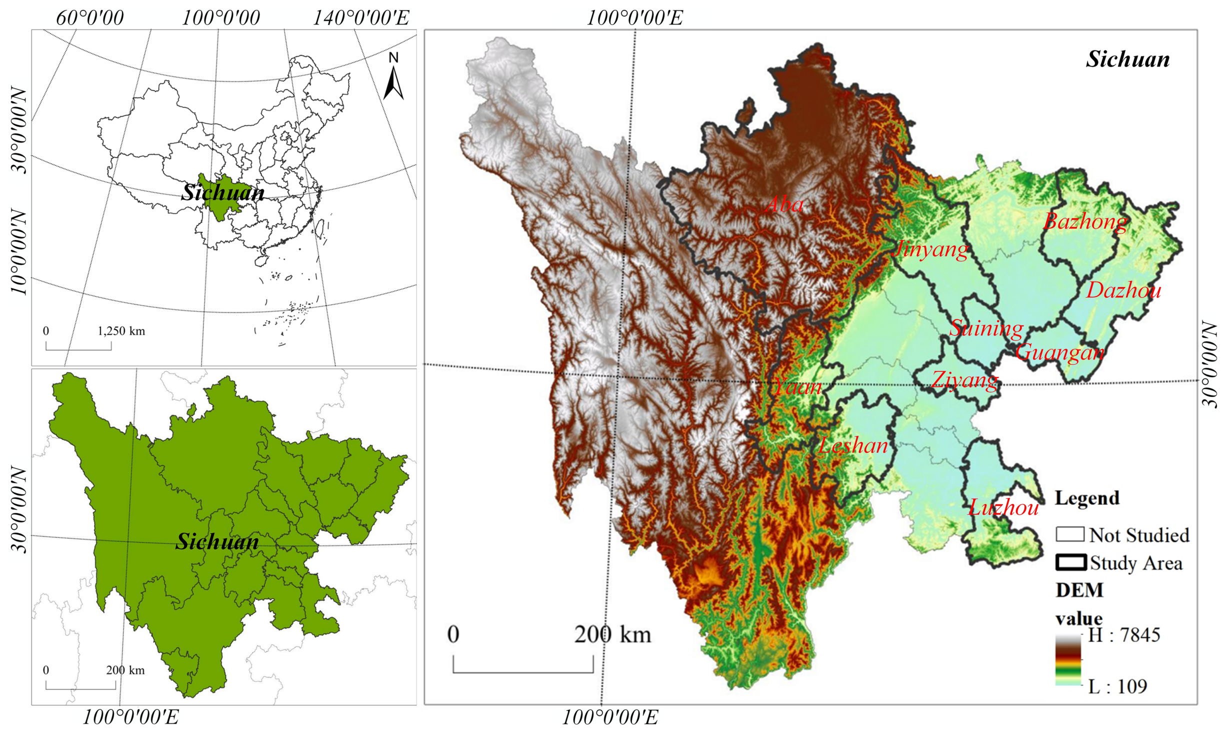

FIGURE 1
Spatial distribution of the study areas.

TABLE 1 Climate Physical Risk Index system.

Variables	Mean	Standard deviation
Extreme low temperature days	13.665	3.601
Extreme high temperature days	57.766	10.940
Extreme rainfall days	15.503	10.987
Extreme drought days	33.471	24.391

TABLE 2 Summary statistics of food security outcomes.

Variables	Mean	Standard deviation
Household food insecurity experience scale	0.084	0.337
Household dietary diversity score	6.553	1.262
Food consumption score	11.716	2.147

3.2.3 Digital economy

There is no unified standard for constructing the digital economy indicator system in academia, but it primarily focuses on the external conditions of digital technology and farmers' ability to apply these technologies (Zahoor et al., 2023). However, for the vast majority of low- and middle-income countries, where modernization has started relatively late, the key concern in the diffusion of digital technology should be whether farmers are willing and able to adopt these technologies. With socio-economic development, the outflow of young labor from rural areas is inevitable. However, whether the elderly population remaining in villages can adapt to the changes brought by the digital economy to their production and lifestyle is a prerequisite for their use of digital technologies (Hunsaker and Hargittai, 2018). In summary, existing research has overlooked the internal factors influencing farmers' acceptance and willingness to adopt digital technologies, which are often key determinants of the effectiveness of digital technology implementation in practice. Therefore, this paper incorporates the Technology Acceptance Model (TAM) into the traditional digital economy indicator system, using the concepts of perceived ease of use and perceived usefulness to understand farmers' attitudes toward digital technology. Additionally, digital infrastructure forms the foundation of the digital economy; digital production examines whether farmers use digital technologies in agricultural production to enhance productivity; and digital finance enables farmers to more easily access loan information, alleviating financial constraints and improving their capacity to buffer risks. Prior to computation, diagnostic tests were conducted: Bartlett's test of sphericity yielded a statistically significant result ($p < 0.001$), and the Kaiser-Meyer-Olkin measure reached 0.986, exceeding the recommended threshold of 0.7, collectively indicating high suitability for factor analysis. The analysis subsequently extracted four distinct factors, with all measured variables demonstrating high factor loadings on their respective components (Table 3).

3.2.4 Control variables

In addition to the main indicators mentioned above, this study selects individual characteristics, household characteristics, and village characteristics as control variables, based on the micro-level perspective of farmers. All indicators are detailed in Table 4.

3.3 Model construction

This paper constructs an equation to examine the impact of extreme weather on farmers' food security. Based on the nature of the dependent variable, the Ordinary Least Squares (OLS) model is used for econometric analysis, and the specific expression is shown in Equation (13):

$$Y_i = \alpha_0 + \alpha_1 CPRI_i + \alpha_2 X_i + \mu_i \tag{13}$$

In this equation, the dependent variable Y_i represents the farmers' food security index, the independent variable $CPRI_i$ represents the Climate Physical Risk Index, and X_i represents control variables that may affect the dependent variable. α_0, α_1 and α_2 are the parameters to be estimated; μ_i represents the error term.

4 Empirical analysis

4.1 The impact of extreme weather on food security

Before performing the regression analysis, this study uses the Variance Inflation Factor (VIF) to test for multicollinearity among the variables. The results indicate that all VIF values are below 10, indicating no multicollinearity. Table 5 presents the impact of extreme weather on farmers' food security. For every one-unit increase in the extreme climate risk index, the household food security index increases by 15.2%, suggesting that an increase in extreme weather events is associated with a higher food security index for farmers. Additionally, this study employs extreme weather data from 2014 and the slope of the study area as instrumental variables to address endogeneity. First, the extreme weather events of 2014 are past natural occurrences, unaffected by current farmer behavior or food security conditions, thereby possessing exogeneity. Additionally, the climate system exhibits continuity, and there is typically a strong correlation between past extreme weather events and current climate conditions. Second, the slope of the study area, as a geographic feature, is a stable and exogenous variable that cannot be influenced by individual behavior. Slope affects local climate conditions, such as precipitation patterns, soil water retention, and erosion risk, all of which are closely linked to the frequency and intensity of extreme weather events. However, this natural feature remains unchanged by farmers' decisions or food production activities. The chosen instrumental variables meet the assumptions of relevance and exogeneity, and pass the relevant tests, fulfilling the selection requirements. Additionally, when the 2SLS model is replaced with the LIML model for regression, the results remain consistent—after accounting for endogeneity and robustness, more extreme weather events still correspond to a higher food security index for farmers.

The control variables revealed significant variations in household food security levels. An increase in female-headed households, younger age demographics, and higher education attainment positively enhanced food security. At the household level, expanded cultivated land area and greater non-agricultural employment participation similarly improved food security outcomes. Village-level proximity to townships and location in plains further amplified these positive effects. Human capital (gender, age, education) and livelihood strategies (cultivated land scale, non-agricultural employment) constituted

TABLE 3 Digital economy indicator system.

Variables	Definition	Mean	Standard deviation
Digital acceptance	Do you believe that using digital devices can contribute to agricultural production? 1 = Yes; 0 = No	0.688	0.463
	Do you believe that using digital devices can enhance market competitiveness? 1 = Yes; 0 = No	0.647	0.478
	Do you believe that using digital devices can improve risk resistance? 1 = Yes; 0 = No	0.258	0.438
	Do you feel confident using digital devices? 1 = Yes; 0 = No	0.674	0.469
	Do you spend less time searching for information with digital devices? 1 = Yes; 0 = No	0.613	0.487
	Do you find using digital devices convenient? 1 = Yes; 0 = No	0.665	0.472
Digital infrastructure	Do you use a mobile phone? 1 = Yes; 0 = No	0.991	0.096
	Can your mobile phone access the internet? 1 = Yes; 0 = No	0.959	0.199
	Are you connected to satellite television? 1 = Yes; 0 = No	0.990	0.101
Digital production	Do you obtain agricultural product prices/market information through digital devices? 1 = Yes; 0 = No	0.629	0.483
	Do you acquire agricultural technical knowledge through digital devices? 1 = Yes; 0 = No	0.774	0.418
	Do you use digital technology in agricultural production? 1 = Yes; 0 = No	0.864	0.343
Digital finance	Do you obtain credit through digital devices? 1 = Yes; 0 = No	0.571	0.495
	Do you use digital payment methods? 1 = Yes; 0 = No	0.757	0.429
	Do you use digital financial products? 1 = Yes; 0 = No	0.262	0.440

TABLE 4 Description and descriptive statistics of variables.

Variables	Name	Definition	Mean	Standard deviation
Explained variables	Food security	Food security index of farmers	0.605	0.187
Explanatory variables	Extreme Weather	Climate Physical Risk Index	30.040	7.105
Mediating variable	Food source	More of the food you get in 2023 will come from self-sufficiency: 1 = yes; 0 = no	0.488	0.497
		More of your food in 2023 will come from external purchases: 1 = yes; 0 = no	0.493	0.500
Moderating variables	Digital Economy	Digital economy index system score	0.520	0.321
Control variables	Sex	1 = male; 0 = female	0.839	0.368
	Age	Actual age of the household head/years	57.713	16.923
	Educational attainment	Years of formal education received by the household head/years	7.551	2.759
	Scale of operation	Total area of family-owned land (km^2)	8.443	21.233
	Land transfer behavior	Whether there will be land transfer behavior in 2023:1 = yes; 0 = no	0.716	0.451
	Dependency ratio	Ratio of household labor force to total household population (%)	0.716	0.156
	Migrant work situation	The proportion of Household migrant workers in the Total household population (%)	0.479	0.500
	Household size	Number of people in the household	3.958	1.469
	Distance to nearest town	Distance from the village to the nearest town/km	11.206	8.592
	Village terrain	1 = Non-plain; 0 = Plain	0.241	0.428

The Food Security Index and Digital Economy Index are calculated using the entropy method, while the Extreme Climate Risk Index is obtained by averaging.

foundational capacities for risk resilience, whereas geographical positioning (urban proximity, plain advantages) amplified protective effects through enhanced resource accessibility (Table 6).

However, this phenomenon is clearly counterintuitive. Typically, climatic shocks disrupt the natural growing conditions for crops, increasing uncertainty and risk in agricultural production, which in turn reduces crop yields and quality, weakening the stability of the food supply (Wineman et al., 2017; Christ and Niles, 2018). Research also confirms that, from a macro perspective, climate change negatively impacts the stability of food security (Hasegawa et al., 2021). Why, then, do conclusions from the micro perspective completely contradict those from the macro perspective? By comparing and reanalyzing the original data, significant differences between extreme weather events and farmers' food security indices were observed across different topographical conditions (Table 6): In plain areas, despite the higher frequency of extreme weather events, farmers' food security indices are also higher. In non-plain areas (mainly hills and mountains), although extreme weather events occur less frequently, farmers' food security indices are lower.

Furthermore, Table 7 demonstrates the differences in extreme weather and farmers' food security across topographies: a one-unit

TABLE 5 The impact of extreme weather on food security.

Variables	Food security (OLS)		Food security (2SLS)		Food security (LIML)	
	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.
CPRI	0.152***	0.001	0.722***	0.004	0.760***	0.004
Sex	−0.055***	0.010	−0.047*	0.014	−0.047*	0.014
Age	−0.271***	0.000	−0.181***	0.001	−0.181***	0.001
Educational attainment	0.236***	0.003	0.133**	0.004	0.133**	0.004
Scale of operation	0.000*	0.000	0.000*	0.000	0.000*	0.000
Land transfer behavior	0.005	0.008	0.043	0.012	0.043	0.012
Dependency ratio	−0.021	0.027	−0.023	0.034	−0.023	0.035
Migrant work situation	0.075	0.008	0.070**	0.010	0.070**	0.010
Household size	0.008	0.003	0.016	0.004	0.016	0.004
Distance to nearest town	−0.046	0.000	−0.046**	0.001	−0.046*	0.001
Village terrain	−0.371***	0.009	−0.284***	0.016	−0.279***	0.016
Numbers of samples	1,066		1,066		1,066	
R^2	0.586		0.309		0.276	

***, **, and * indicate significance at the 1, 5, and 10% levels. Durbin (score) p-value = 0.0026; Wu–Hausman p-value = 0.0020; F-value = 18.1513; Sargan (score) p-value = 0.1600; Basmann p-value = 0.1622.

increase in the extreme weather index raised the food security index by 28.2% in plain areas but reduced it by 9.7% in non-plain areas. A possible explanation is that plains feature flat terrain, better transportation and infrastructure, and more advanced digital economic development, which makes it easier for farmers to access disaster prevention information and technical support, thereby enhancing their ability to cope with extreme weather. Additionally, plain areas have higher levels of agricultural mechanization and production efficiency, so even though climatic shocks occur more frequently, farmers' food security can still be maintained. In contrast, non-plain areas are characterized by more complex terrain, poor transportation networks, underdeveloped infrastructure, and lagging digital economic development. Farmers in these regions have limited access to information and technical support, making them more vulnerable to extreme weather despite relatively stable climatic conditions.

TABLE 6 Comparison of extreme weather and food security in different regions.

Village terrain	Plain	Non-plain
CPRI	31.054	26.845
Food security	0.662	0.428

4.2 The mediating role of food sources

Food sourcing methods (self-sufficiency and external purchasing) serve as complementary mediators between extreme weather and farmers' food security. As shown in Table 8, extreme weather events have significantly different effects on farmers' food supply sources across various topographical conditions. In plain areas, an increase in weather extremes leads farmers to rely more on external food purchases, while their level of self-sufficiency remains largely unaffected. In contrast, in non-plain areas (such as mountainous and hilly regions), extreme weather significantly reduces farmers' self-sufficiency, yet has no significant effect on external food purchases. The core driving factors behind this phenomenon can be attributed to the imbalances in agricultural production efficiency and the allocation of economic resources (Table 9).

First, due to favorable terrain conditions, plain areas have higher levels of agricultural mechanization, with production efficiency far surpassing that of non-plain areas. The agricultural infrastructure in these regions is more advanced, and farmers possess greater resilience to climatic shocks. The well-developed transportation networks in plain areas enable farmers to swiftly compensate for production losses through the market, while the ease of external food purchases further diversifies their supply structure. Therefore, although extreme weather increases their reliance on external food sources, the availability of economic resources ensures that their self-sufficiency remains largely unaffected (Table 9).

In contrast, in non-plain areas, complex terrain constrains the development of agricultural mechanization and large-scale production, leading to lower production efficiency for farmers. Moreover, traditional small-scale farming methods expose them to greater production risks. Additionally, the relatively underdeveloped transportation and market infrastructure in non-plain areas limits access to external food sources, further exacerbating farmers' difficulties in coping with extreme weather. The low production efficiency also results in generally low household incomes for farmers, leaving them without sufficient economic resources to purchase food from the market.

4.3 The moderating role of the digital economy

In summary, food sourcing methods (self-sufficiency and external purchasing) act as mediators between extreme weather and food security, further highlighting the deeper influence of agricultural production efficiency and farmers' income on this relationship.

TABLE 7 Effects of extreme weather on food security in different terrains.

Variables	Food security (Plain)		Food security (Non-plain)	
	Std. Coeff.	S.E.	Std. Coeff.	S.E.
CPRI	0.282***	0.001	−0.097*	0.002
Other variables	Yes		Yes	
Numbers of samples	809		257	
R^2	0.487		0.385	

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

TABLE 8 Mediating role of food sources in different terrain.

Variables	Plain				Non-plain			
	Self-sufficiency		External purchase		Self-sufficiency		External purchase	
	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.
CPRI	0.134	0.007	0.236**	0.007	−0.446**	0.015	−0.055	0.019
Other variables	Yes		Yes		Yes		Yes	
Numbers of samples	809		809		257		257	
R^2	0.018		0.030		0.061		0.157	

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

TABLE 9 Differences in agricultural production efficiency and economic resource allocation under different terrains.

Variables	Plain				Non-plain			
	Agricultural productivity		Household income		Agricultural productivity		Household income	
	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.
CPRI	−0.003*	0.144	−0.353	0.398	−0.007***	0.317	−0.399*	0.263
Other variables	Yes		Yes		Yes		Yes	
Numbers of samples	809		809		257		257	
R^2	0.046		0.098		0.106		0.167	

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

However, with the rapid development of the digital economy, its application in agriculture has profoundly impacted traditional production methods and farmers' livelihoods. Therefore, it is necessary to further explore the moderating role of the digital economy in the relationship between extreme weather and food security, in order to fully understand its mechanisms in mitigating the impacts of extreme weather.

In plain areas, the digital economy demonstrates a clear moderating effect on mitigating the impact of extreme weather on farmers' food security. Data in Table 10 indicate that the digital economy amplifies the positive impact of extreme weather on farmers' food security, a one-unit increase in the extreme weather index amplified the food security improvement in plain areas from 28.2 to 68.9%. Moreover, plain areas facilitate mechanized operations and the rapid dissemination of information technology, enabling farmers to more fully utilize the production tools and financial services enabled by the digital economy, effectively mitigating climate risks.

In contrast, Table 11 presents different dynamics for non-plain areas (such as mountainous and hilly regions). In non-plain areas, extreme weather no longer exerted a significant effect. Although the digital economy has mitigated the negative impact of extreme weather on food security to some extent, particularly in areas like digital acceptance, digital production, and digital finance, the moderating effect of digital infrastructure has had a negative impact. The complexity of non-plain terrains significantly limits the expansion and maintenance of infrastructure, not only increasing costs but also making it more vulnerable to damage from natural disasters. The fragility of digital infrastructure significantly amplifies the uncertainty surrounding food security during weather extremes.

From the previous analysis, it is clear that digital production and digital finance play crucial roles in moderating the impact of extreme weather on farmers' food security. Digital finance not only helps farmers diversify risk by offering a range of financial tools, but also provides timely financial support during climatic shocks, reducing the economic pressure caused by climate fluctuations. At the same time, digital production, through the use of precision agriculture technologies, employs data-driven management and predictive models to increase production efficiency, reduce resource waste, and help farmers optimize production decisions, further enhancing their ability to cope with uncertainties. In this context, how does the involvement of the digital economy affect specific indicators such as agricultural insurance, production efficiency, and farmers' income?

It is evident from the (Table 12) that the digital economy has a significantly positive impact on farmers' adoption of agricultural insurance, improvement of production efficiency, and income growth,

TABLE 10 The regulating effect of digital economy in plain terrain.

Variables	Plain									
	Food security		Food security		Food security		Food security		Food security	
	(1)		(2)		(3)		(4)		(5)	
	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.
CPRI	0.000	0.002	−0.000	0.001	0.377	0.019	0.000	0.002	0.188	0.001
CPRI × Digital Economy	0.689***	0.002								
CPRI × Digital acceptance			0.531***	0.002						
CPRI × Digital infrastructure					0.098	0.019				
CPRI × Digital production							0.631***	0.002		
CPRI × Digital finance									0.617**	0.002
Other variables	Yes		Yes		Yes		Yes		Yes	
Numbers of samples	809		809		809		809		809	
R^2	0.514		0.514		0.488		0.514		0.499	

***, **, and * indicate significance at the 1, 5, and 10% levels. Due to space limitations, this table presents only the interaction term regression results.

TABLE 11 The moderating effect of digital economy in non-plain terrain.

Variables	Non-plain									
	Food security		Food security		Food security		Food security		Food security	
	(6)		(7)		(8)		(9)		(10)	
	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.	Std. Coeff.	S.E.
CPRI	0.001	0.002	−0.002	0.002	0.012*	0.006	−0.001	0.002	−0.003	0.002
CPRI × Digital Economy	−0.572	0.016								
CPRI × Digital acceptance			−0.366	0.004						
CPRI × Digital infrastructure					−0.665**	0.007				
CPRI × Digital production							−0.257	0.003		
CPRI × Digital finance									−0.224	0.004
Other variables	Yes		Yes		Yes		Yes		Yes	
Numbers of samples	257		257		257		257		257	
R^2	0.570		0.487		0.477		0.535		0.5133	

***, **, and * indicate significance at the 1, 5, and 10% levels. Due to space limitations, this table presents only the interaction term regression results.

with an even greater effect in non-plain areas. The key reason behind this is that the complex terrain and higher natural risks in non-plain areas cause farmers to rely more heavily on digital technologies. The digital economy enhances farmers' ability to access insurance and improve production efficiency by optimizing information transmission, risk management, and financial services, thereby significantly boosting their income levels. The digital economy plays a more significant moderating and facilitating role in areas with less favorable resources and conditions (Table 12).

4.4 Differences in the impact of various types of extreme weather

Extreme weather is primarily categorized into extreme low temperature (LTD), extreme high temperature (HTD), extreme rainfall (ERD), and extreme drought (EDD). These different types of extreme weather events show significant heterogeneity across various topographical features. As shown in Table 13, extreme weather events are significantly more frequent in plain areas than in non-plain areas, with extreme high temperatures and droughts being the most common. How, then, do different types of extreme climate affect farmers' food security across various topographies? Further analysis is needed to explore this.

The estimation results in Table 14 reveal the significant impact of extreme weather on farmers' food security across various topographies. In plain regions, a one-unit increase in HTD and EED raises the household food security index by 30.2 and 33.0%, respectively. Moderate high temperatures and droughts can enhance crop photosynthesis and water use efficiency, optimizing the growing environment, especially for heat- and drought-resistant crops. In contrast, a one-unit increase in LTD and RED reduces the index by 4.5 and 7.4%, respectively. Low temperatures not only limit normal crop growth but also disrupt critical processes like pollination, leading to reduced yields. Excessive rainfall oversaturates the soil, increasing the

TABLE 12 The influence of digital economy in different terrain.

Variables	Plain			Non-plain		
	Agricultural insurance	Agricultural productivity	Household income	Agricultural insurance	Agricultural productivity	Household income
Digital economy	0.844*** (0.264)	0.012*** (0.074)	0.148*** (1.095)	0.958*** (0.510)	0.014***(0.103)	0.149**(1.700)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Numbers of samples	809	809	809	257	257	257
R^2	0.328	0.273	0.063	0.414	0.267	0.121

The coefficients in the table are standardized coefficient values. Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10% level.

TABLE 13 Different types of extreme climate under different terrain.

Village terrain (days)	Plain	Non-plain
LTD	13.740	13.376
HTD	58.726	54.254
RED	16.457	14.044
EED	35.295	25.707

risk of disease and negatively impacting harvests. Although irrigation systems can mitigate the effects of excessive rainfall, the damage caused by low temperatures is difficult to address through technological means, making its negative impact on food security more challenging.

In non-plain areas, only LTD has a significant negative impact on farmers' food security, a one-unit increase in LTD reduces the index by 7.1%. In mountainous and hilly regions, the higher elevation and greater temperature variations exacerbate the inhibitory effect of low temperatures on crop growth. As for other types of extreme weather, their impact on food security in non-plain areas is not significant, possibly due to the relatively stable climate in these regions and the more dispersed nature of crop cultivation, which limits the impact of extreme weather on crop growth.

5 Discussion

This study, utilizing a micro-survey of 1,066 farming households in Sichuan Province, China, reveals for the first time a counterintuitive relationship between extreme weather events and household food security compared to macro-level findings: households in plain areas exhibited an increase in their food security index when exposed to more extreme weather, whereas those in non-plain areas showed a significant decrease. This finding challenges the prevailing conclusion among some scholars based on regional and national macro-data regarding the universally negative impact of extreme weather (Balasundram et al., 2023; Lee et al., 2024), demonstrating that under varying topographic conditions, geomorphological factors profoundly shape the transmission pathways of climate shocks by altering production environments, infrastructure accessibility, and market responsiveness. Benefiting from flat terrain, convenient transportation, and superior irrigation infrastructure, plain-area households can rapidly convert localized yield reduction risks into market purchasing demand, thereby maintaining or even enhancing food security levels. Conversely, mountainous and hilly areas, constrained by scarce arable land resources and low mechanization levels, experience greater vulnerability in production efficiency and household income to climate disturbances, leading to a decline in the food security index with shocks—a dimension of topographic heterogeneity insufficiently explored in prior research (Alam et al., 2024).

Critically, this study provides the first empirical examination of the digital economy's moderating role in mitigating climate shocks. The results indicate that digital production tools and digital financial services significantly enhance farmers' capacity to cope with climate risks, with effects particularly pronounced in non-plain areas. This finding aligns with Existing research regarding digital financial inclusion strengthening agricultural supply chain resilience (Hong et al., 2023; Gao and Gao, 2024) and corroborates on the digital economy boosting agricultural resilience through total factor productivity gains (Wang et al., 2024). In regions with higher levels of digital production and finance, farmers not only gain more timely access to agricultural insurance but can also leverage remote weather warnings and online market platforms to transform potential yield losses into income security and sustainable production investments, thereby maintaining or even improving food security levels when facing extreme weather. This not only enriches the theoretical framework on the interactive effects between the digital economy and food security but also provides micro-level empirical support for the application of digital policies in climate adaptation. In summary, through in-depth analysis of micro-data, this study both supplements the singular conclusions of macro-research and recontextualizes the moderating role of the digital economy within the framework of topographic vulnerability, offering significant implications for targeted climate adaptation policies.

Despite systematically revealing the moderating mechanisms of topographic heterogeneity and the digital economy on household food security under extreme weather shocks from a micro-perspective, this study has limitations for further refinement. Firstly, constrained by the difficulty of obtaining micro-survey data, the study employs cross-sectional data, which cannot capture the dynamic evolution of food security impacts from weather extremes, thus hindering the assessment of long-term cumulative effects. Secondly, as the survey was not a full-coverage census, the study was unable to precisely spatially match individual households with high-resolution remote sensing or meteorological observation data, limiting a comprehensive analysis of the spatial distribution patterns of extreme weather and food security. Future research should extend the temporal dimension, expand regional samples, and integrate multi-source data (remote sensing, meteorological, and socio-economic) on the existing framework to construct an analytical system encompassing both spatial and temporal dimensions, thereby deepening the understanding of the long-term impacts of extreme weather, topographic heterogeneity, and the digital economy on household food security. Additionally, Sichuan Province's GDP per capita

TABLE 14 Effects of different extreme weather types on food security under terrain differences.

Variables	Plain				Non-plain			
	Food security	Food security	Food security	Food security	Food security	Food security	Food security	Food security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LTD	−0.045* (0.001)				−0.071* (0.002)			
HTD		0.302*** (0.000)				−0.042 (0.001)		
RED			−0.074*** (0.000)				−0.061 (0.001)	
EED				0.330*** (0.000)				−0.109 (0.000)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Numbers of samples	809	809	809	809	257	257	257	257
R^2	0.420	0.481	0.429	0.472	0.380	0.377	0.378	0.380

The coefficients in the table are standardized coefficient values. Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10% level.

remains within the range typical of developing economies. Its terrain is highly heterogeneous, encompassing a complete spectrum of landforms. Consequently, the conclusions of this study exhibit significant structural similarity to findings applicable to developing economies characterized by complex topography. However, substantial differences exist between countries in key areas, such as the prevalence of digital infrastructure. Therefore, generalizing the conclusions requires rigorous verification and adaptive adjustments based on the specific context of the target region.

6 Conclusion and policy implication

This study, based on a questionnaire survey of 1,066 farmers in Sichuan Province, reveals the micro-level impact of extreme weather on food security and examines how the digital economy mitigates this impact amid rapid digitalization. The conclusions are as follows: Typically, extreme weather events increase uncertainty and risk in agricultural production, leading to lower yields and quality. However, our analysis indicates significant terrain-dependent differences in the relationship between extreme weather events and food security indices. In plain regions, despite a higher frequency of extreme weather, farmers exhibit higher food security indices; conversely, in non-plain areas (primarily hills and mountains), where extreme weather occurs less frequently, food security indices are lower.

Further analysis suggests that this paradox arises from differing food sourcing strategies associated with terrain. In plains, an increase in extreme weather prompts farmers to rely more on external food purchases while leaving self-sufficiency largely unaffected. In non-plains, extreme weather significantly reduces self-sufficiency, and the complex terrain further limits the ability to purchase external food. Fundamentally, the balance between self-sufficiency and external purchases reflects underlying agricultural production efficiency and household income. Under extreme weather, non-plain regions experience a more pronounced decline in both production efficiency and income compared to plains.

Within the context of digitalization, our findings indicate that the digital economy effectively mitigates the negative impact of extreme weather on food security. Specifically, advancements in digital production and digital finance significantly enhance agricultural insurance uptake, production efficiency, and income, with more evident benefits in non-plain regions. Moreover, a breakdown by extreme weather type reveals that while HTD and EED events are more prevalent in plains and contribute positively to food security, LTD events in non-plain regions detract from it.

Based on this analysis, the following policy recommendations are proposed. First, enhance terrain-specific intervention mechanisms. Given the differing climate responses in plains versus mountainous areas, plains should consolidate market circulation systems and digital financial tool coverage to improve external grain allocation efficiency. Mountainous regions should prioritize upgrading smart agricultural infrastructure and promoting stress-resistant crop varieties to prevent subsistence capacity collapse. Second, strengthen the development and application of the digital economy. Accelerate the penetration of digital technologies in mountainous areas by lowering access barriers through mobile agricultural technology service platforms, while concurrently developing inclusive digital financial tools to mitigate post-extreme weather capital constraints on production recovery. Third, optimize climate-resilient planting structures. Aligned with the distribution patterns of extreme weather types across terrains, plains should adopt heat- and humidity-tolerant crop varieties, while mountainous areas focus on cold- and drought-resistant cultivars to reduce biophysical vulnerability through varietal replacement. Fourth, establish integrated market-production coordination networks. Develop regional digital agricultural service platforms consolidating weather alerts, production management, logistics coordination, and insurance claims processing, with particular emphasis on reinforcing mountainous supply chain resilience.

Data availability statement

The data in this article is obtained from on-site research. If necessary, it will be provided according to requirements.

Ethics statement

The studies involving humans were approved by Nanjing Agricultural University, Tianjin University of Finance and Economics, Yangzhou University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

XZ: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. SW: Methodology, Validation, Writing – review & editing. ZS: Investigation, Writing – review & editing. XX: Visualization, Writing – review & editing.

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Supplementary material

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