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Research on the impact of climate change on food production resilience in China

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Climate polarization threatens the food production stabilization and economic development worldwide. As a major agricultural producer, China faces increasing risks to its food security. This study examines the effects of accumulated temperature and precipitation anomaly level on food production resilience, with crop diversity potentially playing a moderating role. To this end, it uses fixed-effects and moderating-effects models based on official statistics from 31 Chinese administrative regions (2010–2022). First, China's overall resilience in food production has shown an upward trend, fluctuating from 0.376 in 2010 to 0.435 in 2022. Second, accumulated temperature has a suppressing effect on food production resilience at the 5% significance level, while precipitation anomalies have a similar effect at the 10% significance level. This inhibitory effect is most pronounced in major food-producing areas, while it is less severe in major food-consuming areas and in regions with production-consumption balanced areas. Third, crop diversity has an important moderating role, mitigating the negative impact of precipitation anomalies on food production resilience, statistically significant at 10% level; conversely, its role in moderating accumulated temperature is insignificant. To cope with climate shocks and safeguard food production security, the study proposes policy recommendations in three areas: building a climate-smart agricultural system, optimizing the application of crop diversity, and implementing targeted zoning strategies.

Keywords Climate change, Food production resilience, Crop diversity, China

Food and food security are fundamental to people's well-being, national security, and sustainable development of society and the economy. The escalating intensity and growing frequency of extreme weather events triggered by global warming pose significant risks to food production worldwide[1]. Extreme weather conditions not only disrupt agricultural production in directly affected regions, but also trigger fluctuations in agricultural exports and ripple effects on food prices in other areas[2] through supply–demand transmission mechanisms within global supply chains[3]. *The State of Food Security and Nutrition in the World 2024* indicates that between 713 and 757 million people were undernourished in 2023. In addition, over 2.33 billion people experienced moderate or severe food insecurity, with more than 864 million people facing severe levels of food insecurity[4]. Meeting the growing nutritional needs of humanity amid resource scarcity and climate extremes is one of the greatest humanitarian challenges in the twenty-first century[5].

Developing countries are substantially vulnerable to climate shocks because they rely on agriculture and have limited access to capital, technology, and infrastructure[6]. As the largest developing country, China faces significant challenges in food security due to its large population and high food demand. Despite steady growth in food production, rapid urbanization and frequent natural disasters continue to threaten food security [7]. Therefore, studying China's food production resilience (FPR) is essential for promoting supply-side structural reform and stabilizing the grain supply–demand balance.

Research on climate change primarily focuses on its impacts on the ecological environment, social life, and agricultural production. Climate change has altered regional evaporation and precipitation patterns, accelerating the degradation of plateau glaciers and permafrost[8]. Global warming also exhibits clear regional differences, with temperatures increasing two to three times faster than the global average in Eurasia and 3 to 4 times faster in the Arctic and Antarctic Peninsula[9]. In terms of social impacts, climate change has increased morbidity and mortality from infectious and respiratory diseases, while exacerbating socio-political tensions and conflicts[10]. In agriculture, while yields may increase in certain regions, declining crop quality could outweigh these gains, ultimately reducing farmers' incomes[11].

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On climate change and food production, most research has focused on food access, utilization efficiency, and food security, with relatively little attention to food production resilience. Research indicates that rising temperatures and water stress decrease agricultural productivity by increasing food prices and threatening agricultural livelihoods[12]. Food production is highly sensitive to climatic anomalies, with droughts or extreme temperatures significantly reducing output. Excessively high temperatures and diurnal temperature variation indices have a significant and negative correlation with corn and soybean yields[13]. Global investigations show that grain yields are declining in about half of all countries under current climate trends[14]. Moreover, climate change intensifies the disruption caused by non-climate disasters to global food production systems[15], generating complex chain reactions and opening up new avenues for research.

The aforementioned research provides a rich theoretical foundation for exploring the role of climate anomalies in food production resilience, but it still has notable gaps and limitations. (1) Existing literature has primarily investigated the resistance of food production to disasters, with limited research on the sustainability and regenerative capacity of food production. (2) Current research has primarily concentrated on the direct impacts of climatic anomalies on the food system, with little attention paid to how crop diversity plays a regulatory role. To address these gaps, this paper develops an evaluation system for food production resilience indicators. By introducing crop diversity as a moderating variable, it constructs a research framework that examines its role in shaping the impacts of climate change on food production resilience. In this way, this study provides significant contributions in the following three key aspects: (1) It examines the impact of climate change on food production resilience through two dimensions—annual average accumulated temperature and precipitation anomaly level—thus overcoming the limitations of single climate indicators and offering deeper insights into the mechanism of composite climate effects on food production resilience; (2) It analyzes the moderating role of crop diversity in the process of climate change influencing food production resilience, enriching the research perspective; (3) It examines regional variations in climate change impacts on food production resilience and the differing moderating effects of crop diversity, providing both theoretical foundations and empirical evidence to support differentiated approaches to resilience governance.

Theoretical framework and proposed hypotheses

Conceptual definition of food production resilience

"Resilience" originally stems from materials physics, describing a material's ability to return to its original state after external stress. In the 1970s, ecologist Holling extended the concept to ecology, defining resilience as an ecosystem's capacity to recover to a stable state and maintain normal functioning after disturbances[16]. By the early twenty-first century, resilience theory integrated human systems with ecological dynamics, achieving expansion and reinforcement within sociology and economics. It is generally defined as a system's capacity to withstand disturbances, undergo reorganization, and maintain its essential functions, structure, identity, and feedback loops while navigating change, thereby achieving dynamic objectives[17]. In economics, resilience has been studied in terms of a system's capacity to resist recessions, adapt to disruptions, and recover from external shocks such as financial crises, geopolitical conflicts, or public health events, with analyses spanning urban[18], regional[19], and macroeconomic scales. In agriculture, resilience describes the capacity of food systems to withstand and respond to disruptions in production, supply, and distribution, encompassing three dimensions: socioeconomic, biophysical, and production diversity[20]. The Food and Agriculture Organization (FAO) of the United Nations defines food production resilience as the food production system's ability to ensure that all people have access to adequate, safe, and nutritious food during disasters and to fulfill the livelihoods of food system participants in agriculture[21]. Scholars have decomposed resilience into dimensions of resistance, adaptability, and innovation[22], and examined how the food system relies on different factors such as urbanization rate[23], digital villages construction, and agricultural insurance coverage[24].

How climatic anomalies affect food production resilience

In its Sixth Assessment Report, the Intergovernmental Panel on Climate Change stated that anthropogenic emissions of greenhouse gases have contributed significantly to climate warming. The surface temperature worldwide during 2011–2020 was 1.1℃ above that during 1850–1900[25]. Climate stress has wide-ranging and profound impacts on both the environment and human society, with particularly notable effects on agricultural production.

Firstly, climate change is reducing both the quantity and quality of food production, while effective irrigation resources continue to dwindle, thereby weakening the food systems' resistance to external environmental pressures. The increasing frequency of extreme weather events, like torrential rain and heat waves, has severely disrupted agricultural environments and substantially decreased food output[26]. Research predicts that by the end of the century, nearly all major staple crops, except for rice, are at risk of yield reductions due to extreme climate change. Under high-emission scenarios, projected declines range within 12–27.8% for maize, 13.5–28.2% for wheat, and 22.4–35.6% for soybean[27]. Rising carbon dioxide emissions, higher temperatures, and increased light intensity have led to shorter crop growth cycles, reduced accumulation of sugars and nutrients, and consequently, low crop quality[28]. For example, as carbon dioxide concentrations increase, the protein content of wheat grains may decrease by 8.6%[29]. Climate-driven depletion of alpine snowpacks will reshape downstream hydrological systems, transforming both supply–demand dynamics and seasonal availability of glacial freshwater sources[30]. Based on statistical modeling, Pinke found that droughts and heat waves, which reduce effective freshwater irrigation resources in Eastern Europe, are degrading soils. Each 1℃ increase in global average temperature will result in a 4.1–6.4% decrease in European wheat production[31].

Secondly, climate change has reduced the sustainability of food systems, weakening their adaptability to external environmental changes. Evidence shows that regional climate events have become more pronounced, with erratic rainfall, prolonged droughts, and severe flooding, all of which negatively impact food production[32].

Less developed regions are often more vulnerable to climate disasters. Farmers in these areas typically have lower incomes, limited knowledge, and restricted capacity to apply technologies that mitigate agricultural climate risks[33]. For example, Sub-Saharan Africa, highly dependent on agriculture, exhibits low utilization of modern irrigation technologies and is particularly affected by high temperatures and reduced rainfall under global warming[34]. Climate change increases atmospheric carbon dioxide concentrations, temperature, and humidity, which exacerbates pest and disease outbreaks in food crops. In order to increase food production, farmers often respond by increasing the application of agricultural chemicals, including pesticides, fertilizers, and herbicides[35]. Excessive use of agrochemicals can result in eutrophication, decreased crop output, soil salinization, and rising soil pH[36], creating a vicious cycle of agricultural pollution and declining productivity.

Thirdly, climate change has led to increased fixed asset investment in agriculture and insufficient total power of agricultural machinery, thereby weakening the food system's regenerative capacity. According to the Cobb–Douglas production function, food output depends on a multifactor combination of land, labor, and capital[37]. In response to yield losses caused by climate change, farmers often increase inputs of labor, capital, materials, and technology. Agricultural development requires infrastructure, encompassing both tangible assets such as roads, irrigation systems, machinery, and repair facilities, as well as intangible components like credit systems, insurance investments, and cooperatives[38]. However, climate extremes can damage key agricultural infrastructure and raise storage and transportation costs[39]. The interaction of climatic factors and soil conditions can lead to waterlogging, which reduces soil permeability, impairs drainage, increases surface runoff and erosion, and heightens susceptibility to compaction. Consequently, root depth is reduced, adversely affecting plant growth. Excess moisture also means that machines can sink into the soil and wheels can slip, reducing the efficiency of agricultural machinery use per unit area[40].

Given this analysis, the research proposes the following hypothesis:

H1: Climate change has a dampening effect on food production resilience.

Moderating effects of crop diversity

To mitigate the impacts of climate change, growers are adapting production strategies to new conditions. Increasing crop diversity is one economically viable adaptation approach, which offers flexible forms and scales, enabling farmers to both withstand disasters and enhance economic returns[41]. Crop diversity creates a selection effect: the more species present in an ecosystem, the greater the likelihood that at least one will tolerate specific climatic conditions[42]. Enhancing diversity is crucial for stabilizing food security, as practices such as intercropping and crop rotation can improve overall productivity. Utilizing ecological niche differentiation among crops within the same spatial scenario[43] can improve resource use efficiency and promote sustainable agricultural development. Additionally, crop diversity has been indicated to enhance the agricultural output capacity and yield consistency of oilseed cropping systems across diverse settings[44].

This analysis introduces the following hypothesis:

H2: Crop diversity mitigates the adverse effects of climate disruption on food production resilience.

Climatic factors such as elevated carbon dioxide levels, rising temperatures, and altered precipitation patterns have expanded the geographical range of pests, increased overwintering survival and generation numbers, and reduced the effectiveness of biological control measures[45]. Simultaneously, climate change directly affects soil microbial systems; higher temperatures lead to the depletion of soil organic carbon, shifts in bacterial community composition, and declines in fungal abundance. Thawing permafrost may also release novel viruses[46]. Crop rotation and increased crop diversity reduce pathogen abundance and transmission through the host-absence effect and ecological regulation by antagonistic organisms arising from the decomposition of diverse plant residues within the soil [47]. Additionally, higher crop diversity enhances inter-root carbon inputs to the soil microbial community, supporting microbial growth that benefits crop development[48]. Accordingly, hypothesis H2a is proposed:

H2a: Crop diversity mitigates the adverse impact of rising accumulated temperature on food production resilience.

Reduced precipitation lowers soil moisture, inhibiting plant and microbial activity[49], while excessive rainfall during critical crop growth stages disrupts pollination and causes root oxygen deprivation and decay, ultimately reducing yields. Crop diversity mitigates these impacts by enhancing soil quality and microbial activation[50]. Crop diversity also optimizes agricultural production choices. Crops with diverse root systems of different depths can effectively increase soil voids and precipitation infiltration rates, which can effectively cope with extreme precipitation conditions[51]. Combining high- and low-level shading systems can protect crops from abnormal precipitation, as the upper canopy reduces soil evaporation and improves soil moisture infiltration[41].

Accordingly, Hypothesis H2b is proposed:

H2b: Crop diversity attenuates the detrimental influence of precipitation anomalies on food production resilience.

Building on these assumptions, this paper analyzes the disruptive effects of climate change on food production resilience across three aspects: resistance, adaptability, and regenerative capacity. It further examines the moderating role of crop diversity under two climate stressors: accumulated temperature and precipitation anomalies. The study integrates the adverse impacts of climate change with the regulatory effects of crop diversity to assess their combined influence on food production resilience. Figure 1 displays the overall framework.

Research design

Data sources

This research analyzes the impact of climate change on FPR based on panel data from 31 provincial-level administrative regions in China (excluding Hong Kong, Macao, and Taiwan) between 2010 and 2022. Data

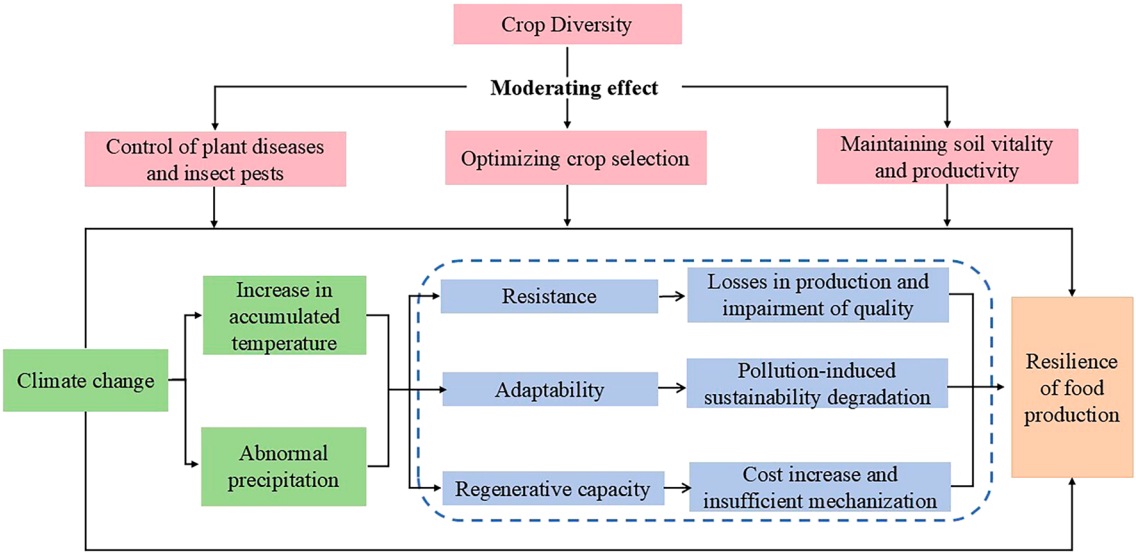

Fig. 1. The mechanism of climate change impact on food production resilience.

primarily originate from the Statistical Yearbook of China (National Bureau of Statistics), the FAO database, the National Meteorological Science Data Sharing Service Platform, and local statistical sources. For individual missing data points, interpolation methods were employed to estimate. Additionally, the 31 provinces were categorized into major food-producing areas, major food-consuming areas, and production-consumption balanced areas based on *The Outline of Medium-and Long-Term Plan for National Food Security (2008–2020)*. Specifically, the major food-producing areas encompass 13 provinces: Liaoning, Jilin, Heilongjiang, Inner Mongolia, Hebei, Shandong, Anhui, Jiangsu, Jiangxi, Henan, Hunan, Sichuan, and Hubei. The major food-consuming areas include 7 provinces: Beijing, Shanghai, Tianjin, Zhejiang, Hainan, Guangdong, and Fujian. The production-consumption balanced areas comprise 11 provinces: Shanxi, Guangxi, Chongqing, Yunnan, Guizhou, Shaanxi, Gansu, Qinghai, Tibet, Ningxia, and Xinjiang.

Selection and definition of variables

Dependent variable

Food production resilience (FPR) is the dependent variable. Based on the previous studies, this paper defines this variable as the capacity of food production systems to maintain stability and resist various internal and external shocks. To measure FPR, the FAO uses the Resilience Index Measurement and Analysis (RIMA) methodology, which calculates the Food System Resilience Index (FSRI) via factor analysis and a Multi-Indicator Multi-Factor (MIMIC) model, covering production, processing, and markets[52]. Academically, FPR is often assessed through multidimensional indicator systems, using weighting methods such as entropy, principal component analysis, or analytic hierarchy process to calculate composite indices. Some studies employ the Pressure-State-Response (PSR) framework, evaluating resilience through resistance, recovery, and transformation capacities[53]. This paper adopts a similar comprehensive approach, dividing FPR into three dimensions: resistance, adaptability, and regenerative capacity. Meanwhile, on relevant research by Zhang Mingdou and Hui Mingwei[54], the resistance is categorized into 2 dimensions of production foundation and production capacity. Adaptability is divided into two dimensions: sustainability and recoverability. Regenerative capacity is segmented into 2 dimensions: diverse collaboration and technological progress. A comprehensive evaluation framework for FPR was developed, consisting of three primary indicators, six secondary indicators, and 18 tertiary indicators. Table 1 represents the details.

Independent variable

The independent variables are the mean annual accumulated temperature (AT) and precipitation anomaly magnitude (measured by the absolute value of the standardized precipitation index, abbreviated as |SPI|). Most crops can only grow stably when the average daily temperature is above 10℃. The accumulated temperature refers to the active accumulated temperature, i.e., the sum of temperatures obtained by accumulating the duration of daily average temperature ≥ 10℃ in a year. For the calculation, daily temperature data from major meteorological stations across all provinces were used to determine monthly accumulated temperatures, from which the annual average accumulated temperature was derived for each province[55]. |SPI| is a kind of climate drought monitoring indicator based on probability statistics. It centers on quantifying the extent to which precipitation deviates from a long-term climate benchmark over a given time period through Gamma distribution fitting and normal normalization. The formulae are as follows:

Assuming that the precipitation x obeys a Gamma distribution, Eq. (1) represents its probability density function.

Tier1	Tier2	Tier3	Unit	Weights		
				Objective empowerment method	Subjective empowerment method	Game theory combinatorial empowerment method
Resistance	Production foundation	Cultivated land area	kha	0.1316	0.1113	0.1269
		Effective irrigation rate	%	0.0995	0.0701	0.0927
		Number of employees in primary sector	10 thousand persons	0.1205	0.0884	0.1131
	Production capacity	Food production per unit area	t/kha	0.0572	0.1113	0.0697
		Food production per capita	kg/cap	0.1189	0.0701	0.1076
		Food production price index	%	0.0187	0.0884	0.0348
Adaptability	Sustainability	Fertilizer application per unit area	t/kha	0.0308	0.0495	0.0351
		Pesticide application per unit area	t/kha	0.0145	0.0495	0.0226
		Amount of agricultural film applied per unit area	t/kha	0.0232	0.0495	0.0293
	Recoverability	Multiple cropping index	%	0.0602	0.0245	0.0520
		Value added of gross agricultural output	%	0.0248	0.0245	0.0247
		Soil erosion control area	kha	0.0182	0.0412	0.0235
		Damage rate	%	0.0229	0.0583	0.0311
Regenerative capacity	Diverse collaboration	Total power of agricultural machinery per unit area	kW/kha	0.1226	0.0272	0.1006
		Value added of agriculture, forestry, animal husbandry, and fishery services	¥ 100 million	0.0492	0.0272	0.0441
	Technological progressiveness	Investment in agricultural fixed assets	¥ 100 million	0.0205	0.0357	0.0240
		Share of financial support to agriculture	¥ 100 million	0.0343	0.0450	0.0368
		Application for Plant Variety Rights and Grant of Plant Variety Rights	pcs	0.0323	0.0283	0.0314

Table 1. Comprehensive evaluation indicator system for FPR.

$$f(x) = \frac{x^{\alpha-1}e^{-x/\beta}}{\beta^{\alpha}\Gamma(\alpha)}\ (x > 0) \tag{1}$$

where α is the shape parameter, controlling for deviations from the distribution, β shows the scale parameter, reflecting the degree of precipitation variability, x denotes the annual precipitation, and $\Gamma(\alpha)$ signifies the Gamma function.

Equations (2) and (3) represent the calculation of parameters α and β using the method of maximum likelihood estimator (MLE):

$$\alpha = \frac{1+\sqrt{1+4A/3}}{4A}, A = \ln\overline{x} - \frac{1}{n}\sum_{i=1}^{n}\ln x_i \tag{2}$$

$$\beta = \frac{\overline{x}}{\alpha} \tag{3}$$

where x is the annual precipitation, $\overline{x}$ denotes the precipitation time series mean, and n signifies the time series length.

Equation (4) represents the cumulative probability function.

$$G(x) = \int_0^x f(x)dx = \frac{\int_0^x x^{\alpha-1}e^{-x/\beta}}{\beta^{\alpha}\Gamma(\alpha)} \tag{4}$$

Given that the Gamma function requires the independent variable to be a positive real number, the actual precipitation data may be zero-valued, according to Eq. (5).

$$H(x) = \begin{cases} q + (1-q)\cdot G(x), x > 0 \\ q, x = 0 \end{cases} \tag{5}$$

where q is the probability of the occurrence of the value 0 in the precipitation series. Equation (6) shows the Gaussian function used to convert the cumulative probability to a standard normal distribution variable Z (i.e., the SPI value)

$$SPI = \Phi^{-1}(H(x)) \tag{6}$$

where Φ^{-1} serves as the inverse function of the standard normal distribution. Equation (7) indicates the calculation process using the approximate solution method:

$$\text{When } H(x)_{\leq 0.5,\text{ let}}\, t = \sqrt{\ln\left(1/H(x)^2\right)}, \text{ then}$$

$$SPI \approx -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \tag{7}$$

When $H(x) > 0.5$, substituting $1 - H(x)$ into Eq. (7) gives the opposite number. The constant values are as follows:

$$c_0 = 2.515517\, c_1 = 0.802853\ c_2 = 0.010328$$

$$d_1 = 1.432788\ d_2 = 0.189269\, d_3 = 0.001308$$

This paper employs |SPI| to reflect the level of precipitation irregularity. Higher absolute values indicate a greater degree of precipitation anomaly. In concrete terms, |SPI| between $[0.0, 1.0]$ indicates slight abnormality, $[1.0, 1.5]$ shows moderate abnormality, $[1.5, 2.0]$ presents severe abnormality, and $|SPI| > 2.0$ denotes extreme abnormality[56].

Moderating variables

Crop diversity is the moderating variable. This investigation utilizes the Simpson Index of Diversity (SID)[6] to measure the level of crop diversity in a given region. By quantifying the probability of randomly selecting two individuals from a sample to belong to the same species, a numerical value can be obtained to describe the diversity level of the sample. Specifically, this can be expressed in the formula: $SID = 1 - \sum {S_i}^2$, where is the share of crop i in the total planted area. SID ranges between $[0, 1]$, where a higher index represents a higher diversity of crops and vice versa. The SID focuses diversity assessment more on the contribution of dominant species by weighting species abundance (i.e., crop area share). Within agricultural ecosystems, this approach sensitively captures shifts in the distribution of major crops, providing an accurate reflection of regional crop diversity. This study focused on diversity indices for eight major crops: rice, wheat, maize, sorghum, legumes (soybeans), and tubers (potatoes, sweet potatoes, and cassava).

Control variables

Building upon existing research[57], the paper adds additional variables effective in the FPR, including (1) the level of agricultural trade openness, calculated through the proportion of total agricultural exports and imports to total agricultural output; (2) rural electric power facilities, expressed by rural electricity consumption; (3) the proportion of the non-agricultural economy, calculated as the sum of the value added by the secondary and tertiary industries, divided by the regional gross domestic product; (4) the urbanization level, defined by the ratio of the urban resident population to the total; (5) crop cultivation structure, expressed as the ratio of land planted with food crops to that planted with non-food crops; (6) the urban–rural income disparity, qualified by the ratio of urban national income per capita to rural national income. Table 2 presents the description of the variables.

Model construction

FPR index measurement

Entropy value method

Variable type	Variable name	Variable definition	Average value	Standard error
Dependent variable	Resilience	The food system's capacity to sustain stable production and resilience against both internal and external shocks, measured by a comprehensive system of evaluation indicators	0.41	0.09
Independent variable	AT	Monthly mean cumulative temperature obtained by summing and averaging the effective cumulative temperatures based on daily mean temperatures ≥ 10 °C; monthly mean active cumulative temperatures averaged for the 12-month period	19.08	2.22
	|SPI|	The extent of precipitation variation in a given time period relative to a long-term climate benchmark quantified by Gamma distribution fitting with normal normalization	0.80	0.60
Moderating variable	SID	Probability that two individuals randomly selected from the sample belong to the same species	0.58	0.18
Control variable	Trade	Logarithm of total agricultural exports and imports/total agricultural output value	-2.15	1.70
	Electricity	Logarithmic value of rural electricity consumption	4.73	1.48
	Non-farm share	(Secondary sector + tertiary sector)/GDP	90.27	5.08
	Urbanization	Proportion of urban population to total population	58.57	13.21
	Cropping structure	Area under food crops/area under non-food crops	3.25	4.39
	Income gap	Urban residents' income/rural residents' income	2.63	0.45

Table 2. Definition and Description of Variables.

(1) Normalization: Eq. (8) represents the positive correlation indicators.

$$Z_{ij} = (x_{ij} - x_{\min}) / (x_{\max} - x_{\min}) \tag{8}$$

Equation (9) shows the negative correlation indicators.

$$Z_{ij} = (x_{\max} - x_{ij}) / (x_{\max} - x_{\min}) \tag{9}$$

(2) Equation (10) presents the calculation of indicator weights.

$$P_{ij} = Z_{ij} / \sum_{i=1}^{m} Z_{ij} \tag{10}$$

(3) Eq. (11) indicates the calculation of the metric entropy value.

$$e_j = -k \sum_{i=1}^{m} P_{ij} \ln P_{ij} \tag{11}$$

Equation (12) provides the redundancy of information entropy.

$$d_j = 1 - e_j \tag{12}$$

(4) Eq. (13) shows the calculation of the indicator weights.

$$W_j = d_j / \sum\nolimits_{j=1}^{n} d_j \tag{13}$$

Game theory combinatorial empowerment approach Game theory-based weighting integrates indicator weights derived from multiple methods to determine optimal values. This study used the Analytic Hierarchy Process (AHP) and entropy method to measure subjective and objective weights, respectively, which were then optimized via game theory to obtain final indicator weights. Subsequently, it applied a comprehensive evaluation method to measure the food system resilience index. AHP captures decision-makers' preferences through pairwise comparisons, while entropy quantifies uncertainty in the data. This hybrid approach balances expert judgment with empirical data, enhancing the rationality and robustness of the evaluation[58]. The calculation procedure is as follows:

The subjective weight vector of AHP is denoted as w1. The objective weight vector of the entropy method is denoted as w2. The weight matrix obtained by both methods is optimized by linear combination to obtain the minimum optimized value:

$$\min = \left\| \sum\nolimits_{k=1}^{i} a_k w_k^T \right\|_2 (i = 1, 2) \tag{14}$$

The first-order derivatives of the matrix are taken and expanded to obtain:

$$\begin{pmatrix} w_1 w_1^T & w_1 w_2^T \\ w_2 w_1^T & w_2 w_2^T \end{pmatrix} \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} = \begin{pmatrix} w_1 w_1^T \\ w_2 w_2^T \end{pmatrix} \tag{15}$$

The above equation gives (a_1, a_2), and its normalization obtains the following linear coefficients, a_k^*.

$$a_k^* = a_k \Big/ \sum\nolimits_{k=1}^{2} a_k \tag{16}$$

Equation (17) obtains the final combination weight matrix w*.

$$w^* = \sum\nolimits_{k=1}^{2} a^* w_k^T \tag{17}$$

Equation (18) shows the composite index of food system resilience.

$$U = \sum\nolimits_{i=1}^{n} X_i \times w_i \tag{18}$$

Benchmark regression model

The FPR index in this study is based on annual observations from 31 provinces. A two-way fixed effects model is employed to capture both provincial heterogeneity and temporal dynamics, providing a robust framework for assessing the marginal impact of climate change on food production resilience. This model also accommodates moderating variables, enabling evaluation of the effectiveness of adaptive measures. Based on the research

hypotheses and analytical framework described above, the following two-way fixed effects model is constructed to examine the impact of climate change on food production resilience:

$$\mathrm{Re}silience_{it} = \alpha_0 + \alpha_1 AT_{it} + \alpha_2 \left|SPI\right|_{it} + \alpha_3 X_{it} + u_i + v_t + \varepsilon_{it} \tag{19}$$

where $\mathrm{Re}silience_{it}$ represents the FPR in province i in year t; AT_{it} and $|SPI|_{it}$ are, respectively, the average annual accumulated temperature and annual precipitation anomaly index in province i in year t; X_{it} is control variable; u_i represents the individual fixed effects; v_t shows the time fixed effects; α_0 is a constant term; ε_{it} indicates a random perturbation term; and α_1, α_2, and α_3 are the parameters to be estimated.

Moderating effects model

Drawing on the models already set up[55], the following moderating effects model is constructed:

$$\begin{aligned}\mathrm{Re}silience_{it} &= \beta_0 + \beta_1 AT_{it} + \beta_2 \left|SPI\right|_{it} + \beta_3 SID_{it} + \\ &\beta_4 SID_{it} \times AT_{it} + \beta_5 SID_{it} \times \left|SPI\right|_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it}\end{aligned} \tag{20}$$

where SID_{it} represents the crop diversity index of area i in year t; $SID_{it} \times AT_{it}$ and $SID_{it} \times |SPI|_{it}$ signify the interaction terms; β_0 is a constant term; β_1, β_2, β_3, β_4, β_5, and γ are the parameters to be estimated.

Results of empirical analysis

Analysis of the present status

Trends in FPR

The FPR of different provinces was visualized using ArcMap 10.8.1. Given that FPR exhibits long-term trends, short-term changes are less apparent. This analysis covers 2010–2022. As shown in Fig. 2, substantial spatial variation exists. Higher FPR is concentrated in major food-producing provinces—Hebei, Henan, Heilongjiang, Shandong, and Sichuan—benefiting from favorable geography, fertile soils, and strong agricultural output, as well as preferential policy support. In contrast, production-consumption balanced areas face natural constraints. For example, Gansu and Ningxia suffer from persistent drought and soil erosion, while Qinghai and Tibet are hindered by high altitude, cold climate, and underdeveloped agricultural infrastructure. Major food-consuming areas such as Shanghai and Tianjin exhibit high economic development but limited arable land; industrial upgrading and urbanization have shifted labor away from agriculture, causing FPR to lag behind economic growth.

Figure 3 displays the time-series evolution characteristics of different regions obtained by homogenizing. FPR fluctuates between 0.25 and 0.55 during the study period. A peak in 2019 likely reflects favorable climatic conditions, absence of droughts and floods during critical growing periods, and increased per-hectare yields. As a whole, the change curve of the country's FPR level is relatively flat and on an upward trend. It rose from 0.376

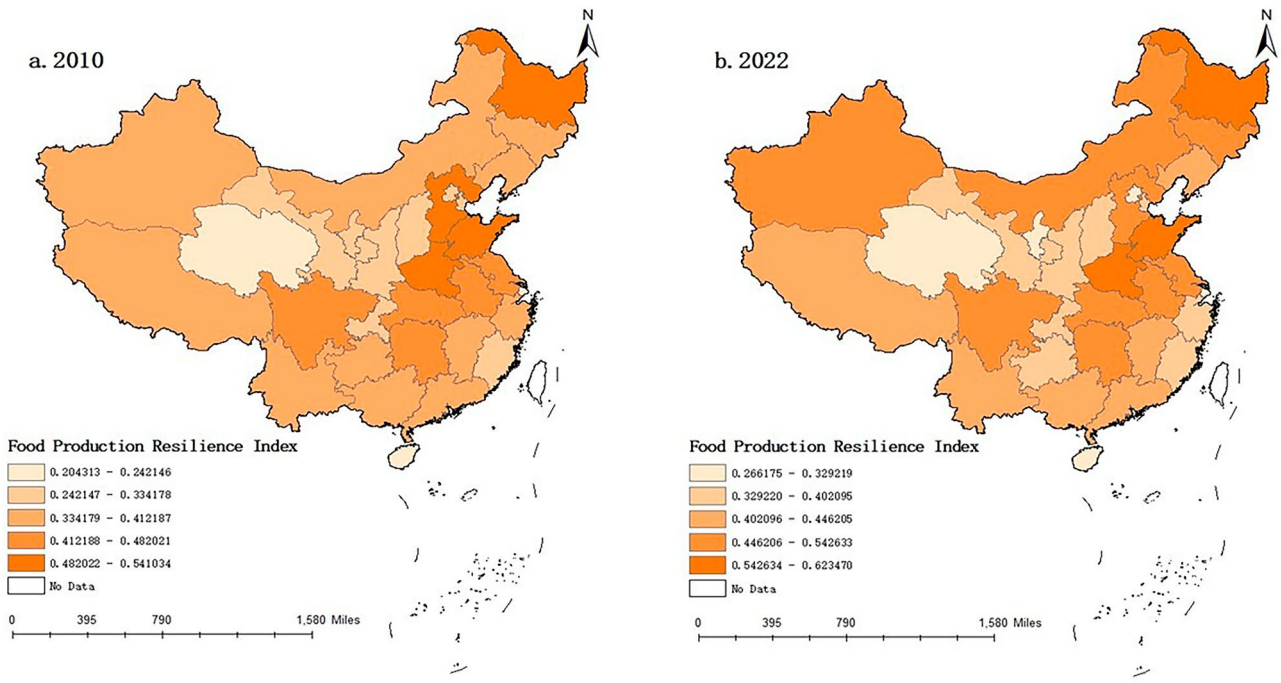

Fig. 2. Spatial distribution of food production resilience in China. This map was created using the standard map with review number GS(2020)4619, which was downloaded from the Standard Map Service website of China's Ministry of Natural Resources. The base map remains unmodified.

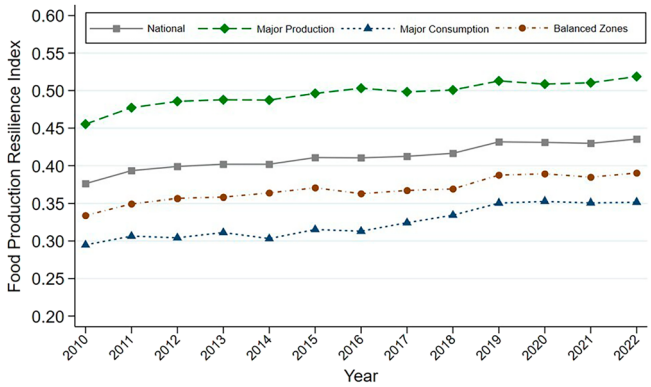

Fig. 3. Trends in FPR in China's three major functional subregions from 2010 to 2022.

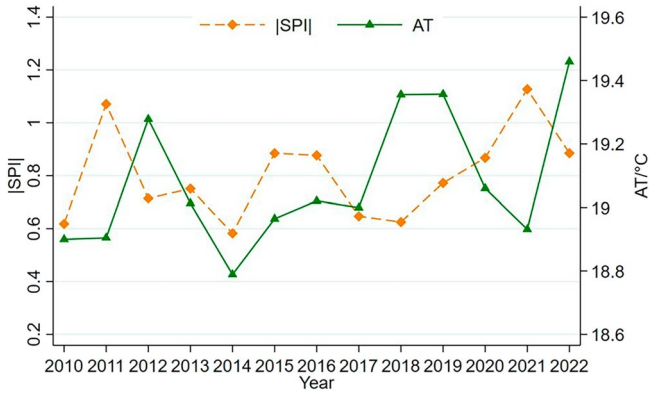

Fig. 4. National climate trends from 2010 to 2022.

to 0.435, probably because agricultural technological progress and policy dissemination in agriculture have improved the adaptability of crops to climate stress. The temporal patterns of FPR in the subregions mirror the national trend, all exhibiting upward trajectories, but with notable spatial variation. The mean value of the major food-producing areas is 0.496 (the whole country: 0.412), which is significantly higher than that of the major food-consuming areas (0.324) and the balanced area (0.368). The main reason may be the obvious differences in resource endowment and institutional environment of each functional sub-region.

Trends in climate change development

Processing the absolute value data of the AT and |SPI| obtains the climate change trend of the whole country from 2010 to 2022, as depicted in Fig. 4. |SPI| experiences peak values in 2011, 2013, 2015, and 2021, indicating the prominent degrees of precipitation anomalies in China within these years. AT shows a fluctuating upward trend, ranging between 18.8 and 19.6. Four peak values occur in 2012, 2018, 2019, and 2022, and three low minimum values are in 2010, 2014, and 2021. The primary characteristics of climate change during this period are a general increase in cumulative temperature and erratic precipitation patterns. While higher temperatures can promote a northward shift in crop maturity and increase regional grain yields[59], they can also intensify water evaporation and exacerbate pest and disease outbreaks[60]. Both extreme precipitation and drought events increase the vulnerability of food systems.

Analysis of baseline regression results

The data were used to acquire the baseline regression results, estimating the impacts of climate change on the level of FPR (Table 3). Then, the Driscoll-Kraay test is employed to check the heteroskedasticity, serial correlation, and cross-sectional correlation issues. In Table 3, Model 1, including only the independent variable, shows that both AT and precipitation anomaly negatively affect FPR. Model 2, incorporating control variables, reveals that both AT and precipitation anomalies have negative impacts on FPR, which are statistically significant at 5% and 10% levels, respectively. These results indicate that climate change considerably inhibits FPR, thereby supporting Hypothesis H1.

In the control variables, rural electricity consumption has a significant and positive impact on the FPR, indicating that electricity fuels modern agricultural technologies and rural informatization, thereby enhancing the FPR. Urbanization level has a remarkable and negative effect on FPR. This result suggests that increased urbanization accelerates the reallocation of resources, such as shifting land investment from low-value

Model	Model1		Model2	
	Coefficient	Standard error	Coefficient	Standard error
AT	-0.0026*	0.0013	– 0.0027**	0.0012
|SPI|	-0.0030**	0.0012	– 0.0024*	0.0012
Trade			– 0.0038	0.0023
Electricity			0.0030*	0.0016
Non-farm share			– 0.0005	0.0012
Urbanization level			– 0.0026***	0.0004
Cropping structure			0.0026***	0.0005
Urban–rural income gap			– 0.0089	0.0056
Constant term	0.4272***	0.0253	0.6052***	0.0599
N	403		403	
R^2	0.6420		0.7050	

Table 3. Benchmark regression results. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; the values in parentheses represent the Driscoll-Kraay standard error.

Model	Model3	Model4	Model5	Model6
AT	– 0.0026*	– 0.0027**	– 0.0027*	– 0.0027**
	(0.0013)	(0.0012)	(0.0013)	(0.0012)
|SPI|	– 0.0030**	– 0.0029**	– 0.0025*	– 0.0024*
	(0.0012)	(0.0011)	(0.0012)	(0.0012)
Direct effect variable	Not introducing	Not introducing	Introducing	Introducing
Other control variables	Not introducing	Introducing	Not introducing	Introducing
AT	19.47		35.49	
|SPI|	21.10		28.57	

Table 4. Omitted variable bias. Coefficient of variation ε =|βn/(βm-βn)|, ε > 1 indicates that omitted variables have a small effect, *$p < 0.1$, **$p < 0.05$, ***p < 0.01.

agricultural uses to higher-value industries, resulting in reduced food production[61]. The gradual shift toward a "food-oriented" cropping structure has a substantial and beneficial effect on FPR. The policy, often coupled with land transfers and large-scale operations, enhances resource use efficiency and farmers' risk resilience. Several factors may explain why agricultural trade openness, rural electricity consumption, the non-farm economy share, and the urban–rural earnings inequality show insignificant impacts on FPR. China's minimum purchase price and tariff quota system buffer domestic food production from international price fluctuations. Additionally, growth in the non-farm economy may compensate for agricultural labor shifts through industrial income. Grain subsidy policies help secure farmers' income, mitigating the impact of the urban–rural income gap on FPR.

Robustness tests

Omitted variable bias

Referring to the method of Wang[62], this study constructs different models using existing variables to evaluate the possible erroneous tendency introduced by variables not monitored. First, it develops Models 3 and 5. Model 3 introduces only explanatory variables. Considering that the proportion of the non-farm economy, urbanization level, and cropping structure directly affect the validity of the FPR, Model 5 incorporates these three control variables, so as to estimate coefficients for the predictor variables under the two constrained models β_m. Second, the research constructs two complete models and introduces other control variables based on Models 3 and 5 to get Models 4 and 6. The estimated coefficients under the two complete models are β_n. Finally, the coefficient of variation is calculated $\varepsilon = |\beta_n / (\beta_m - \beta_n)$. The larger the coefficient is, the more it can indicate that the potential impact of unobserved variables on the parameter estimation of predictor variables is smaller. Table 4 represents the specific test results. The coefficients of variation of AT and |SPI| are much larger than 1, indicating that the estimation results of the explanatory variables are less likely to be affected by the bias of the omitted variables. The results support the robustness of the model estimates.

Replacement models

The FPR values calculated by the indicator system are between $[0, 1]$, which is consistent with the characteristics of a restricted dependent variable. Therefore, the Tobit model is used to re-estimate Model 2. Column (1) of Table 5 shows the estimation results of the Tobit model. The direction of the influence of the estimated coefficients on the AT and |SPI| in the Tobit model and the baseline regression model remains the same, and the statistical significance does not change significantly, which further verifies the reliability of the baseline regression results.

Project	(1) Tobit	(2) Reduced samples	(3) Replacement of variables
AT	-0.0023**	− 0.0026**	− 0.0002***
	(0.0010)	(0.0010)	(0.0001)
|SPI|	-0.0024***	− 0.0024**	− 0.0027**
	(0.0009)	(0.0011)	(0.0010)
_cons	0.5770***	0.6373***	0.3943***
	(0.1396)	(0.1777)	(0.0059)
N	403	325	403
R^2		0.6981	0.6523

Table 5. Robustness test. *p < 0.1, **p < 0.05, ***p < 0.01.

Model	Model 7	
	Coefficient	Standard error
AT	− 0.0026**	0.0012
|SPI|	− 0.0026**	0.0011
SID	− 0.0828**	0.0303
SID*AT	0.0088	0.0056
SID*|SPI|	0.0099*	0.0053
Trade	− 0.0044*	0.0022
Electricity	0.0031***	0.0009
Non-farm share	− 0.0005	0.0005
Urbanization level	− 0.0022***	0.0006
Cropping structure	0.0030**	0.0012
Urban–rural income gap	− 0.0099*	0.0056
Constant term	0.5297***	0.0837
N	403	
R^2	0.7220	

Table 6. Moderating effects model. *p < 0.10, **p < 0.05, ***p < 0.01.

Rejecting samples
To focus on FPR, the analysis excludes six regions with low food production—Beijing, Tianjin, Shanghai, Hainan, Qinghai, and Tibet. The remaining 325 samples are used for parameter estimation. Column (2) of Table 5 presents the results of the model. Based on the results, the coefficients of AT and |SPI| are negative and significant at 5% level, demonstrating the robustness of the estimates with the reduced sample size.

Replacement of the independent variable
The number of days with maximum daily temperatures exceeding the 90th percentile of a historical baseline (HTD, or extreme high-temperature days) was used as an alternative to accumulated temperature as the independent variable for temperature [63]. As shown in column (3) of Table 5, HTD also had a significant and negative effect on crop production resilience, confirming the robustness of the baseline regression results.

Moderation effects analysis

To examine the moderating effect of crop diversity, this study incorporates the SID as a moderator and introduces interaction terms into the regression analysis. In Table 6, Model 7 presents the results after including SID and the interaction terms SID × AT and SID × |SPI| with the independent variables. Precipitation anomalies show a significantly negative effect on FPR at the 5% level, while the interaction with crop diversity is positive and significant at 10% level, indicating that crop diversity mitigates the negative impact of precipitation anomalies on FPR, supporting Hypothesis H2b. The effect of accumulated temperature on FPR is negative and significant at 5% level, but its interaction with crop diversity is insignificant, failing to support Hypothesis H2a. Overall, enhancing crop diversity reduces single-disaster risks, buffers climate shocks, and strengthens the stability and security of food systems, consistent with Hypothesis H2.

SID × AT is insignificant, which may be due to the non-linear and threshold effects of high temperatures on crops. Once a certain temperature is exceeded, all crops are reduced, resulting in the interaction being masked[64]. The buffering effect of crop diversity is highly dependent on differences in crop functional traits. Even species richness may fail to regulate if crop functional traits converge[65]. For example, a region with high crop diversity but similarity in key heat tolerance traits (e.g., all C3 crops) fails to show differentiated adaptive responses to increasing AT[66].

Analysis of regional heterogeneity

The paper further analyzes the spatial heterogeneity to measure the influence of climatic shocks on the FPR in the three principal functional food zones. As shown in Table 7, in major food-producing areas, AT and |SPI| have negative coefficients, which are statistically significant at 10% and 1% levels, implying the considerable inhibitory effects of climate change on FPR. This is mainly because the main food-producing provinces are located in the Central China region, Northeast China region, and East China region, within climate transition zones (e.g., warm temperate to mesothermal, semi-moist to semi-arid). Small climate changes in these areas can exceed crop adaptation thresholds. The predominance of monoculture staple crops in these regions also increases vulnerability to climatic shocks. In major food-consuming areas, AT has a prominent negative effect on FPR, while |SPI| is insignificant, which can be explained by the limited arable land resources of these areas, including the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei regions. These regions have advanced urbanization and development, and the heat island effect exacerbates the rise in nighttime temperatures, inhibiting the accumulation of sugar in grain crops. These areas can regulate water demand through facility-based agriculture, buffering the dampening effect of precipitation fluctuations on FPR. The coefficients of AT and |SPI| on FPR in production-consumption balanced areas are insignificant because most of these places are located in arid or high-cold zones, where long-term climatic stresses have contributed to the formation of inherent crop resilience. Drought and cold-resistant technologies for grain cultivation have been promoted. Some examples are drought-tolerant potatoes in Gansu and barley-rape rotation in Tibet's river valleys. Water conservation projects such as Karez in Xinjiang and rainwater harvesting cellars in Shanxi effectively buffer the effects of climate disruption.

Table 8 represents the spatial differences in the effects of crop diversity in the three regions. The results show that the interaction term coefficient between crop diversity and |SPI| in the major food-producing regions is positive and significant at 10% level, while the interaction term between AT and crop diversity is insignificant. This suggests that crop diversity significantly mitigates the suppressive impact of anomalous precipitation on FPR in the major food-producing areas, but insignificantly moderates the AT. Most main production areas are located in plains with deep soil layers. A three-dimensional pattern of water use is formed through the construction of a "deep-rooted system–shallow-rooted system" multi-type crop vertical complementary system. Together with improvements in irrigation systems, this effectively mitigates the impact of precipitation anomalies. The main crops in these areas are mostly high-light-efficiency crops. As a result of the convergence effect of photosynthetic efficiency, the optimal temperature ranges for photosynthesis among crops are highly overlapping, and the range of temperature adaptation cannot be expanded through crop diversity[67]. The lack of vertical topographic differentiation in the plains limits the compensation of diversity for AT. The coefficient associated with the AT and FPR interaction item is not significantly positive but significantly negative in major food-consuming areas. The |SPI| and FPR interaction item is insignificant because of the limited and fragmented distribution of arable land in the main consumption area, which hinders the formation of large-scale crop diversity. Even if localized diversification occurs, the total area and spatial continuity are insufficient to effectively diversify the systemic risk of precipitation anomalies. The regulatory effect of crop diversity in production-consumption balanced

Variable	(1) Major-production	(2) Major-consumption	(3) Balanced areas
AT	– 0.0026**	– 0.0044**	0.0031
	(0.0011)	(0.0015)	(0.0020)
|SPI|	– 0.0038***	– 0.0023	0.0001
	(0.0009)	(0.0021)	(0.0020)
Trade	– 0.0013	0.0151	– 0.0039
	(0.0063)	(0.0145)	(0.0036)
Electricity	0.0092	0.0016	0.0025
	(0.0062)	(0.0016)	(0.0076)
Non-farm share	– 0.0014	0.0098**	0.0023
	(0.0014)	(0.0029)	(0.0017)
Urbanization level	– 0.0067***	– 0.0033	0.0000
	(0.0012)	(0.0026)	(0.0014)
Cropping structure	0.0017	0.0044	0.0037
	(0.0010)	(0.0036)	(0.0043)
Urban–rural income gap	-0.0263	– 0.0165	0.0145**
	(0.0187)	(0.0236)	(0.0065)
Constant term	0.9751***	– 0.2763	– 0.0057
	(0.1916)	(0.3256)	(0.2289)
N	169	91	143
R^2	0.8006	0.8087	0.7500

Table 7. Difference analysis of the three functional zoning districts. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Variable	(1) Major-production	(2) Major-consumption	(3) Balanced areas
AT	− 0.0004	− 0.0085***	0.0041
	(0.0018)	(0.0031)	(0.0033)
|SPI|	− 0.0031*	− 0.0044	− 0.0008
	(0.0018)	(0.0033)	(0.0026)
SID	− 0.2525***	− 0.0132	− 0.1835***
	(0.0616)	(0.0372)	(0.0661)
SID*AT	− 0.0016	− 0.0342*	− 0.0032
	(0.0126)	(0.0182)	(0.0177)
SID*|SPI|	0.0234*	− 0.0218	0.0085
	(0.0130)	(0.0194)	(0.0168)
Trade	0.0010	0.0366***	− 0.0099**
	(0.0049)	(0.0053)	(0.0041)
Electricity	0.0004	0.0030	0.0048
	(0.0044)	(0.0019)	(0.0054)
Non-farm share	− 0.0039***	0.0087**	0.0025**
	(0.0009)	(0.0034)	(0.0012)
Urbanization level	0.0018***	0.0024*	0.0016***
	(0.0006)	(0.0013)	(0.0005)
Cropping structure	− 0.0302**	0.0094	− 0.0075
	(0.0131)	(0.0162)	(0.0075)
Urban–rural income gap	0.7896***	-0.7288**	0.0606
	(0.0959)	(0.2788)	(0.1224)
Constant term	− 0.0004	− 0.0085***	0.0041
	(0.0018)	(0.0031)	(0.0033)
N	169	91	143
R^2	0.6610	0.7911	0.6757

Table 8. Analysis of regional differences in regulatory effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

areas is insignificant. The balanced areas rely more on traditional cultivation modes and lack technological means such as precision irrigation and intelligent monitoring, preventing the full activation of crop diversity's climate adaptation potential. As young and middle-aged laborers migrate to cities, the farmers tend to simplify the planting structure to reduce labor intensity, further limiting the effectiveness of crop diversity.

Discussion

This study aims to examine the impact of climate change on the food production resilience. Building on a traditional analytical framework, the research develops a comprehensive indicator system to quantify FPR across three dimensions: resistance, adaptability, and regenerative capacity. Using this framework, the study validates the findings of Su Fang et al., which established a food security indicator system using the standardized range method. This system assesses availability, accessibility, usability, and stability, highlighting the negative impact of temperature and precipitation on food security in China[55]. Furthermore, building on the framework developed by Zhou Mi et al., this paper examines regional differences in food production resilience across China's three major food-producing regions, which are categorized based on food policies[68]. These findings resonate with the existing literature, which indicates that climate change results in reduced yields of key food crops[13], increased variability in production, and a heightened risk of simultaneous crop failures[69]. Collectively, these studies highlight the complex relationship between climate change and food production systems[70]. The extensive research on the effects of climate change on yields and food security provides important support for this study, further underscoring the need to investigate resilience in food production.

Unlike the aforementioned scholars, this study incorporates both heat stress (measured by accumulated temperature) and moisture stress (evaluated through precipitation anomalies) into a composite climate indicator. This integrated approach addresses the limitations associated with relying on a single or simple climatic variable, thereby offering a more holistic assessment of climate-related threats to agricultural productivity. Methodologically, a game-theoretic weighting approach is employed to integrate subjective and objective weights, addressing the limitations of entropy-based methods and enhancing the robustness of FPR measurement. The study further examines heterogeneity in climate impacts across major production regions and the moderating role of crop diversity, revealing interaction mechanisms and marginal effects among climate change, FPR, and crop diversity. These insights offer policymakers evidence for differentiated, region-specific climate governance strategies, improving the feasibility and effectiveness of policy implementation.Although this study yields findings of practical significance, it has several limitations. First, it primarily investigates provincial-level samples in China. Analysis at this scale, based on macroeconomic indicators, may obscure intra-provincial

variations and micro-level mechanisms. Future research could refine the sample to finer regional levels, such as cities or counties, to more comprehensively explore the local dynamics and boundary conditions of climate change impacts on food production. Second, this study focuses on macro-level climate variables, leaving the resilience mechanisms for specific types of climate disasters underexplored. Future work could investigate these mechanisms to inform more targeted and precise policy interventions. Third, this study focuses mainly on China. Future research could strengthen international comparative studies to more deeply understand China's relative position in global FPR and to formulate more effective food security strategies.

Conclusion and implications

Main conclusions

This paper analyzes the mechanism of climate anomalies' effect on FPR and the mitigating effects of crop diversity through empirical data. The principal conclusions are outlined as follows. First, the overall trend of FPR is upward in Chinese provinces, with the major food-producing areas higher than the national average, the major food-consuming areas, and the balanced areas. Second, AT and |SPI| show a significant and inhibitory effect on FPR. Improving crop diversity can effectively mitigate the inhibitory effect of climate change on FPR, mainly by significantly weakening the negative effect of extreme precipitation, but not that of AT. Third, the inhibitory effect of climate change is most statistically significant in the major food-producing areas. The major food-consuming areas rely significantly on the negative effect of precipitation anomalies, while the effect of AT is insignificant. Neither AT nor precipitation anomalies have significantly negative effects in the balanced areas. The moderating role of crop diversity on FPR is reflected in its mitigation of precipitation anomalies. This effect is most pronounced in the major food-producing areas and is insignificant in the major food-consuming areas and balanced areas.

Policy implications

The following policy implications are relevant for stabilizing food security production:

First, addressing the inhibitory effects of rising AT and precipitation anomalies on the FPR requires implementing many policies, for example, building a climate-smart agricultural production system. Another policy is the establishment of a climate monitoring and early warning platform based on the big data wisdom platform to enhance the ability to forecast and mitigate meteorological disasters. In terms of technological empowerment, the focus should be on developing crop breeding and improvement for flood and drought resistance, as well as smart water management technologies. Regarding engineering prevention and control, initiatives should be undertaken to enhance the multi-dimensional disaster early warning and response system and food production infrastructure, starting with drainage systems, water storage projects, and wind and sand control projects.

Second, regarding the regulatory role of crop diversity, it is crucial to develop policies for the promotion of regionally differentiated crop planting structures. By combining modern biological breeding with traditional cultivation methods, emphasis should be placed on cultivating crops with advantageous traits, such as resistance to humidity, drought, salinity, and alkalinity. Additionally, a systematic promotion system for high-quality seeds should be established. Through policy subsidies, insurance, and other tools, farmers should be encouraged to adopt diversified cultivation practices to enhance the adaptability of food crops to extreme climate stresses. The moderating effect of crop diversity is significant for precipitation anomalies but not for rising accumulated temperatures, indicating that China's current crop diversity is uneven in responding to different climate stressors. Its capacity to buffer high-temperature stress remains underutilized. Strengthening China's crop diversity system requires further refinement in variety breeding, cultivation pattern optimization, and technical support.

Third, regionally differentiated food security measures should be implemented. Given the strategic importance of the main producing areas, policy preferences and investments in resources and technology should be strengthened. Emphasis should be placed on supporting the establishment of high-standard farmland and the research and development of superior crop varieties. Agricultural infrastructure and equipment should be upgraded rapidly to enhance the comprehensive grain production capacity. Due to their economic development and high urbanization, the main marketing areas should fully leverage their economic advantages. Focus should be on developing capital- and technology-intensive agriculture, facilitating the integration of new energy technologies in food production systems, promoting intensive and modernized agricultural models, increasing food self-sufficiency, and reducing dependence on foreign food supplies. Since the ecological balance in the production-marketing balance areas is more fragile, the government should increase policy support, especially by collaborating with financial institutions to provide agricultural loans and insurance support for grain farmers. Attempts should be made to strengthen the agricultural industrial route and enhance the market competitiveness of food products.

Data availability

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

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Declaration

Competing interests
The authors declare no competing interests.

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