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Extreme rainfall, farmer vulnerability, and labor mobility—Evidence from rural China

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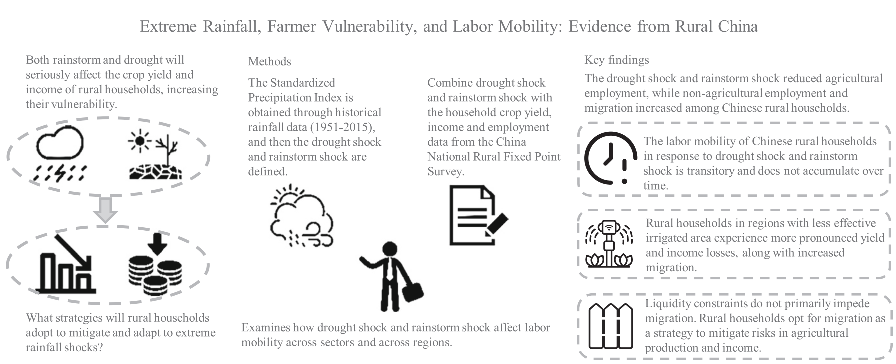
HIGHLIGHTS

- Extreme rainfall can significantly reduce crop yields and income, reflecting the vulnerability of rural households in China.
- In order to mitigate and adapt to extreme rainfall shocks, rural labor will move across sectors and regions.
- Less affluent rural households experience more pronounced yield and income losses, along with increased migration.
- Liquidity constraints do not impede migration. Rural households migrate to mitigate risks in yields and income.

GRAPHICAL ABSTRACT



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ABSTRACT

The recurrent occurrence of extreme weather events poses a significant threat to agricultural production, food security, and sustainable economic development. Understanding farmers' adaptive responses to cope with these challenges is pivotal for informing and implementing effective climate resilience policies. This study utilizes the Spatial Precipitation Index (SPI) to assess rainfall patterns and applies fixed effects methods to analyze extreme rainfall shocks' impact on rural households, using panel data from China's 2006–2015 National Rural Fixed Point Survey. Below are the results. Firstly, both drought and rainstorm shocks negatively affect agricultural yield and income, highlighting farmers' vulnerability to extreme rainfall events. Secondly, farmers respond to these shocks by reallocating labor from agriculture to non-agricultural sectors or migrating to urban areas, with these labor mobility patterns typically being temporary. Thirdly, there's notable heterogeneity linked to household affluence. Less affluent rural households experienced more pronounced declines in yield and income, compelling higher migration rates. Collectively, our findings shed light on how Chinese rural households strategically adjust their labor decisions to respond to extreme rainfall shocks through inter-sectoral and inter-regional labor mobility.

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1. Introduction

Since the Industrial Revolution, escalating greenhouse gas emissions have fueled global warming, precipitating the thawing of glaciers, heightened evaporation, elevated sea levels, and alterations in rainfall patterns. The interaction within the ocean-land-atmosphere system has amplified the frequency and intensity of extreme weather events during the current century, posing unprecedented challenges to natural resources, the ecological environment, and human society (IPCC, 2021). Given the imminent climate threat, "adaptation" is considered the primary means of response. If households make salient adjustments to climate change, the resulting economic losses could be mitigated. But if households struggle to adapt to weather shocks, the overall damages could be substantial (Bohra-Mishra et al., 2014; Burke and Emerick, 2016; Branco and Féres, 2021).

Agriculture is highly dependent on climatic conditions. Extreme weather shocks directly affect crop production and income, making agriculture more vulnerable than manufacturing and services (Acevedo et al., 2020). Therefore, in the face of the uncertainty brought by extreme weather, the adaptation strategies adopted by rural households, the primary decision-making unit of agricultural production, are crucial for mitigating climate risks (Aragón et al., 2021). Several studies have explored adaptation strategies adopted by these households. Such strategies include adjustments in crop planting patterns (Sesmero et al., 2018), modifications in the use of inputs like fertilizers and pesticides (Muller et al., 2017), augmentation of precautionary savings or acquisition of loans (Hisali et al., 2011), and innovation directed toward distressed crops (Moscona and Sastry, 2023).

Labor mobility is another strategy for adapting to income shocks caused by weather events (Jessoe et al., 2017; Colmer, 2021). This coping strategy may be important in developing countries where options for adaptation are limited. The credit market in these rural areas is not well-developed, and households may not be able to access a large amount of liquid capital in the short term to smooth consumption (Nan et al., 2019). Additionally, the overall seed industry in these areas is underdeveloped and cannot quickly develop and promote multiple superior trait seeds (Fadda et al., 2020). In this context, labor mobility may be one of the few short-term adaptation options available to rural households. Understanding the relationship between extreme weather shocks and labor mobility will be useful for supporting the implementation of labor market policies aimed at reducing the vulnerability of rural households, ensuring the well-being of rural dwellers, and promoting sustainable economic development.

China, as the world's largest developing country, provides a compelling research background. Firstly, China is a major agricultural country, producing approximately 20 % of the world's rice, wheat, and corn.[1] Moreover, China has nearly 500 million inhabitants located in rural areas. A large part of this population engages in agricultural activities.[2] Secondly, China is vulnerable to extreme weather shocks. From 1980 to 2021, the average annual crop area affected by rainstorms and droughts in China was 20.50 million hectares and 10.51 million hectares respectively, accounting for 13.28 % and 6.81 % of the total sown area during that period.[3] Furthermore, similar to other developing countries like Pakistan and India, China's agriculture is characterized by small-scale household production, which, in contrast to large-scale mechanized production methods, exhibits weaker resilience to climate risks (Yan et al., 2015). Consequently, weather shocks such as rainstorms and droughts are important influencing factors for agricultural production and household income in this region.[4]

The purpose of this study is to analyze how rural households adjust labor supply in response to vulnerability caused by extreme rainfall shocks in rural China. Initially, the Spatial Precipitation Index (SPI) is employed to define drought shock and rainstorm shock. We then examine their impact on diverse crop yields and household income to demonstrate rural households' vulnerability. Subsequently, we investigate how these households adjust labor supply to cope with climate risks from two dimensions: inter-sectoral labor mobility and inter-regional labor mobility. Additionally, we consider the time dimension, exploring the intertemporal effects of extreme rainfall shocks on labor mobility. Furthermore, we categorize rural households into two groups according to household affluence to explore the heterogeneity of vulnerability and labor mobility in different groups.

Our identification strategy leverages temporal rainfall fluctuations within counties. This empirical approach involves comparing the diverse crop yields, income, and labor supply between households exposed to extreme rainfall shocks and those under more favorable rainfall conditions. The extreme rainfall can be treated as an exogenous shock, given households are unlikely to predict it accurately (Sesmero et al., 2018; Deschênes and Greenstone, 2007). Moreover, our strategy incorporates controls for year-fixed effects, village-fixed effects, year-province interaction fixed effects, household-level characteristics, and other climate control variables to comprehensively mitigate potential endogeneity concerns.

The marginal contribution of this study consists of three aspects: Firstly, this study uses household-level micro-data to systematically analyze the vulnerability of Chinese rural households to droughts and rainstorms from the perspective of diverse crop yields and income structure. As global extreme weather events rise, there is heightened scholarly attention to the impact of climate change on agriculture (Chen et al., 2016; Schlenker and Roberts, 2009). While existing literature predominantly assesses the macro-level effects of climate risks on agricultural output, our study introduces micro-level evidence. Secondly, our focus on the adaptation of rural households to climate change aligns with a growing body of research on agriculture in developing countries (Cui and Xie, 2022; Chen and Gong, 2021). This research emphasizes the importance of adaptive behaviors within agriculture to mitigate climate risks, such as increased fertilizer use, re-arrangement of growing seasons, and precautionary savings. Complementing this literature, our study reveals labor mobility, both temporally and spatially, as a crucial coping strategy. Third, this study also contributes to research on structural transformation and labor mobility. The inter-sectoral and inter-regional flow of labor is considered an important driving force for China's rapid urbanization expansion and long-term economic growth (Bosker et al., 2012). While existing literature often concentrates on geographical and cultural factors influencing labor mobility (Dahlberg et al., 2012; Imbert et al., 2022), this study introduces a perspective of climate change, illustrating how labor mobility serves as an insurance behavior for rural households mitigating climate risks.

[1] The data comes from the Global Agricultural Information Network report from the Foreign Agricultural Service (FAS) of the US Department of Agriculture.

[2] The data comes from the China Census Yearbook.

[3] The data comes from the China Statistical Yearbook.

[4] Extreme weather events present substantial threats to agricultural production globally, affecting both developing and developed nations. For example, in the United States, these events have resulted in severe crop yield losses, causing a substantial $27 billion in damages to the crop insurance program from 1991 to 2017 (Diffenbaugh et al., 2021). Similarly, Canada confronts climate change risks in its agricultural sector, with anticipated economic losses accounting for 0.2 % of GDP by 2080 (Ochuodho and Lantz, 2015). However, compared with developing countries, developed countries have richer adaptation strategies. This study focuses on the climate change adaptation strategies of rural households in developing countries represented by China.

2. Conceptual framework

Extreme weather events pose a significant agricultural risk, influencing crop output, quality, and cultivation costs, ultimately affecting income. On the one hand, these events induce abiotic stress that affects the growth and development of crops (Malhi et al., 2021; Sánchez-Bermúdez et al., 2022). Specifically, droughts, rainstorms, and extreme heat can lead to reduced photosynthetic efficiency, flower decay, and abnormal metabolism in crops. On the other hand, climate change increases the speed of development and overwintering rate of bacteria, fungi, and viruses, escalating the pest and disease incidence rates (Singh et al., 2023; Shahzad et al., 2021). These impacts collectively result in diminished agricultural output and quality. As agriculture constitutes the primary income source for rural households, extreme weather events heighten the risks associated with production, negatively impacting incomes.[5] Understanding agricultural production and income risks is pivotal for revealing the vulnerability of rural households to extreme weather events. Therefore, this study puts forward the following hypothesis:

Hypothesis 1. Extreme weather shocks will lead to a decrease in crop yield and household income of rural households.

Risk stands as a critical determinant in shaping labor supply decisions within rural households.[6] Assuming labor can move freely, risk-neutral farmers would optimize labor allocation between agricultural and non-agricultural employment to equalize marginal returns. When the expected income of one employment type decreases, farmers would reallocate labor resources to the other type. However, risk-averse farmers, upon recognizing greater income volatility in one employment type, would opt for the lower-risk alternative, even if it offers reduced income. This risk premium would escalate with their heightened risk aversion and income volatility (Branco and Féres, 2021).

Compared with agriculture, which has inherent weather-related risks, non-agricultural activities in rural areas, such as handicrafts and small businesses, are less risky to extreme weather (Branco and Féres, 2021; Jessoe et al., 2017; Rose, 2001; Mishra and Goodwin, 1997; Cameron and Worswick, 2003). Mishra and Goodwin (1997) utilize the coefficient of variation of farm income to assess the risk faced by farmers. Their findings indicate that increased income volatility reduces agricultural employment while boosting local non-agricultural employment. Cameron and Worswick (2003) reaffirm this conclusion, highlighting the necessity of additional income for rural households experiencing agricultural risk to maintain their consumption levels. Branco and Féres (2021) investigate the impact of extreme weather events on households in rural Brazil, focusing on working hours. They reveal that during droughts, the total working hours of rural households remain consistent. However, the hours allocated to agricultural activities decrease, accompanied by a corresponding increase in local non-agricultural activities. Therefore, this study proposes hypothesis 2a:

Hypothesis 2a. Extreme weather shocks will drive rural households to change their labor supply decisions, and labor will flow across sectors.

Extreme weather events may extend their impact beyond rural labor markets and influence farmers' rural-to-urban migration decisions. Urban environments, with superior infrastructure, abundant resources, and a diversified economic structure compared to rural areas, exhibit greater resilience to extreme weather events (Cutter et al., 2016). However, the connection between extreme weather shocks and migration is complex. Some studies indicate that adverse weather shocks prompt migration, with farmers opting for migration to seek employment (Jessoe et al., 2017; Feng and Oppenheimer, 2012). Conversely, other research suggests that adverse weather shocks can impede migration, particularly among impoverished households. This hindrance may be attributed to the upfront costs associated with migration, which negative weather shocks exacerbate by affecting rural households' incomes, dissuading them from departing rural areas (Angelucci, 2015; Bazzi, 2017). Therefore, this study proposes hypothesis 2b:

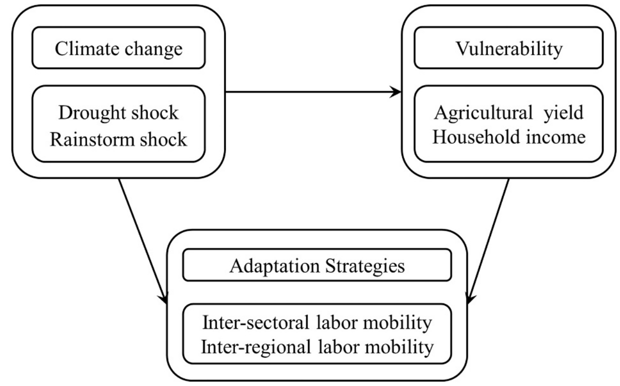

Fig. 1. Research framework.

Hypothesis 2b. Extreme weather shocks will drive rural households to change their labor supply decisions, and labor will flow across regions.

The research framework diagram is shown in Fig. 1. Drought shock and rainstorm shock pose a significant agricultural risk, impacting both crop yield and household income. These risks reflect the vulnerability of rural households to climate change. In response, rural households may shift labor toward less risky rural non-agricultural activities and consider urban migration for employment opportunities. This study investigates rural household adaptation strategies, examining labor mobility from both inter-sectoral and inter-regional perspectives.

The literature on adaptation strategies of Chinese rural households concerning labor mobility in response to extreme weather events is limited. Previous research falls primarily into two categories. The first category employs qualitative methods, such as surveys and interviews, to categorize farmers' adaptation strategies. For instance, Hou et al. (2018) categorize rural households' strategies into three areas: production, livelihood, and security.[7] The second category analyzes farmers' adjustments, particularly in crop planting arrangements and methods, in response to extreme weather conditions. For example, Cui and Xie (2022) study changes in sowing and harvesting schedules. To contribute to this literature, this study conducts a micro-level analysis, quantifying the vulnerability of rural households and examining their decision-making regarding labor supply when faced with extreme weather events.

Overall, while the existing literature offers a solid foundation for this study, there remains scope for enhancement. Prior research has primarily focused on either the link between extreme weather shocks and labor supply decisions at a macro level or has confined the weather measure to temperature (Jessoe et al., 2017; Feng and Oppenheimer, 2012). In contrast, micro-level investigations have concentrated on singular dimensions of labor mobility spanning sectors or regions (Branco and Féres, 2021; Rose, 2001). Moreover, in the context of China, there is relatively little quantitative analysis of rural households' adaptation strategies to extreme rainfall events from the perspective of labor

[5] In China, the government directly controls agricultural product prices, when the output of agricultural products declines, the growth in prices is limited and is not enough to make up for the loss in output, so agricultural income will also decline.

[6] The predominant risk attitude among farmers is either risk aversion or risk neutrality (Hu et al., 2022).

[7] Production refers to strategies to increase agricultural inputs and conservation measures. Livelihood refers to strategies to increase income. Security refers to the adjustment in loans and insurance (Hou et al., 2018).

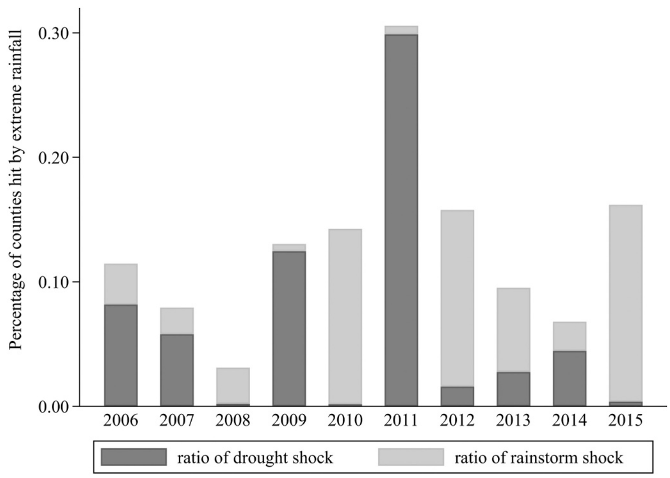

Fig. 2. Proportion of Chinese counties affected by extreme rainfall shocks.
Note: Fig. 2 illustrates the prevalence of drought shock and rainstorm shock across over 2800 Chinese counties during the 2006–2015 period. In the initial five years of the study, 5.36 % of counties experienced drought shock, while 4.60 % faced rainstorm shock. Over the latter half of the period, both drought and rainstorm-affected counties witnessed an increase, reaching 7.81 % and 7.96 %, respectively.

mobility. Therefore, our study seeks to contribute micro-level and comprehensive evidence aimed at discerning the marginal causal effects of extreme rainfall, encompassing rainstorms and droughts, on the labor mobility of households within rural China.

3. Data and model specification

3.1. Definition of drought shock and rainstorm shock

To accurately quantify extreme rainfall, this section investigates China's diverse rainfall patterns shaped by its extensive geography, intricate topography, and substantial latitude range (Yuan et al., 2019). In general, southern regions experience relatively abundant rainfall, primarily in summer and autumn, with drier conditions in winter and spring. In contrast, northern regions receive less rainfall, concentrated in late summer and early autumn, with other seasons remaining comparatively dry (W. Zhao, 2020). This results in regional and temporal variations in China's rainfall, characterized by a skewed distribution pattern (Liu et al., 2016).

Commonly used measurements in current literature for assessing rainfall patterns include the rainfall deviation coefficient and subjective weather evaluation (Kochar, 1999; Menon, 2009; Skoufias et al., 2016). The rainfall deviation coefficient calculates the difference between annual rainfall and historical average rainfall, assuming a normal distribution of rainfall. However, China's rainfall patterns exhibit regional and seasonal variations that deviate from a normal distribution. Additionally, subjective weather evaluation relies on respondents' perceptions in questionnaire surveys, which may be influenced by local economic conditions, crop planting structures, and individual differences. This subjectivity introduces a higher likelihood of errors in the data compared to objective evaluation indicators. Consequently, both the rainfall deviation coefficient and subjective weather evaluation fail to accurately capture China's diverse rainfall patterns.

This study adopts the method of defining extreme rainfall shocks based on Dinkelman (2017) and Branco and Féres (2021), using the SPI to assess rainfall patterns. The SPI quantifies the likelihood of recent rainfall events by comparing them to the historical distribution of all rainfall occurrences within a specific temporal and geographical context. Recognizing the non-normal distribution of rainfall data, the SPI procedure entails fitting a gamma distribution to empirical data distributions. In our approach, we fit a gamma distribution to the annual rainfall of each county, enabling us to derive scale and location parameters tailored to each county's unique rainfall patterns. Subsequently, for each year in the dataset, we utilize the county-specific gamma distribution to compute the probability of observing the rainfall recorded for that year. This probability is then transformed into a standard normal random variable through the application of the normal cumulative distribution function, resulting in the county-year-specific SPI. Positive values indicate above-average rainfall, while negative values signify below-average rainfall.[8]

China's agricultural landscape is diverse, featuring a broad spectrum of crops, including staples such as rice, wheat, and corn, along with vegetables, oil crops, and fruits. These crops exhibit diverse growth and maturity seasons throughout the year. To capture the overall rainfall patterns, we employ annual rainfall measurements, without considering monthly or quarterly variations.

3.2. Data source

Data on agricultural yield, income, and labor supply of rural households are sourced from the China National Rural Fixed Point Survey, the largest panel data household survey conducted by the Chinese Ministry of Agriculture (X. Zhao, 2020). Initiated in 1986, this survey has been systematically developed and consistently expanded, covering 31 provinces, autonomous regions, and municipalities (excluding special administrative regions). This extensive coverage allows for long-term tracking and comprehensive analysis of rural households. To ensure data consistency and mitigate the impact of agricultural tax abolition on rural households' production and income, we have retained samples from 2006 onward.[9]

The rainfall data is sourced from the Daily Value Dataset of the China Meteorological Administration (National Meteorological Information, 2020). This dataset aggregates daily meteorological data, including rainfall, temperature, and sunshine duration from over 800 meteorological observation stations across China, with records dating back to 1951. These stations are strategically distributed across diverse regions, including plains, mountains, deserts, and other geographical settings, enabling the comprehensive tracking and documentation of meteorological conditions in varied environments. Additionally, to transform the daily rainfall data from these meteorological observation stations into annual rainfall data at the county level for SPI calculation and the definition of drought shock and rainstorm shock, we employ the Barnes interpolation method[10] (Dirks et al., 1998).

Following the standardized county coding principle in China, we match the survey data with rainfall data to construct a comprehensive panel dataset. Focusing on households' vulnerability in yield and income, we exclude those with zero crop planting areas. This process results in a final dataset containing 22,487 households, for a total of 120,477 household-year observations.

[8] Typically, rainfall intensity is categorized into seven levels based on the SPI value (McKee et al., 1993; Dinkelman, 2017): greater than or equal to 2 is classified as "extremely wet", between 1.5 and 1.99 is classified as "severely wet", between 1.0 and 1.49 is classified as "moderately wet", between −0.99 and 0.99 is classified as "near normal", between −1.49 and − 1.0 is classified as "moderately dry", between −1.99 and − 1.5 is classified as "severely dry", and less than or equal to −2 is classified as "extremely dry".

[9] The agricultural tax abolition was included in 2005.

[10] This process entails dividing China's county-level administrative divisions into a grid-based map. Subsequently, leveraging the geographic coordinates of meteorological observation stations, we interpolate the respective daily rainfall data into the coordinate system of these grid divisions. Ultimately, we compute the annual rainfall values within each grid, corresponding to county-level administrative divisions, to establish annual rainfall datasets for every county in China.

3.3. Empirical strategy and descriptive statistics

To identify the effects of drought shock and rainstorm shock on rural households, we establish the following specification:

$$L_{ijt} = \alpha + \beta_1 drought_{jt} + \beta_2 rainstorm_{jt} + \gamma H_{ijt} + \varphi_j + \pi_t + \sigma_{p,t} + \omega_{ijt} \quad (1)$$

where L_{ijt} represents the yield, income and labor supply of household i in village j and year t. Crop yield and income are linked to the vulnerability of rural households, while labor supply is associated with agricultural employment, non-agricultural employment, and migration. To assess yield, this study employs various proxy variables. Firstly, crops are categorized into grain crops and non-grain crops, and then the logarithm of their respective yields is taken to obtain ln(Agricultural yield), ln (Grain crop yield), and ln(Non-grain crop yield).[11] Secondly, crops are further subdivided into rice, maize, wheat, soybean, vegetables, oil crops, fruits, and other crops. The logarithm of their respective yields is taken to obtain ln(Rice yield), ln(Maize yield), ln(Wheat yield), ln (Soybean yield), ln(Vegetable yield), ln(Oil crops yield), ln(Fruit yield) and ln(Other yield).[12] This dual classification enables a holistic understanding of crop variations and offers detailed insights into each crop's vulnerability. Regarding income, we divide total income by the labor force number and take the logarithm to obtain ln(Total income per capita). Similarly, we respectively divide agricultural income by the agricultural labor force number, non-agricultural income by the non-agricultural labor force number, and take the logarithm to obtain ln (Agricultural income per capita) and ln(Non-agricultural income per capita).[13] For labor supply, our proxies include agricultural employment, non-agricultural employment, and migration. Data on crop yield, income, and labor supply can be directly obtained from the China National Rural Fixed Point Survey.

The model includes village-fixed effects (φ_j), year-fixed effects (π_t), and province-year interaction fixed effects (σ_{pt}). Additionally, we incorporate H_{ijt} to control for household characteristics, including rural cadre status, ethnicity of family members, and the age, gender, and education level of the household head. Consistent with Jessoe et al. (2017), we also control for other climate variables like temperature, squared temperature, and sunshine duration.[14]

$drought_{jt}$ represents drought shock faced by rural households in village j at year t, while $rainstorm_{jt}$ represents rainstorm shock faced by rural households in village j at year t. Following the definitions of Dinkelman (2017) and Branco and Féres (2021), $drought_{jt}$ is defined as 1 if SPI is less than or equal to -1.5; otherwise, it is 0 for year t in village j. Similarly, $rainstorm_{jt}$ is defined as 1 if SPI is greater than or equal to 1.5; otherwise, it is 0 for year t in village j. This study employs a fixed effects method with a specific focus on estimating β_1 and β_2, which measure the relationship between drought shock and rainstorm shock with rural households' yield, income, and labor supply.

Our identification strategy capitalizes on temporal rainfall fluctuations within counties. Assuming that drought shock and rainstorm shock are unrelated to omitted determinants of agricultural production and labor market outcomes, this strategy will yield consistent estimates of parameters. By including controls for household characteristics, year-fixed effects, village-fixed effects, province-year interaction fixed effects, and other climate variables, we account for the fact that rural households are unlikely to accurately predict rainfall intensity (Sesmero et al., 2018; Deschênes and Greenstone, 2007). This suggests that extreme rainfall shocks can be regarded as "randomly assigned" natural occurrences, validating our identification assumption. Table 1 reports descriptive statistics of the main variables.

4. Results

In this section, we begin by assessing the vulnerability of rural households in terms of drought shock and rainstorm shock impacting crop yield and income. Subsequently, we examine their strategies for adaptation, focusing on inter-sectoral and inter-regional labor mobility. Lastly, we categorize households into two groups based on their affluence level and investigate the heterogeneity in the impact of extreme rainfall shocks.

4.1. The impact of extreme rainfall on the vulnerability of rural households

Table 2 presents the impact of extreme rainfall on crop yield. Column (1) reveals that drought shock and rainstorm shock lead to an average decrease of 8.4 % and 10.3 %, respectively, in agricultural yield for rural households in China. Over the 2006 to 2015 period, the annual average agricultural yield for rural households stood at 355.36 kg. Consequently, the yield reduction due to drought shock and rainstorm shock amounts to approximately 29.85 kg and 36.60 kg, respectively, with rainstorm shock causing a more significant yield loss.

Various types of crops are cultivated in China, with a primary focus on grain crops (Xin et al., 2020). Consequently, we categorize crops into two groups: grain crops and non-grain crops, and study the effects of drought shock and rainstorm shock on each type. Columns (2) and (3) demonstrate that both drought shock and rainstorm shock lead to reduced yields in grain crops and non-grain crops, with rainstorm shock having a more pronounced adverse impact. In order to analyze the differential impact of drought shock and rainstorm shock, we further subdivide grain crops and non-grain crops. Among grain crops, rice, maize, wheat, and soybean contribute over 95 % of total grain output. Among non-grain crops, vegetables, oil crops, and fruits are widely cultivated. Therefore, this study subdivides grain crops into rice, maize, wheat, and soybean, and non-grain crops into vegetables, oil crops, fruits, and other crops. Table A.1 in the supplementary material shows the impact of extreme rainfall shocks on the yield of subdivided crops.

In Table A.1, panel A reveals that rice and maize are more sensitive to rainstorm shock, and wheat and soybean are more sensitive to drought shock. Panel B reveals that vegetables and oil crops are more sensitive to rainstorm shock, and fruits are more sensitive to drought shock. Given the expansive planting areas and significant output proportions of rice and maize in grain crops, the overall sensitivity of grain crops mirrors that of rice and maize, demonstrating greater responsiveness to rainstorm shocks. Similarly, considering the extensive planting areas of vegetables and oil crops within non-grain crops, the overall sensitivity of non-grain crops corresponds to that of vegetables and oil crops, indicating greater susceptibility to rainstorm shocks.[15]

The differential effects of drought shock and rainstorm shock on crops hinge on factors such as the photosynthetic pathway and inherent growth characteristics. Wheat and soybeans, classified as C3 plants utilizing the Calvin cycle for carbon fixation, exhibit limited drought adaptability, rendering them less adaptable to drought shock than

[11] Taking the logarithm can protect the normal data and avoid the influence of extreme outliers.

[12] The unit of yield is kilograms per mu, mu is a land unit in China.

[13] The unit of income is yuan, which is also the basic unit of Chinese currency.

[14] Control variables for household characteristics are obtained directly from the China National Rural Fixed Point Survey. Temperature and Sunshine duration data align with rainfall data, sourced from the Daily Value Dataset of the China Meteorological Administration. In order to convert daily data from meteorological observation stations into annual data at the county level, we also use the Barnes interpolation method.

[15] Maize and rice collectively contribute over 70 % to China's total grain output, encompassing a planting area exceeding 60 % of the total grain crop planting area. Additionally, vegetables and oil crops constitute approximately 72.86 % of the planting area devoted to non-grain crops. The data comes from the National Bureau of Statistics of China.

Table 1
Descriptive statistics: China, 2006–2015.

Classification	Var name	Obs	Mean	Std	Min	Max
Dependent variables	ln(Agricultural yield)	120,477	5.665	0.726	0	14.375
	ln(Grain crop yield)	120,477	5.981	0.548	0	14.375
	ln(Non-grain crop yield)	45,204	4.725	1.661	0	14.291
	ln(Total income per capita)	120,477	9.387	0.735	0	14.119
	ln(Agricultural income per capita)	120,477	8.295	1.125	0	13.822
	ln(Non-agricultural income per capita)	120,477	8.396	1.410	0	14.111
	Agricultural employment	117,177	1.623	1.090	0	10
	Non-agricultural employment	117,177	1.190	1.166	0	9
	Migration	117,177	0.704	0.933	0	8
Independent variable	Drought shock	120,477	0.066	0.247	0	1
	Rainstorm shock	120,477	0.061	0.239	0	1
Control variables	Age of household head	98,260	52.156	10.352	27	80
	Education level of household head	95,702	6.860	2.455	0	12
	Gender of household head	98,287	0.044	0.205	0	1
	Minority	98,759	0.137	0.344	0	1
	Village cadres	120,270	0.042	0.201	0	1
	Temperature	120,477	13.291	5.182	−0.037	25.741
	Sunshine duration	120,477	1992.902	535.091	0	3460.369

Note: Minority, Village cadres, and Gender are dummy variables, Minority equals 1 if there is a minority in the household and 0 otherwise. Village cadres equals 1 if there is a village cadre in the household and 0 otherwise. Gender equals 1 if the household head is female and 0 otherwise. Age of household head represents the actual age of the household head. Educational level of household head represents the number of years of education received by the household head.

Table 2
Impact of extreme rainfall on crop yield.

Variables	(1)	(2)	(3)
	ln(Agricultural yield)	ln(Grain crop yield)	ln(Non-grain crop yield)
Drought shock	−0.084**	−0.081**	−0.093*
	(−2.432)	(−2.537)	(−1.702)
Rainstorm shock	−0.103***	−0.088***	−0.141*
	(−2.840)	(−5.243)	(−1.940)
Basic controls	Yes	Yes	Yes
Other weather controls	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province by year FE	Yes	Yes	Yes
Mean	355.364	446.618	142.439
Observations	120,477	120,477	45,204
R-squared	0.601	0.702	0.797

Note: The standard errors of the estimated results are clustered at the county level, and the t-statistic values are reported in parentheses. *, **, and *** indicate that the estimated coefficients are significant at the 10 %, 5 %, and 1 % significance levels.

rainstorm shock (Häusler et al., 2002). Conversely, maize, a C4 crop with efficient photosynthesis in high-temperature and drought conditions, demonstrates robust drought tolerance. However, rainstorm shock adversely affects maize due to reduced light availability, hindered pollen spread, and increased leaf moisture, making it more susceptible to rainstorm shock than drought shock (Correia et al., 2021). For rice, crucial nutrients come from root growth. Excessive rainfall leads to waterlogging, affecting aeration, inducing hypoxia in the roots, and limiting nutrient absorption, hindering plant growth. In contrast, during drought, rice can access water through its deeper root system, making it more adaptable to drought shock than rainstorm shock (Yang et al., 2004).

In contrast to grain crops, vegetables, with stringent growth requirements and a short growth cycle, are highly sensitive to rainstorm shock. Insufficient light and increased pest and disease probabilities during heavy rainfall impede vegetable growth. Moreover, heavy rain disrupts harvesting and maintenance activities, exacerbating the negative impact on vegetable yields (Welbaum, 2015). Consequently, vegetables are more susceptible to rainstorm shock than drought shock. Oil crops, such as rapeseed, peanuts, and sunflowers, are severely affected by heavy rains due to reduced oxygen supply in the soil, impeding nutrient absorption, and increasing disease risks. However, oil crops exhibit greater adaptability to drought, with features like strong root systems in peanuts and spontaneous growth adjustments in sunflowers (Gupta and Gupta, 2016). Fruits, with a long growth cycle, are vulnerable to the cumulative effects of climate change. Insufficient water supply during growth stages causes irreversible damage to fruit development, making fruits more susceptible to droughts than rainstorms (Salama et al., 2021).

Table 3 presents the impact of extreme rainfall on the income of rural households in China. In Column (1), it is evident that both drought shock and rainstorm shock result in an average per capita total income reduction of 3.7 % and 4.2 %, respectively. Throughout the period spanning 2006 to 2015, the annual average per capita total income for rural households stood at 15,983.41 yuan. Therefore, the annual per capita income losses attributable to drought shock and rainstorm shock amount to approximately 591.39 yuan and 671.30 yuan, respectively. Notably, rainstorm shock is associated with more pronounced reductions in per capita total income.

Rural households in China typically generate income from two main sources: agriculture and non-agricultural activities. This study examines the impact of extreme rainfall shocks on these income streams. In column (2), we observe a significant reduction in agricultural income due to both drought and rainstorm shocks, with rainstorm shocks exhibiting a more pronounced adverse effect. Column (3) indicates that both types of shocks contribute to an increase in non-agricultural income, while lacking statistical significance. Consequently, the primary factor driving the decline in total income for rural households is the reduction in agricultural income. In China, government control over agricultural product prices limits compensatory price growth when yields decline (Lele and Goswami, 2020). Therefore, compared to drought shock, rainstorm shock leads to a more substantial reduction in agricultural yield, resulting in a greater decline in both agricultural and total income.

The varying impact of extreme rainfall on different income categories can be attributed to two factors. Firstly, agriculture plays a crucial role in the income of rural China (Wang et al., 2022). Extreme weather significantly affects crop yields, subsequently impacting agricultural income, which is a significant component of total income. Secondly, non-agricultural employment in Chinese rural areas primarily consists of informal occupations such as street vending and small-scale manufacturing, which are less susceptible to the effects of extreme rainfall (Huang et al., 2018). Consequently, during extreme rainfall events, non-agricultural household income does not experience

Table 3
Impact of extreme rainfall on income.

Variables	(1) ln(Total income per capita)	(2) ln(Agricultural income per capita)	(3) ln(Non-agricultural income per capita)
Drought shock	−0.037*	−0.108***	0.024
	(−1.789)	(−3.581)	(0.757)
Rainstorm shock	−0.042*	−0.126***	0.030
	(−1.943)	(−4.826)	(0.609)
Basic controls	Yes	Yes	Yes
Other weather controls	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province by year FE	Yes	Yes	Yes
Mean	15,983.408	7473.310	8510.098
Observations	120,477	120,477	120,477
R-squared	0.750	0.773	0.670

Note: The standard errors of the estimated results are clustered at the county level, and the t-statistic values are reported in parentheses. * and *** indicate that the estimated coefficients are significant at the 10 % and 1 % significance levels.

Table 4
The impact of extreme rainfall on labor mobility.

Variables	(1) Agricultural employment	(2) Non-agricultural employment	(3) Migration
Drought shock	−0.082***	0.069***	0.031*
	(−3.193)	(2.771)	(1.690)
Rainstorm shock	−0.074**	0.048*	0.041*
	(−2.524)	(1.820)	(1.917)
Basic controls	Yes	Yes	Yes
Other weather controls	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province by year FE	Yes	Yes	Yes
Mean	1.623	1.19	0.704
Observations	117,177	117,177	117,177
R-squared	0.699	0.709	0.659

Note: The standard errors of the estimated results are clustered at the county level, and the t-statistic values are reported in parentheses. *, **, and *** indicate that the estimated coefficients are significant at the 10 %, 5 %, and 1 % significance levels.

significant negative consequences.

4.2. The impact of extreme rainfall on labor mobility

To cope with the adverse impacts of extreme rainfall, rural households would employ risk mitigation and adaptation strategies. This study investigates how Chinese rural households adjust their labor supply in response to extreme rainfall shocks, focusing on two dimensions: inter-sectoral labor mobility and inter-regional labor mobility. Inter-sectoral mobility involves labor movement between agricultural and non-agricultural sectors in rural areas, while inter-regional mobility, referred to as migration, pertains to labor movement from rural to urban areas.

Table 4 presents the effects of extreme rainfall shocks on agricultural employment, non-agricultural employment, and migration.[16] In column (1), the results reveal a significant negative correlation between drought shock, rainstorm shock, and rural households' agricultural employment, indicating that extreme rainfall shocks lead to reduced participation in the local agricultural labor market. Economic pressures resulting from decreased crop yields and income prompt laborers to seek more stable income sources, either through local non-agricultural activities or migration to urban areas. Columns (2) and (3) display results demonstrating positive and significant associations between drought shock, rainstorm shock, and non-agricultural employment, as well as migration. Between 2006 and 2015, there was an average of 165.50 million households in rural China per year. This study estimates that drought shock and rainstorm shock have caused inter-sectoral labor mobility of approximately 11.42 million and 7.94 million respectively, and inter-regional labor mobility of approximately 5.13 million and 6.79 million respectively. Overall, the scale of labor mobility triggered by extreme rainfall shocks is substantial in rural China.

Compared to migration to urban areas, transitioning to the local non-agricultural labor market is a more prevalent choice for laborers exiting agriculture. Table 4 results indicate that, following drought shock or rainstorm shock, a greater number of individuals entered the local non-agricultural labor market than those who migrated. This trend may stem from the substantial development of China's rural areas, particularly in non-agricultural sectors like small-scale manufacturing and service industries, facilitated by reforms and opening up (Liao et al., 2022). The resultant economic diversification has shifted rural areas from sole reliance on agriculture to a more resilient, jointly developing structure with non-agricultural sectors. Notably, these non-agricultural sectors demonstrate increased stability in the face of rainfall shocks, as evidenced by the less pronounced impact on non-agricultural income in Table 3. Opting for local non-agricultural labor markets thus emerges as a strategic approach for income risk diversification. Simultaneously, despite the occurrence of migration, when considering migration costs and local social networks and family connections in rural areas, the number of migrants is lower than the number of individuals entering the local non-agricultural labor market (Xue et al., 2019).

Examining the influence of extreme rainfall shocks on migration, this study observes a more pronounced effect during rainstorms. This is likely due to rainstorms not only impacting agricultural production but also posing risks such as house damage or collapse, resulting in property losses and threats to rural residents' lives (Dewan, 2015). Consequently, the migration scale induced by rainstorm shock surpasses that caused by drought shock.

This study further explores the time dimension, examining the intertemporal effects of extreme rainfall shocks on the rural labor market and revealing patterns in rural labor mobility. Following the method of Emerick (2018), we study the impact of lagged extreme rainfall shocks on labor supply. Table A.3 presents estimates of the effects of lagged extreme rainfall shocks on agricultural employment, non-agricultural employment, and migration. The results indicate that the estimated effects of past drought shock and rainstorm shock are statistically insignificant. This suggests that the labor mobility—across sectors and regions—undertaken by Chinese rural households in response to extreme rainfall shocks is temporary and does not accumulate over time. This stands in contrast to policy-driven long-term labor mobility (Hornbeck and Keskin, 2015; Bustos et al., 2016). Our findings emphasize the timely nature of labor supply adjustments in response to climate extremes. For policymakers, this underscores the importance of implementing timely strategies during extreme weather events to enhance the workforce's resilience to environmental shocks. Such strategies may involve launching temporary public works projects, like housing repairs and soil and water conservation initiatives, to alleviate agricultural underemployment resulting from droughts or rainstorms.

Overall, rural households will engage in inter-sectoral labor mobility and inter-regional labor mobility to cope with climate risks, whether they are facing drought shock or rainstorm shock. This is manifested in a

[16] The results presented in Table A.2 reveal that extreme rainfall shocks do not exert a significant impact on the labor market participation rate of rural households. Consequently, the expansion of the non-agricultural labor force and migration primarily emanates from the agricultural sector.

decrease in agricultural employment, an increase in non-agricultural employment, and an increase in migration. These findings corroborate hypotheses 2a and 2b.

4.3. Heterogeneity analysis

The empirical findings above demonstrate that both drought shock and rainstorm shock lead to yield and income losses in rural households, prompting inter-sectoral and inter-regional labor mobility in rural areas. These extreme rainfall shocks are essentially random events, reflecting the average disparities in yield and income changes, as well as variations in labor mobility, between rural households experiencing these shocks and those not affected. This naturally raises the question: do variations exist in yield and income losses, as well as in labor mobility, among the subset of rural households that have encountered extreme rainfall shocks? To explore this, we segment the entire sample into two groups based on the affluence levels of rural households, aiming to discern whether affluence disparities among rural households result in heterogeneous impacts of extreme rainfall shocks.

The effective irrigated area serves as a determinant for categorizing rural households based on their affluence levels. Firstly, it is important to note that the effective irrigated area is influenced by long-term factors such as geographical location, soil quality, and local policies, and it remains unaffected by short-term rainfall fluctuations (Emerick, 2018). Secondly, effective irrigation significantly contributes to agricultural development by ensuring a consistent water supply, reducing uncertainties in output, and improving crop quality and yield. Additionally, it promotes crop diversification, enhancing income sources and stabilizing agricultural earnings. Generally, regions with larger effective irrigated areas experience more robust agricultural development and exhibit greater affluence among rural households (Xiao et al., 2022). In this study, we categorize all rural households into two groups based on the effective irrigated area.[17] The group exceeding the median is classified as more affluent, while the group below the median is categorized as less affluent. We conduct separate investigations to assess the impact of extreme rainfall on agricultural yield, income, and migration within each group.[18]

Table 5 reports the impact of drought shock and rainstorm shock on the yield, income, and migration of rural households across distinct groups. The results in columns (1) and (2) indicate that rural households in regions with lower effective irrigated areas suffer more noticeable agricultural yield losses whether facing drought shock or rainstorm shock. Similarly, columns (3) and (4) show that rural households in these regions also confront more substantial income losses. Additionally, columns (5) and (6) reveal a heightened tendency for migration among rural households in regions with lower effective irrigated areas, regardless of experiencing drought shock or rainstorm shock.

Differences in the impact of extreme rainfall shocks on rural households across distinct groups can be attributed to several factors. Firstly, regions with larger effective irrigated areas benefit from abundant irrigation resources, catering to the water needs of diverse crops, and fostering diversified agricultural production. Moreover, these regions typically feature more comprehensive irrigation infrastructure, enhancing the efficiency of water resource utilization. Additionally, regions with larger effective irrigated areas tend to exhibit higher rural economic development. Increased rural economic development enables more substantial investments in agricultural irrigation technology and infrastructure, bolstering the local agriculture sector's resilience to climate change. In contrast, rural households in regions with smaller effective irrigated areas may encounter limitations in accessing water resources and complete irrigation infrastructure. Consequently, these households experience more pronounced yield and income losses when confronted with extreme rainfall shocks, prompting a greater reliance on migration as an adaptive strategy to extreme weather events.

We also note disparities in the effects of drought shock and rainstorm shock within the two groups. A comparison of results in (1), (3), and (5) reveals that rural households in regions with limited effective irrigated areas exhibit heightened vulnerability to drought shock, possibly due to resource constraints in irrigation, making crops more susceptible to drought. Simultaneously, the impact on migration induced by drought shock is evident. In contrast, when comparing results in (2), (4), and (6), the agricultural yield and income losses for rural households situated in regions with more effective irrigated areas are less influenced by drought shock. Additionally, migration is less pronounced in response to drought shock. This may be attributed to regions with sufficient effective irrigated areas being able to supply water to crops promptly during droughts. Consequently, compared to the impact of rainstorms, the negative effects of droughts on yield and income in these regions are relatively low.

In summary, our results indicate that both drought shock and rainstorm shock result in yield and income losses, as well as increased migration, for both more affluent and less affluent households. However, less affluent rural households experience more severe yield and income losses and exhibit a higher propensity for migration when facing extreme rainfall shocks. This disparity may arise from their limited access to water resources and complete irrigation infrastructure in the face of extreme weather events. To mitigate these losses, they may rely more on migration.[19]

4.4. Robustness checks

In this section, we perform robustness tests on the primary estimation results using alternative model specifications. Table 6 presents the estimates of drought shock and rainstorm shock. In Row 1, we adjust the clustering level from the county level to the provincial level, adopting a more conservative clustering approach. At higher levels of clustering, the sample size in each cluster unit is larger, which may reduce the potential instability of the estimation results due to small samples or outliers and help estimate the fixed effects model more stably. Row 2 represents a model specification that excludes control variables. Removing control variables simplifies the model, reducing potential problems with overcontrol or collinearity. At the same time, the estimation results obtained by the new model setting can also reflect the sensitivity of the model to the control variables. Row 3 represents a model specification that excludes province-year interaction fixed effects. By excluding province-year interaction fixed effects, this study relaxes the control of time and space. In row 4, this study excludes provinces with a sample size of less than 1 %, aiming to mitigate the potential impact of small sample sizes in some regions.[20] Overall, all the estimated results closely align with those obtained from the baseline specification, demonstrating robustness to outliers, small sample areas, potential issues of over-control or collinearity, and dynamic changes in specific provinces and years. This affirms the reliability and stability of the estimation results in the study.

[17] In this study, “effective irrigated area” refers to the effective irrigated area per unit of cultivated land. Moreover, the data comes from the National Bureau of Statistics of China.

[18] Using the median to classify rural households can reduce the impact of outliers, balance the number of sub-samples, and thus improve the robustness of analysis results.

[19] We also employ an alternative method to categorize rural households based on whether their average income exceeds the median income of all households in the county where they are situated. This division separates households into wealthier and less wealthy categories, yielding similar estimation results, as depicted in Table A.4.

[20] The distribution of sample data by region is outlined in the Table A.5.

Table 5
Impact of extreme rainfall shocks on rural households with different levels of wealth.

	ln(Agricultural yield)		ln(Total income per capita)		Migration	
	(1)	(2)	(3)	(4)	(5)	(6)
Ranking of effective irrigated area	Below median	Above median	Below median	Above median	Below median	Above median
Drought shock	−0.116***	−0.071**	−0.049***	−0.035*	0.047***	0.022*
	(−3.264)	(−2.095)	(−2.735)	(−1.951)	(2.643)	(1.654)
Rainstorm shock	−0.109***	−0.095**	−0.044**	−0.038*	0.047**	0.029*
	(−4.472)	(−2.454)	(−2.464)	(−1.843)	(2.381)	(1.905)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province by year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	321.449	390.475	15,731.940	16,472.313	0.727	0.686
Observations	60,989	56,188	60,989	56,188	60,989	56,188
R-squared	0.694	0.728	0.744	0.763	0.671	0.671

Note: The standard errors of the estimated results are clustered at the county level, and the t-statistic values are reported in parentheses. *, **, and *** indicate that the estimated coefficients are significant at the 10 %, 5 %, and 1 % significance levels.

Table 6
Robustness checks.

	Var	(1)	(2)	(3)	(4)	(5)
		ln(Agricultural yield)	ln(Total income per capita)	Agr employment	Non-agr employment	Migration
1. Cluster by province	Drought shock	−0.084**	−0.042*	−0.082***	0.069***	0.031**
		(−2.099)	(−1.771)	(−3.842)	(3.400)	(2.371)
	Rainstorm shock	−0.103***	−0.046**	−0.074**	0.048*	0.041**
		(−3.004)	(−2.083)	(−2.522)	(1.900)	(2.093)
2. Control variables excluded	Drought shock	−0.084**	−0.037*	−0.082***	0.069***	0.032*
		(−2.472)	(−1.812)	(−3.182)	(2.845)	(1.733)
	Rainstorm shock	−0.095***	−0.042*	−0.073**	0.047*	0.038*
		(−2.614)	(−1.945)	(−2.510)	(1.842)	(1.808)
3. Province by year FE excluded	Drought shock	−0.072**	−0.022	−0.093***	0.070***	0.029**
		(−2.376)	(−1.434)	(−3.664)	(3.594)	(1.997)
	Rainstorm shock	−0.120***	−0.052***	−0.081***	0.065***	0.038**
		(−3.663)	(−3.246)	(−2.718)	(2.902)	(2.198)
4. Restricted sample	Drought shock	−0.079**	−0.034*	−0.083***	0.071***	0.029**
		(−2.302)	(−1.667)	(−3.173)	(2.813)	(2.136)
	Rainstorm shock	−0.099***	−0.036*	−0.077**	0.053*	0.040*
		(−2.667)	(−1.699)	(−2.547)	(1.946)	(2.047)

Note: The different specification is used for each row. Due to space limitations, we do not list the estimated results of control variables, and readers can ask the authors for them. *, **, and *** indicate that the estimated coefficients are significant at the 10 %, 5 %, and 1 % significance levels.

5. Discussion

The above research findings indicate that drought shock and rainstorm shock reduce crop yield and household income, and promote labor mobility. Additionally, the following aspects are worth further consideration. Firstly, this study categorizes crops into grain and non-grain types based on China's planting structure, with grain crops further classified into rice, maize, wheat, and soybean, and non-grain crops into vegetables, oil crops, fruits, and others. A detailed analysis of the impact of drought shock and rainstorm shock on each crop type reveals significant variations in their responses, potentially attributed to differences in photosynthesis pathways and growth characteristics. Several studies focus on the relationship between specific crop yield and climate change. For example, Dinkelman (2017) studies the relationship between droughts and maize yield. In contrast, this paper introduces the SPI as a robust measure of rainfall intensity to systematically evaluate the influence of drought shock and rainstorm shock on subdivided crops in rural China. Rice, maize, vegetables, and oil crops demonstrate heightened sensitivity to rainstorm shock, necessitating increased attention to flood risk management and water flow regulation by policymakers and rural households in primary cultivation areas. Conversely, wheat, soybeans, and fruits exhibit greater susceptibility to drought shock, prompting a focus on improving water use efficiency and promoting research in water-saving technologies for policymakers and rural households in their primary cultivation areas. Additionally, the differentiation of household income into agricultural and non-agricultural components reveals that extreme rainfall shocks lead to a decrease in agricultural income, subsequently causing a decline in total income. This approach underscores the vulnerability of rural households to climate change and infers the potential importance of adaptation.

Second, the study finds that rural labor would leave the agricultural sector and either join the local non-agricultural sector or migrate to urban areas to mitigate and adapt to the adverse effects of drought shock or rainstorm shock. The free flow of labor across sectors and regions may benefit from rural modernization development and household registration system reform in China. The development of rural modernization has gradually transformed rural areas from relying solely on agriculture to a diversified economic structure in which agriculture and non-agriculture develop together, providing opportunities for labor to engage in non-agricultural activities locally. Simultaneously, the household registration system reform has removed obstacles to rural-to-urban migration, allowing people with rural household registration to seek employment in urban areas. Contrary to some studies suggesting that adverse weather shocks exacerbate liquidity constraints in rural households, hindering migration (Angelucci, 2015; Bazzi, 2017), this study indicates that liquidity constraints in rural China may not be a significant impediment. Instead, rural households, aiming to mitigate their income risks, would opt for migration.

Moreover, incorporating the time dimension aids in uncovering trends in rural labor mobility. Our findings indicate that extreme rainfall shocks exhibit no lagged impact on the rural labor market. Instead, rural households are primarily influenced by the immediate extreme rainfall shock when making labor mobility decisions. Different from the technology-driven or policy-driven long-term labor mobility (Hornbeck and Keskin, 2015; Bustos et al., 2016), this study underscores the paramount importance of real-time decision-making in the face of extreme weather. Policymakers should proactively implement timely strategies during extreme weather events to enhance the workforce's ability to cope with environmental shocks. This may involve initiating temporary public works projects, such as housing repairs and soil and water conservation initiatives, to mitigate agricultural underemployment resulting from droughts or rainstorms.

Furthermore, to investigate variations in the impact of extreme rainfall shocks on yield, income, and labor supply across diverse rural households, this study utilizes the effective irrigated area as a proxy variable to categorize samples. The aim is to conduct a detailed analysis of how more affluent and less affluent households respond differently to extreme rainfall shocks. The effective irrigated area serves as a reasonable indicator of rural household affluence. On one hand, it reflects the long-term effects of factors such as topography and soil, remaining resilient to short-term rainfall fluctuations. On the other hand, regions with larger effective irrigated areas boast more abundant irrigation resources and more comprehensive infrastructure, leading to more stable agricultural development and greater affluence among rural households. Heterogeneity results indicate that less affluent households experience greater losses in yield and income, exhibiting a pronounced tendency toward mitigating these losses through increased migration. This discrepancy may arise from the limitations these households face in accessing essential resources like water and robust irrigation infrastructure during extreme weather conditions. Differing from migration driven by educational pursuits or cultural exploration, as highlighted by previous research (Bosker et al., 2012), the study suggests that migration could also serve as a self-insurance strategy against climate risks. Therefore, policymakers can implement educational campaigns in regions with constrained irrigation resources. These initiatives aim to enhance farmers' understanding of climate change impacts and promote the adoption of advanced irrigation technologies, like drip irrigation or rainwater harvesting systems. By minimizing water waste and decreasing reliance on traditional rainwater irrigation, these technologies contribute to the stability of agricultural systems. Simultaneously, policymakers can disseminate timely employment information for urban areas, assisting potential migrants in comprehending the job market dynamics and increasing their chances of securing opportunities in urban employment sectors.

Lastly, there are limitations to this study. On one hand, constrained by data availability, the study does not obtain remittances to rural households from laborers who migrate from rural to urban areas, which could potentially mitigate the vulnerability of rural households to climate change. On the other hand, beyond labor supply adjustments, rural households may employ other climate change adaptation strategies. Recognizing these limitations, there is room for enhancement. Future research endeavors will systematically integrate migrants' remittances and explore additional adaptation strategies, contributing to a more comprehensive and refined analytical framework.

6. Conclusion

The increased frequency and intensity of extreme weather events in the current century, linked to global warming, have heightened the vulnerability of rural households to climate change. Extensive literature underscores the role of adaptation strategies in mitigating climate risks for rural households. Utilizing data from the China National Rural Fixed Point Survey and precise meteorological data, this study initially assesses the impact of drought shock and rainstorm shock on crop yield and household income. Subsequently, we explore how rural households strategically adjust labor supply decisions to cope with climate risks, focusing on inter-sectoral and inter-regional labor mobility during the period 2006–2015.

This study reveals that both drought shock and rainstorm shock significantly decrease crop yield. In grain crops, rice and maize exhibit higher sensitivity to rainstorm shock, while wheat and soybean are more responsive to drought shock. In non-grain crops, vegetables and oil crops are more susceptible to rainstorm shock, and fruits are more affected by drought shock. Besides, extreme rainfall shocks reduce the total income of rural households. Categorizing income into agricultural and non-agricultural, the study identifies that the decline primarily occurs in agricultural income. The decrease in rural household yield and income highlights the vulnerability of Chinese farmers to extreme rainfall shocks. Furthermore, the study observes that rural households respond to these shocks by engaging in labor mobility, leading to a decline in agricultural employment and an increase in local non-agricultural employment and migration. However, labor mobility in response to rainfall shocks is temporary and does not accumulate over time. Lastly, the heterogeneous findings highlight that less affluent rural households experience more significant yield and income losses during extreme rainfall shocks, coupled with a more pronounced migration trend.

The findings of this study have several policy implications for reducing the vulnerability of rural households and safeguarding the well-being of rural dwellers. Households cultivating drought-sensitive crops can consider constructing small reservoirs to collect and store excess rainwater, ensuring agricultural continuity during droughts. Those cultivating crops sensitive to rainstorm impacts may strengthen drainage systems, improving ditches and channels to prevent water damage to crops. Besides, research institutions can contribute by developing crop varieties resilient to climate change, enhancing characteristics like drought and disease resistance.

Moreover, the government, as a crucial resource integrator, plays an important role in helping rural households cope with extreme rainfall shocks. Firstly, the government should strengthen rural infrastructure construction, including road transportation and irrigation facilities to empower rural households, particularly those in resource-poor regions, in adopting climate change adaptation strategies. Secondly, the government can support the diversification of household income by encouraging the growth of non-agricultural sectors, such as tourism and agricultural product processing industries, thereby expanding non-agricultural employment opportunities in rural areas. Thirdly, in response to extreme weather events, the government can launch temporary public works projects, such as house repairs and water conservation projects, to alleviate the problem of insufficient agricultural employment caused by rainstorms or droughts. Finally, for individuals migrating from rural to urban areas, the government must safeguard their fundamental rights and interests in urban settings, including housing, medical care, and education, to foster social stability and sustainable development.

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CRediT authorship contribution statement

Heer Wang: Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Bo Chen:** Writing – review & editing, Writing – original draft. **Xuhang Shen:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.170866.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., Topalova, P., 2020. The effects of weather shocks on economic activity: what are the channels of impact? J. Macroecon. 65, 103207 https://doi.org/10.1016/j.jmacro.2020.103207.

Angelucci, M., 2015. Migration and financial constraints: evidence from Mexico. Rev. Econ. Stat. 97 (1), 224–228. https://doi.org/10.1162/REST_a_00487.

Aragón, F.M., Oteiza, F., Rud, J.P., 2021. Climate change and agriculture: subsistence farmers' response to extreme heat. American Economic Journal: Economic Policy 13 (1), 1–35. https://doi.org/10.1257/pol.20190316.

Bazzi, S., 2017. Wealth heterogeneity and the income elasticity of migration. Am. Econ. J. Appl. Econ. 9 (2), 219–255. https://doi.org/10.1257/app.20150548.

Bohra-Mishra, P., Oppenheimer, M., Hsiang, S.M., 2014. Nonlinear permanent migration response to climatic variations but minimal response to disasters. Proc. Natl. Acad. Sci. 111 (27), 9780–9785. https://doi.org/10.1073/pnas.1317166111.

Bosker, M., Brakman, S., Garretsen, H., Schramm, M., 2012. Relaxing Hukou: increased labor mobility and China's economic geography. J. Urban Econ. 72 (2–3), 252–266. https://doi.org/10.1016/j.jue.2012.06.002.

Branco, D., Féres, J., 2021. Weather shocks and labor allocation: evidence from rural Brazil. Am. J. Agric. Econ. 103 (4), 1359–1377. https://doi.org/10.1111/ajae.12171.

Burke, M., Emerick, K., 2016. Adaptation to climate change: evidence from us agriculture. American Economic Journal: Economic Policy 8 (3), 106–140. https://doi.org/10.1257/pol.20130025.

Bustos, P., Caprettini, B., Ponticelli, J., 2016. Agricultural productivity and structural transformation: evidence from Brazil. American Economic Review 106 (6), 1320–1365. https://doi.org/10.1257/aer.20131061.

Cameron, L.A., Worswick, C., 2003. The labor market as a smoothing device: labor supply responses to crop loss. Rev. Dev. Econ. 7 (2), 327–341. https://doi.org/10.1111/1467-9361.00194.

Chen, S., Gong, B., 2021. Response and adaptation of agriculture to climate change: evidence from China. Journal of Development Economics 148, 102557. https://doi.org/10.1016/j.jdeveco.2020.102557.

Chen, S., Chen, X., Xu, J., 2016. Impacts of climate change on agriculture: evidence from China. J. Environ. Econ. Manag. 76, 105–124. https://doi.org/10.1016/j.jeem.2015.01.005.

Colmer, J., 2021. Temperature, labor reallocation, and industrial production: evidence from India. Am. Econ. J. Appl. Econ. 13 (4), 101–124. https://doi.org/10.1257/app.20190249.

Correia, P.M.P., da Silva, A.B., Vaz, M., Carmo-Silva, E., Marques da Silva, J., 2021. Efficient regulation of Co2 assimilation enables greater resilience to high temperature and drought in maize [original research]. Front. Plant Sci. 12 https://doi.org/10.3389/fpls.2021.675546.

Cui, X., Xie, W., 2022. Adapting agriculture to climate change through growing season adjustments: evidence from corn in China. Am. J. Agric. Econ. 104 (1), 249–272. https://doi.org/10.1111/ajae.12227.

Cutter, S. L., Ash, K. D., & Emrich, C. T. (2016). Urban–rural differences in disaster resilience. Ann. Am. Assoc. Geogr., 106(6), 1236–1252. doi:https://doi.org/10.1080/24694452.2016.1194740.

Dahlberg, M., Eklöf, M., Fredriksson, P., Jofre-Monseny, J., 2012. Estimating preferences for local public services using migration data. Urban Studies 49 (2), 319–336. https://doi.org/10.1177/0042098011400769.

Deschênes, O., Greenstone, M., 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. Am. Econ. Rev. 97 (1), 354–385. https://doi.org/10.1257/aer.97.1.354.

Dewan, T.H., 2015. Societal impacts and vulnerability to floods in Bangladesh and Nepal. Weather and Climate Extremes 7, 36–42. https://doi.org/10.1016/j.wace.2014.11.001.

Diffenbaugh, N.S., Davenport, F.V., Burke, M., 2021. Historical warming has increased U.S. crop insurance losses. Environ. Res. Lett. 16 (8), 084025 https://doi.org/10.1088/1748-9326/ac1223.

Dinkelman, T., 2017. Long-run health repercussions of drought shocks: evidence from South African homelands. The Economic Journal 127 (604), 1906–1939. https://doi.org/10.1111/ecoj.12361.

Dirks, K.N., Hay, J.E., Stow, C.D., Harris, D., 1998. High-resolution studies of rainfall on Norfolk Island: part II: interpolation of rainfall data. J. Hydrol. 208 (3), 187–193. https://doi.org/10.1016/S0022-1694(98)00155-3.

Emerick, K., 2018. Agricultural productivity and the sectoral reallocation of labor in rural India. J. Dev. Econ. 135, 488–503. https://doi.org/10.1016/j.jdeveco.2018.08.013.

Fadda, C., Mengistu, D.K., Kidane, Y.G., Dell'Acqua, M., Pè, M.E., Van Etten, J., 2020. Integrating conventional and participatory crop improvement for smallholder agriculture using the seeds for needs approach: a review [mini review]. Front. Plant Sci. 11 https://doi.org/10.3389/fpls.2020.559515.

Feng, S., & Oppenheimer, M. (2012). Applying statistical models to the climate–migration relationship. Proc. Natl. Acad. Sci., 109(43), E2915. doi: https://doi.org/10.1073/pnas.1212226109.

Gupta, R.D., Gupta, S.K., 2016. Chapter 1 - strategies for increasing the production of oilseed on a sustainable basis. In: Gupta, S.K. (Ed.), Breeding Oilseed Crops for Sustainable Production. Academic Press, pp. 1–18. https://doi.org/10.1016/B978-0-12-801309-0.00001-X.

Häusler, R.E., Hirsch, H.J., Kreuzaler, F., Peterhänsel, C., 2002. Overexpression of C4-cycle enzymes in transgenic C3 plants: a biotechnological approach to improve C3-photosynthesis. J. Exp. Bot. 53 (369), 591–607. https://doi.org/10.1093/jexbot/53.369.591.

Hisali, E., Birungi, P., Buyinza, F., 2011. Adaptation to climate change in Uganda: evidence from micro level data. Glob. Environ. Chang. 21 (4), 1245–1261. https://doi.org/10.1016/j.gloenvcha.2011.07.005.

Hornbeck, R., Keskin, P., 2015. Does agriculture generate local economic spillovers? Short-run and long-run evidence from the Ogallala aquifer. Am. Econ. J. Econ. Pol. 7 (2), 192–213. https://doi.org/10.1257/pol.20130077.

Hou, Z., Chen, Q., Zhou, Q., Liu, F., Ma, W., 2018. The perception of climate change and adaptation strategies of farmers in the northeast edgemountianous of the Tibetan Plateau: a case of the middle reach of the Huangshui River. Adv. Clim. Chang. Res. 14 (2), 175. https://doi.org/10.12006/j.issn.1673-1719.2017.099.

Hu, X., Chen, X., Yao, S., Zhang, G., 2022. The Great Chinese Famine (1959–1961) and farm households' adoption of technology: evidence from China. Aust. J. Agric. Resour. Econ. 66 (1), 93–117. https://doi.org/10.1111/1467-8489.12444.

Huang, G., Zhang, H.-o., Xue, D., 2018. Beyond unemployment: informal employment and heterogeneous motivations for participating in street vending in present-day China. Urban Stud. 55 (12), 2743–2761. https://doi.org/10.1177/0042098017722738.

Imbert, C., Seror, M., Zhang, Y., Zylberberg, Y., 2022. Migrants and firms: evidence from China. American Economic Review 112 (6), 1885–1914. https://doi.org/10.1257/aer.20191234.

IPCC, 2021. In: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J.B.R., Maycock, T.K., Waterfield, T., Yelekçi, O., Yu, R., Zhou, B. (Eds.), Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. https://doi.org/10.1017/9781009157896.

Jessoe, K., Manning, D.T., Taylor, J.E., 2017. Climate change and labour allocation in rural Mexico: evidence from annual fluctuations in weather. Econ. J. 128 (608), 230–261. https://doi.org/10.1111/ecoj.12448.

Kochar, A., 1999. Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. Rev. Econ. Stat. 81 (1), 50–61. https://doi.org/10.1162/003465399767923818.

Lele, U., Goswami, S., 2020. Agricultural policy reforms: roles of markets and states in China and India. Glob. Food Sec. 26, 100371 https://doi.org/10.1016/j.gfs.2020.100371.

Liao, W., Zeng, F., Chanieabate, M., 2022. Mechanization of small-scale agriculture in China: lessons for enhancing smallholder access to agricultural machinery. Sustainability 14 (13), 7964. https://www.mdpi.com/2071-1050/14/13/7964.

Liu, Y., Yan, J., Cen, M., Fang, Q., Liu, Z., Li, Y., 2016. A graded index for evaluating precipitation heterogeneity in China. J. Geogr. Sci. 26, 673–693. https://doi.org/10.1007/s11442-016-1292-1.

Malhi, G.S., Kaur, M., Kaushik, P., 2021. Impact of climate change on agriculture and its mitigation strategies: a review. Sustainability 13 (3), 1318. https://doi.org/10.3390/su13031318.

McKee, T.B., Doesken, N.J., Kleist, J., 1993. The relationship of drought frequency and duration to time scales. In: Proceedings of the 8th Conference on Applied Climatology, vol. 17(22), pp. 179–183.

Menon, N., 2009. Rainfall uncertainty and occupational choice in agricultural households of rural Nepal. J. Dev. Stud. 45 (6), 864–888. https://doi.org/10.1080/00220380902807387.

Mishra, A.K., Goodwin, B.K., 1997. Farm income variability and the supply of off-farm labor. Am. J. Agric. Econ. 79 (3), 880–887. https://doi.org/10.2307/1244429.

Moscona, J., Sastry, K.A., 2023. Does directed innovation mitigate climate damage? Evidence from U.S. agriculture. Q. J. Econ. 138 (2), 637–701. https://doi.org/10.1093/qje/qjac039.

Muller, A., Schader, C., El-Hage Scialabba, N., Brüggemann, J., Isensee, A., Erb, K.-H., Smith, P., Klocke, P., Leiber, F., Stolze, M., Niggli, U., 2017. Strategies for feeding the world more sustainably with organic agriculture. Nat. Commun. 8 (1), 1290. https://doi.org/10.1038/s41467-017-01410-w.

Nan, Y., Gao, Y., Zhou, Q., 2019. Rural credit cooperatives' contribution to agricultural growth: evidence from China. Agricultural Finance Review 79 (1), 119–135. https://doi.org/10.1108/AFR-06-2017-0042.

National Meteorological Information, C, 2020. Daily Meteorological Dataset of Basic Meteorological Elements of China National Surface Weather Station (V3.0). National Tibetan Plateau/Third Pole Environment Data Center.

Ochuodho, T., Lantz, V., 2015. Economic impacts of climate change on agricultural crops in Canada by 2051: a global multi-regional CGE model analysis. Environmental Economics 6, 113–125.
Rose, E., 2001. Ex ante and ex post labor supply response to risk in a low-income area. Journal of Development Economics 64 (2), 371–388. https://doi.org/10.1016/S0304-3878(00)00142-5.
Salama, A.-M., Ezzat, A., El-Ramady, H., Alam-Eldein, S.M., Okba, S.K., Elmenofy, H.M., Hassan, I.F., Illés, A., Holb, I.J., 2021. Temperate fruit trees under climate change: challenges for dormancy and chilling requirements in warm winter regions. Horticulturae 7 (4), 86. https://www.mdpi.com/2311-7524/7/4/86.
Sánchez-Bermúdez, M., del Pozo, J.C., Pernas, M., 2022. Effects of combined abiotic stresses related to climate change on root growth in crops [review]. Front. Plant Sci. 13 https://doi.org/10.3389/fpls.2022.918537.
Schlenker, W., Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to us crop yields under climate change. Proc. Natl. Acad. Sci. 106 (37), 15594–15598. https://doi.org/10.1073/pnas.0906865106.
Sesmero, J., Ricker-Gilbert, J., Cook, A., 2018. How do African farm households respond to changes in current and past weather patterns? A structural panel data analysis from Malawi. Am. J. Agric. Econ. 100 (1), 115–144. https://doi.org/10.1093/ajae/aax068.
Shahzad, A., Ullah, S., Dar, A.A., Sardar, M.F., Mehmood, T., Tufail, M., Shakoor, A., Muhammad, H., 2021. Nexus on climate change: agriculture and possible solution to cope future climate change stresses. Environ. Sci. Pollut. Res. 28, 1–22. https://doi.org/10.1007/s11356-021-12649-8.
Singh, B.K., Delgado-Baquerizo, M., Egidi, E., Guirado, E., Leach, J.E., Liu, H., Trivedi, P., 2023. Climate change impacts on plant pathogens, food security and paths forward. Nature Reviews Microbiology. https://doi.org/10.1038/s41579-023-00900-7.
Skoufias, E., Bandyopadhyay, S., Olivieri, S., 2016. Occupational diversification as an adaptation to rainfall variability in rural India. Agric. Econ. 48 https://doi.org/10.1111/agec.12296.
Wang, H., Hu, X., Yang, S., Xu, G., 2022. Climate change adaptation and upland rice yield: evidence from a farm survey in Yunnan, China. China Agricultural Economic Review. https://doi.org/10.1108/CAER-02-2022-0038 (ahead-of-print).
Welbaum, G.E., 2015. Vegetable production and practices, CABI. https://books.google.com.hk/books?id=zq4tBgAAQBAJ.
Xiao, H., Zheng, X., Xie, L., 2022. Promoting pro-poor growth through infrastructure investment: evidence from the targeted poverty alleviation program in China. China Econ. Rev. 71, 101729 https://doi.org/10.1016/j.chieco.2021.101729.
Xin, F., Xiao, X., Dong, J., Zhang, G., Zhang, Y., Wu, X., Li, X., Zou, Z., Ma, J., Du, G., Doughty, R.B., Zhao, B., Li, B., 2020. Large increases of paddy rice area, gross primary production, and grain production in Northeast China during 2000–2017. Sci. Total Environ. 711, 135183 https://doi.org/10.1016/j.scitotenv.2019.135183.
Xue, K., Xu, D., Liu, S., 2019. Social network influences on non-agricultural employment quality for part-time peasants: a case study of Sichuan Province. China. Sustainability 11 (15), 4134. https://www.mdpi.com/2071-1050/11/15/4134.
Yan, M., Luo, T., Bian, R., Cheng, K., Pan, G., Rees, R., 2015. A comparative study on carbon footprint of rice production between household and aggregated farms from Jiangxi. China. Environmental Monitoring and Assessment 187 (6), 332. https://doi.org/10.1007/s10661-015-4572-9.
Yang, C., Yang, L., Yang, Y., Ouyang, Z., 2004. Rice root growth and nutrient uptake as influenced by organic manure in continuously and alternately flooded paddy soils. Agric Water Manag 70 (1), 67–81. https://doi.org/10.1016/j.agwat.2004.05.003.
Yuan, W., Hu, X., Tian, Q., 2019. Regional differences in rainfall frequency and amount over southwestern China. Atmospheric and Oceanic Science Letters 12 (5), 313–319. https://doi.org/10.1080/16742834.2019.1626194.
Zhao, W., 2020a. Extreme weather and climate events in China under changing climate. Natl. Sci. Rev. 7 (5), 938–943. https://doi.org/10.1093/nsr/nwaa069.
Zhao, X., 2020b. Land and labor allocation under communal tenure: theory and evidence from China. Journal of Development Economics 147, 102526. https://doi.org/10.1016/j.jdeveco.2020.102526.