Population and Environment (2023) 45:25
https://doi.org/10.1007/s11111-023-00441-4

ORIGINAL PAPER

Temperature effects on rural household outmigration: Evidence from China

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Accepted: 16 October 2023 / Published online: 23 October 2023

Abstract

Changes in temperature extremes under climate change are expected to affect outmigration in rural areas through an agricultural mechanism. This study examines the effect of rising temperatures on rural outmigration in Jiangxi Province, China, a cold region where agricultural livelihoods predominate. The study contributes novel results by using large-scale household smart meter data to identify rural household outmigration. These data are combined with temperature data from meteorological stations to reveal a nonlinear effect of temperature on rural outmigration through an agricultural livelihood mechanism. The study projects the influence of rising temperatures on rural outmigration based on two representative concentration pathways (RCPs): RCP4.5 and RCP8.5. The results of the study show that extremely low temperatures significantly increase rural outmigration in Jiangxi Province, China, a rice-growing region. Moreover, projections show that warmer temperatures will improve rice yields and diminish outmigration. According to the medium-term (2041–2060) and long-term (2061–2080) prediction results, rural household outmigration will decrease by 0.55–1.40% and 1.23–2.96%, respectively. These findings contribute to research showing that rising global temperatures affect rural areas in cold regions by improving crop yields and diminishing outmigration.

Keywords Temperature · Outmigration · Economic impacts · Rural households

Introduction

Extreme temperatures are expected to increase outmigration from agriculturally based rural areas by diminishing crop yields, thereby reducing agricultural income and increasing outmigration. Rural areas are restricted by production conditions, and agricultural production is heavily dependent on external weather conditions,

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especially in developing countries. To avoid the risk of agricultural income loss caused by temperature rise, rural residents leave their hometowns and move to other regions (Mueller et al., 2014). Temperature rise may exert a broad global impact on migration in rural areas (Delazeri et al., 2022), and population migration may become an important adaptive measure for households in rural areas to respond to temperature rise.

In 2018, China, the world's largest developing country with a population of more than 1.4 billion people, still had 564 million people living in rural areas (National Bureau of Statistics, 2019). China is also the largest agricultural country, and in 2018, its total agricultural production value was 978,452.52 million US dollars, ranking first in the world and accounting for approximately 30% of the world's total agricultural production value (World Bank, 2019). Therefore, temperature rise could exert a serious impact on rural areas in China, increasing the risk of agricultural income loss and triggering outmigration (Chen et al., 2021). Jiangxi Province, China, is located in the subtropical region of China and is known for its significant outmigration. In the province, an outmigration of 1.117 million people was recorded in 2020 (Wang, 2022). Agriculture plays a crucial role in this province, which has an agricultural output value of 179.631 billion yuan.[1] The rural population is estimated at approximately 17.41 million people.

Population outmigration in China presents the following characteristics. First, the scale of population migration is considerable. In 2018, the number of rural migrant workers in China reached 288.36 million (National Bureau of Statistics, 2019). Rural population outmigration has become a high-profile economic and social phenomenon. In contrast to earlier individual-based migration patterns, population migration is now primarily characterized by household migration (Li & Ren, 2021). Household migration serves to mitigate issues stemming from left-behind children in rural areas, elderly people living in isolation, and spouses living separately, thus alleviating related domestic and societal problems (Xu et al., 2022).

Literature review

Studies have focused on the impact of sudden natural disasters, including storms, floods, earthquakes, and volcanic eruptions (Gray & Mueller, 2012; Noonan & Sadiq, 2019), on human migration. In recent years, with the increasingly severe issue of temperature rise, the impact of temperature rise on population migration has sparked widespread concern (Sun & Guo, 2023). Šedová et al. (2021) claimed that a slow-onset temperature rise is generally more likely to increase migration than sudden-onset events. The reason is that a slow-onset temperature rise allows people to gather the necessary resources for their outmigration. However, there are different perspectives on the impact of temperature rise on population outmigration, especially in economically underdeveloped areas.

[1] One US dollar is approximately equivalent to 7 yuan.

The severe impact of temperature rise on economic activities is a major reason for population outmigration, which mainly includes two aspects: household income and crop production. Regarding income losses, Ling (2017) found that temperature is an important factor influencing income. For every 1 °C increase in the annual average temperature, the per capita income in rural China decreases by 7.5%. Moreover, the impact of temperature on rural incomes is greater than that on urban incomes. Regarding the impact on crop production, Zhang (2017) found that temperature rise leads to extreme weather events, significantly reducing agricultural yields. By the end of this century, crops in China, such as rice, wheat, and corn, could exhibit a reduction in yield of 36.25%, 18.26%, and 45.10%, respectively. Falco et al. (2019) found that temperature rise severely impacts agriculture, thereby triggering population outmigration. For every 1% decrease in agricultural productivity, population migration increases by 2.54–4.5%.

However, other studies suggest that there is currently no evidence that temperature rise causes population outmigration in economically underdeveloped areas. The main points include the following two aspects: first, rural residents lack sufficient economic capacity to bear the costs associated with population outmigration (Cattaneoa and Peri, 2016; Kaczan & Orgill-Meyer, 2020). Second, migration is associated with diverse external environmental risks. Higher social capital is needed to adapt to life at the destination location. Differences in language and culture can pose challenges and difficulties for migrants in their daily lives (Huang & Yang, 2020). It is also uncertain whether there are enough employment opportunities at the destination locations to meet the basic needs of migrants. These factors increase migration risks. Economically underdeveloped areas do not have sufficient capacity to bear migration risks (Bohra & Massey, 2009; Bohra-Mishra et al., 2014).

Compared to existing research on population migration, this paper contributes in the following two ways. First, there is ongoing debate regarding the impact of temperature rise on population outmigration. Existing research suggests that residents in economically disadvantaged areas may not be able to afford the economic costs and unknown risks of migration; thus, temperature rise may not cause migration in low-income areas. However, existing studies do not consider the economic characteristics of low-income areas. Agriculture is highly dependent on temperature conditions, and therefore, temperature rise may impact population migration in rural areas. This paper focuses on the outmigration of rural households due to future temperature rise, and it identifies the impact of future temperature rise on rural outmigration and the mechanism of this impact.

Second, there is a considerable lack of data on population migration in rural areas, especially in developing countries. Official statistics may also be severely distorted. A comprehensive census requires very high economic, time, and labor costs. This study innovatively uses large-scale monthly household smart meter data to identify household outmigration in rural areas, which holds practical significance for meter data mining and compensates for the lack of migration data in rural areas.

Data and models

Data

Large-scale smart meter data

The large-scale smart meter data cover 46.47 million people (13.41 million households) in Jiangxi Province, China, over a 36-month period from January 2016 to December 2018. The smart meter dataset contains the monthly electricity consumption data (in kWh) of all households, the longitude and latitude information of smart meters, and the locations of meters (urban area or rural area), which is useful for calculating the outflow of the rural population.

This study calculates the household outmigration rate in rural areas based on the electricity consumption of each household. First, this study determines the number of rural residents whose monthly electricity consumption is zero. Then, this study calculates the proportion of these zero-electricity consumption households to the total number of households in rural areas; thus, it can obtain the outmigration rate of the rural population. This study assumes that if the monthly electricity consumption of a household is zero, then the household is part of the outmigration population (Call et al., 2017). However, if the reading of a residential electricity meter is zero in urban areas, then the house is likely a vacant house for investment purposes. The Chinese Lunar New Year Holiday occurs in February or March every year, and people return to their rural homes to celebrate the Lunar New Year. Thus, the level of rural outmigration is relatively low in February and March. To identify the impact of temperature on rural outmigration, this study controls for month fixed effects in the model.

The identification of the outmigration rate in rural areas based on meter readings is original, and it can compensate for the gap in data on household outmigration in rural areas. In recent years, the scale of rural household outmigration has been unprecedented, greatly impacting social and economic development. The demographic statistics system is imperfect, and statistical data are missing for rural areas, especially in developing countries. Moreover, there are serious distortions in official statistics (National Bureau of Statistics, 2018). Identifying household outmigration in rural areas based on smart meter data, which can save billions of dollars in cost, is an efficient and accurate strategy.

Weather data

The weather data contain daily mean temperature, daily minimum temperature, monthly precipitation, monthly mean humidity, and wind speed data. The latitude and longitude of each weather station are also included in the weather dataset. This study constructs a temperature bin variable based on the daily minimum temperature data. Figure 1 shows the temperature distribution. The temperature mainly ranges from 30 to 80 °F; thus, the endpoints of the temperature bins are <30 °F and >80 °F. In addition, this study constructs temperature bins based on the daily mean temperature data, which are used for robustness checks. Other weather data are used as control variables. The period of the weather dataset ranges from January 1, 2016, to December 31, 2018, which matches the period of the smart meter data.

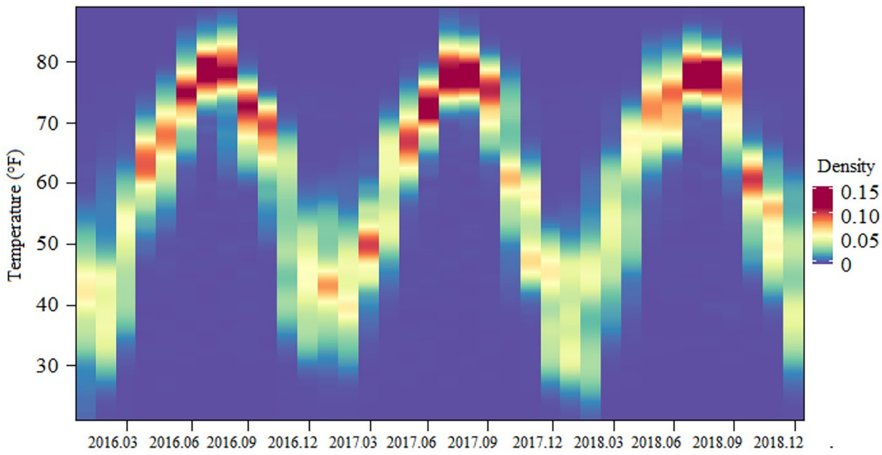

Fig. 1 Distribution of the temperature from 2016 to 2018. The column shows the distribution of the daily temperature in each month. Red indicates that the density of the temperature distribution is high, light yellow indicates a low density, and dark blue indicates the lowest density. Low temperatures are distributed in December, January, and February, and high temperatures are distributed in June to August

Figure 2 shows the distribution of the lowest temperature. The results indicate that there are obvious differences in the lowest temperature among the different counties in the research sample. The difference in the lowest temperature is greater than 16 °F in winter. The obvious temperature difference in each county provides a basis for accurately identifying the impact of temperature on rural household outmigration.

Projected data on temperature rise

Projected data on temperature rise include downscaled projections across the globe for two representative concentration pathways (RCPs): RCP4.5 and RCP 8.5. The two pathways are labeled based on a possible range of radiative forcing values in 2100 relative to preindustrial values (+4.5 W/m^2 and +8.5 W/m^2 for RCP4.5 and RCP 8.5, respectively), and they also coincide with different greenhouse gas (GHG) concentration trajectories. The RCP4.5 scenario assumes that global GHG emissions will peak by approximately 2040. Under the RCP8.5 scenario, it is assumed that emissions will continue to rise throughout the twenty-first century. The prediction data are downscaled to a spatial resolution of 0.25° × 0.25° based on bias-correction spatial disaggregation (BCSD). The NEX-GDDP dataset encompasses projected temperature data based on 21 temperature prediction models.[2] To reduce analysis

[2] These 21 temperature prediction models were developed by research institutes in different countries around the world. The 21 temperature models are as follows: the ACCESS1-0 model, bcc-csm1-1 model, BNU-ESM model, CanESM2 model, CCSM4 model, CESM1-BGC model, CNRM-CM5 model, CSIRO-Mk3-6–0 model, GFDL-CM3 model, GFDL-ESM2G model, GFDL-ESM2M model, inmcm4 model, IPSL-CM5A-LR model, IPSL-CM5A-MR model, MIROC5 model, MIROC-ESM model,

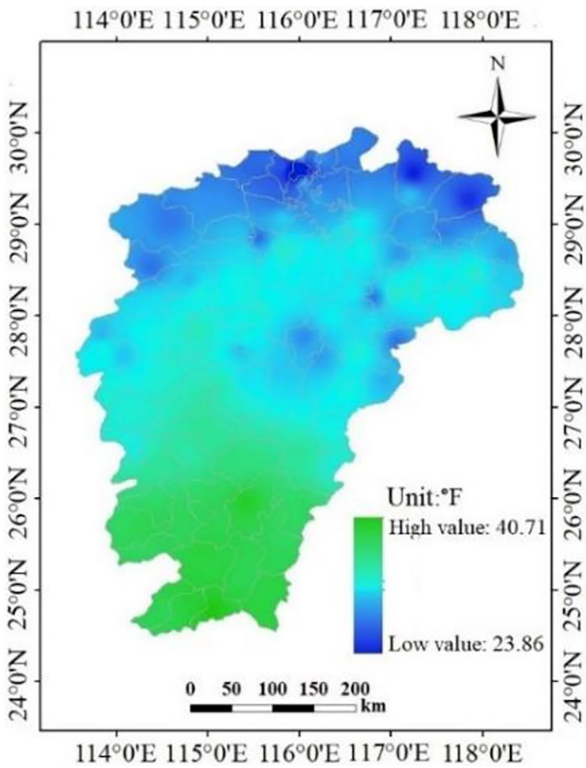

Fig. 2 Distribution of the lowest temperature among counties. The figure shows the distribution of the lowest temperature in winter in the different counties. The lower the temperature in the county, the bluer the color is. The higher the temperature in the county is, the greener the color

errors, this study utilizes the average values of these 21 temperature prediction models to analyze the impact of temperature rise on population outmigration.

This study uses the predicted daily minimum temperature data from 2041 to 2060 to construct a mid-term temperature rise variable. A long-term temperature rise variable is constructed using the predicted daily minimum temperature data from 2061 to 2080 (Yu et al., 2019). Figure 3 shows the annual temperature distribution.

Economic data

The economic data include the per capita disposable income of rural residents, the total regional rice output, the regional economic development level, population size, and the industrial structure. Rice is the main crop in rural areas; thus, this study uses rice yield as a proxy variable for agricultural productivity. The growth of rice involves strict temperature requirements. Temperature may significantly impact agricultural productivity, which in turn may affect the income of rural residents.

Footnote 2 (continued)
MIROC-ESM-CHEM model, MPI-ESM-LR model, MPI-ESM-MR model, MRI-CGCM3 model, and NorESM1-M model.

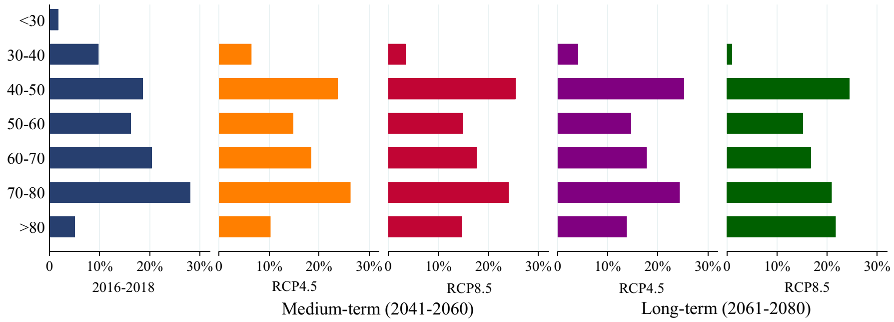

Fig. 3 Annual distribution of the daily minimum temperature. The blue bar graph shows the temperature distribution from 2016 to 2018. The orange and red bar graphs denote the temperature distributions from 2041 to 2060, which correspond to the RCP4.5 and RCP8.5 scenarios, respectively. The purple and green bar graphs are the temperature distributions from 2016 to 2080, which correspond to the RCP4.5 and RCP8.5 scenarios, respectively

The data sources in this study are as follows: The outmigration variable (OM) is estimated based on smart meter data. The large-scale smart meter data are sourced from the National Grid Data Platform. Electricity data are confidential and cannot be published. The original dataset is stored in the data center, which is available for academic research only under a security agreement. Regarding the temperature bins, TEMP (< 30), TEMP (30–40), TEMP (40–50), TEMP (50–60), TEMP (60–70), TEMP (70–80), and TEMP (> 80) are constructed based on temperature data. Other weather variables, including PREC, WIND, and HUMID, are obtained from weather stations through the Meteorological Data Service Center of China (MDSCC) (http://data.cma.cn). Economic variables such as INCOME, RICE, ECONO, POPU, and STRUC originate from the EPS global statistics/analysis platform (http://www.epsnet.com.cn). Projected data on temperature rise are obtained from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset (https://dataserver.nccs.nasa.gov).

The empirical analysis is based on data at the county level. This study establishes connections between smart meter data, weather data, projected temperature rise data, and economic data using the following methods. First, the study utilizes smart meter data to estimate the number of vacant houses in each county and identifies the population outmigration rate for each county by calculating the proportion of vacant houses to total houses. The historical weather data for each county, as well as the latitude and longitude of meteorological stations (each county corresponds to a meteorological station), are provided by the MDSCC. Therefore, this study links the outmigration rates calculated from the smart meter data with the weather data based on county names. Second, raster data for temperature rise projections are obtained at the county level based on the latitude and longitude of the meteorological stations. This study connects the projected temperature rise data with the weather data at the county level. The descriptive statistics of the main data are presented in Table 1.

Table 1 Descriptive statistics

Variable	Interpretation	Unit	Mean	Std	Min	Max
OM	Outmigration rate	–	0.18	0.05	0	0.34
TEMP (< 30)	Temperature bin < 30 °F	day	0.53	1.61	0	19
TEMP (30–40)	Temperature bin 30–40 °F	day	2.99	4.76	0	21
TEMP (40–50)	Temperature bin 40–50 °F	day	5.62	6.46	0	23
TEMP (50–60)	Temperature bin 50–60 °F	day	4.96	5.64	0	24
TEMP (60–70)	Temperature bin 60–70 °F	day	6.22	7.35	0	28
TEMP (70–80)	Temperature bin 70–80 °F	day	8.56	10.52	0	31
TEMP (> 80)	Temperature bin > 80 °F	day	1.54	4.25	0	26
PREC	Precipitation	millimeter	147.04	114.45	1.30	899.50
WIND	Wind velocity	meter per second	13.64	3.94	5.40	68
HUMID	Humidity	%	78.56	5.85	58.40	95.70
INCOME	Per capita disposable income	yuan	10,396.68	3,002.55	4,370.61	20,129.90
RICE	Regional rice output	1,000 metric tons	219.86	170.75	29.89	1,000
ECONO	Regional economic level	100 million yuan	174.30	128.58	33.95	811.69
POPU	Population	1,000 people	491.85	291.74	120	1,590
STRUC	Industrial structure	%	48.63	9.69	22.08	74.62

Models

This study constructs the following model to identify the nonlinear and lagged effects of temperature on household outmigration in rural areas:

$$\begin{aligned} lnOM_{cmy} = \sum_{b} \beta_1^b TEMP_{cmy-L}^b + \beta_2 PREC_{cmy-L} + \beta_3 WIND_{cmy-L} \\ + \beta_4 HUMID_{cmy-L} + \beta_5 ECONO_{cy-L} + \mu_{my} + \varphi_{cm} + e_{cym} \end{aligned} \tag{1}$$

where $lnOM_{cmy}$ denotes the log of the monthly rural outmigration rate in county c, year y, and calendar month m; L denotes the lagged month to identify the lagged effect of temperature on household outmigration in rural areas ($L=0$, 6, 12, and 18 months); *TEMP* is the set of temperature variables that represents the number of days that county c is exposed to the minimum temperature within a given temperature bin b[3]; *PREC*, *WIND*, and *HUMID* denote monthly precipitation, the monthly

[3] Since the number of days per month is between 28 and 31 days, we normalize the temperature bins to ensure that the sum of the temperature bins equals 30. These results are reported in the "Robustness check" section.

mean wind speed, and humidity, respectively; *ECONO* denotes the economic level, which is the control variable; μ is a set of unrestricted time effects; and φ is a set of unrestricted county-by-calendar-month fixed effects. The inclusion of the county-by-calendar-month fixed effects can account for fixed differences across counties that may be correlated with unobservable seasonal factors (e.g., seasonal outmigration). For example, during nonagricultural periods, farmers migrate to make a living. Including month fixed effects allows us to control for seasonal outmigration. The standard errors are clustered at the county level, which allows the error terms within counties to be correlated over time.

This study divides the daily minimum temperature data into seven 10 °F bins. The extreme temperature bins are less than 30 °F and greater than 80 °F bins. For example, $TEMP^{1}_{cmy}$ indicates the number of days when the daily minimum temperature is below 30 °F in county c, year y, and calendar month m, while $TEMP^{7}_{cmy}$ denotes the number of days when the daily minimum temperature is above 80 °F in county c, year y, and calendar month m. The distribution of the temperature bins is shown in the bar graph in Fig. 3. This study defines the minimum temperature below 30 °F as an extremely low temperature, which occurs in the 1st-2nd percentile range. A temperature above 80 °F is defined as an extremely high temperature, which occurs in the 95*th* percentile of the sample. It is reasonable to define extreme temperatures as those below the 5*th* percentile and above the 95th percentile (Auffhammer, 2018). The implicit assumption is that the effect of temperature on rural outmigration is consistent within each temperature bin. In Eq. (1), this study omits the temperature bin in which the minimum temperature varies between 70 and 80 °F, which means that the temperature bin $TEMP^{6}_{cmy}$ (70–80 °F) is selected as the baseline group (this study assesses the accuracy and robustness of the selected temperature bin as the baseline group in the empirical analysis section). By dropping the specified variable, the remaining parameters of the temperature bins can be considered as deviating from the specified temperature bin. This study can accurately identify the nonlinear effects of temperature on household outmigration in rural areas.

This study further analyzes the impact of future temperature rise on household outmigration in rural areas based on the model above. This study generates mid-term and long-term predictions based on two representative concentration pathways (RCP 4.5 and RCP 8.5). Following existing research, this study proposes that the coefficient of influence of temperature on household migration remains constant (Yu et al., 2019). The prediction model considering the population weight is defined in Eq. (2):

$$PI = \sum_{b} \beta_1^b \times \frac{\sum_c \Delta TEMP_c^b \times POP_c}{\sum_c POP_c} \tag{2}$$

where PI is the coefficient of influence of temperature on household outmigration under the representative concentration pathways; β_1^b is the coefficient of influence of temperature bin b on outmigration, which can be obtained based on Eq. (1); $\Delta TEMP$ denotes the predicted change in the number of days per year in each temperature bin; and POP_c denotes the population in county c.

Results and discussion

Effect of temperature on household outmigration

This study uses Eq. (1) to identify the effect of temperature on household outmigration in rural areas. To ensure the accuracy of the results, this study gradually adds weather and economic factors to the model to assess the contemporaneous and lagged effects of temperature on outmigration. The lagged period in the model is set to 6 months, 12 months, and 18 months. The results show that temperature exerts no contemporaneous impact on outmigration. There is a 1-year lag in the impact on rural outmigration. The results are shown in Fig. 4.

Figure 4 shows a summary of the lagged effect of temperature on rural household outmigration. The results show that temperature follows a U-shaped nonlinear relationship with household outmigration in rural areas. The effect of extremely low temperatures (< 30 °F) on household outmigration is more significant than the effect of extremely high temperatures (> 80 °F). When the minimum temperature varies between 70 °F and 80 °F, the household outmigration rate is the lowest. When the temperature is lower than 70 °F, the outmigration rate increases with decreasing temperature. When the temperature is higher than 80 °F, the outmigration rate increases with increasing temperature, but the results are not statistically significant. For example, one additional day in the < 30 °F (−1.1 °C) range can result in an increase of 1.87% in the outmigration rate relative to temperatures between 70 °F and 80 °F, which indicates that 33 out of 10,000 households can exhibit outmigration behavior (the average outmigration rate is 1760 per 10,000 households). As the temperature rises, the impact of temperature on outmigration decreases. In addition, as shown in Table 2, this study finds that precipitation plays a significant role in reducing household outmigration in rural areas.

Although the samples of this study are from Jiangxi Province, China, the conclusions have reference value for other regions as well. Jiangxi Province primarily relies on agriculture and has abundant crop resources, such as rice. Moreover, the province is located inland in China and is classified as a subtropical humid climate zone, with severe cold temperatures in winter. In rural areas, agricultural production is highly dependent on weather conditions. Low temperatures may have adverse effects on crop yields, thereby leading to population outmigration. Therefore, the conclusions of this study hold significant reference value for rural regions where low temperatures prevail and agriculture is the mainstay.

Robustness check

This study conducts a robustness check by constructing new temperature bins and excluding seasonal outmigration in rural areas. This study constructs new temperature bins based on daily mean temperature data to examine the effect of temperature on rural outmigration. Because the daily mean temperature is higher than the daily minimum temperature, this study shifts the original temperature bins to the right by 10 °F under the mean temperature framework, with temperatures less than 40 °F and

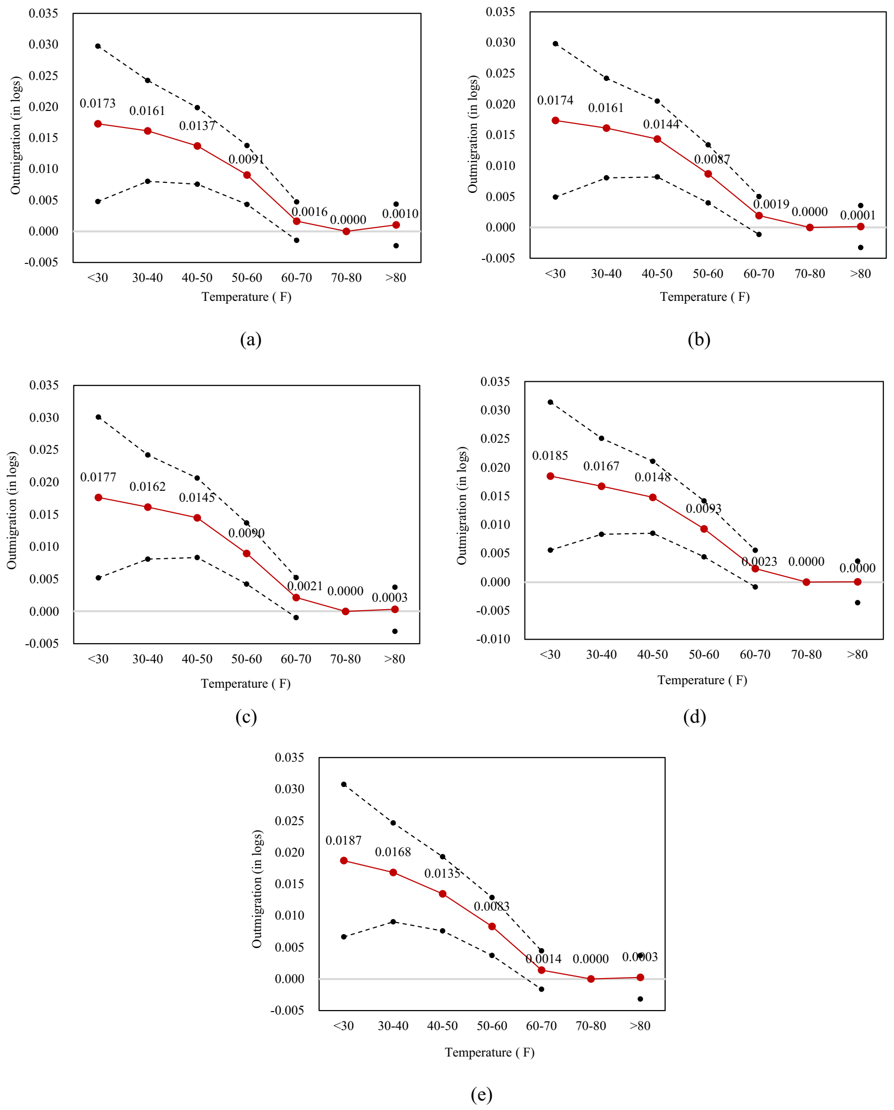

Fig. 4 Impact of temperature on outmigration. It depicts the lagged effect of temperature on rural outmigration. There is a 1-year lag in the impact of temperature-induced outmigration. The dotted line denotes a 95% confidence interval. The red line denotes the influence value of the minimum temperature on population migration. **a** shows only the temperature factor. This study gradually adds precipitation, wind velocity, humidity, and economic level to the model corresponding to **b**–**e**. **b** shows precipitation as well. **c** shows precipitation and wind velocity as well. **d** shows precipitation, wind velocity, and humidity as well. **e** also shows precipitation, wind velocity, humidity, and economic level. This study analyzes and describes the impact of temperature on population migration based on the results of **e**, thereby considering weather and economic factors. The results for the contemporaneous effects are not statistically significant, so this study does not report them

Table 2 Impact of temperature on rural outmigration

Variable	(1)	(2)	(3)	(4)	(5)
TEMP (< 30)	0.0173**	0.0174**	0.0177**	0.0185**	0.0187**
	(0.0064)	(0.0063)	(0.0063)	(0.0066)	(0.0061)
TEMP (30–40)	0.0161**	0.0161**	0.0162**	0.0167**	0.0168**
	(0.0041)	(0.0041)	(0.0041)	(0.0043)	(0.0040)
TEMP (40–50)	0.0137**	0.0144**	0.0145**	0.0148**	0.0135**
	(0.0031)	(0.0031)	(0.0031)	(0.0032)	(0.0030)
TEMP (50–60)	0.0091**	0.0087**	0.0090**	0.0093**	0.0083**
	(0.0024)	(0.0024)	(0.0024)	(0.0025)	(0.0023)
TEMP (60–70)	0.0016	0.0019	0.0021	0.0023	0.0014
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0015)
TEMP (> 80)	0.0010	0.0001	0.0003	0.00004	0.0003
	(0.0017)	(0.0017)	(0.0017)	(0.0018)	(0.0017)
PREC		− 0.0001*	− 0.0001**	− 0.0001*	− 0.0001*
		(0.00004)	(0.00004)	(0.00004)	(0.00004)
WIND			0.0016	0.0016	0.0015
			(0.0010)	(0.0010)	(0.0009)
HUMID				− 0.0005	− 0.0012
				(0.0011)	(0.0010)
ECONO					− 0.0004
					(0.0003)
Constant	− 1.8290**	− 1.8211**	− 1.8430**	− 1.8120**	− 1.7142**
	(0.1171)	(0.1168)	(0.1175)	(0.1342)	(0.1265)
N	3168	3168	3168	3168	3168
R-squared	0.9669	0.9671	0.9672	0.9672	0.9740
F	28.1013	28.2332	28.2517	28.1972	33.3138
p	0.0000	0.0000	0.0000	0.0000	0.0000

The explanatory variables are lagged by 12 months. Weather variables are gradually added to the model to ensure the robustness of the results. The numbers reported in parentheses are standard errors

$^{*}p < 0.05$; $^{**}p < 0.01$

greater than 90 °F as the endpoints. Additionally, this study chooses the 80–90 °F bin as the baseline group, which is 10°F higher than the baseline group used in the minimum temperature framework. The robustness check results based on the mean temperature are shown in Fig. 5.

In terms of the temperature range corresponding to the lowest outmigration rate, the results show that the mean temperature range corresponding to the lowest outmigration rate varies between 80 °F and 90 °F. In terms of statistical significance, the results show that a mean temperature below 70 °F can significantly cause outmigration in rural areas, and the lower the temperature is, the greater the impact. However, a mean temperature above 90 °F does not significantly increase rural outmigration. In terms of estimating the coefficient values, the results based

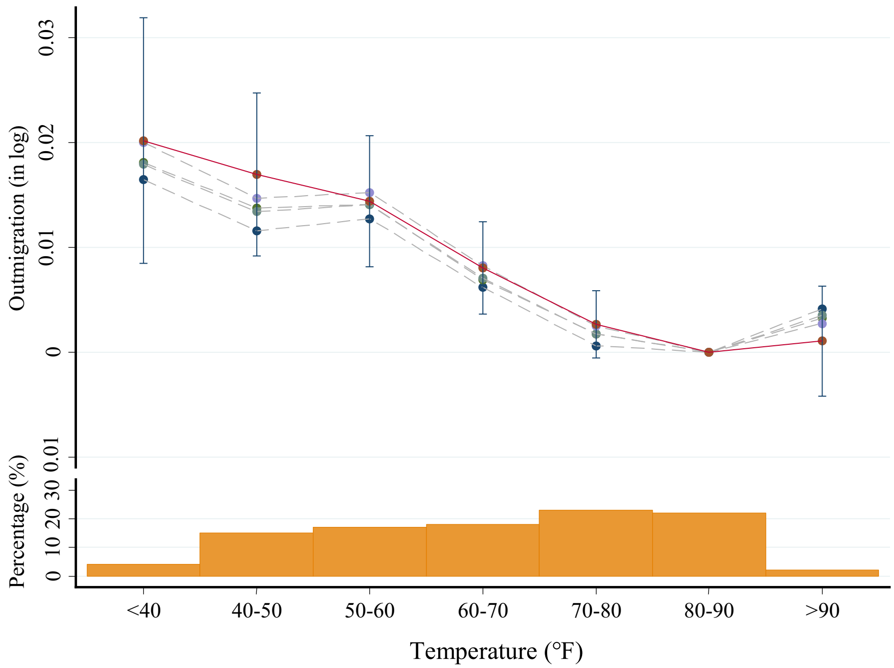

Fig. 5 Robustness check of the impact of temperature on outmigration based on mean temperature. The red line denotes the influence value of the mean temperature on population migration, which considers weather and economic factors. The dashed line denotes the stepwise regression results, which does not include all the control variables mentioned in this study. The vertical line denotes a 95% confidence interval. The dark orange histogram shows the temperature distribution

on the mean temperature are also highly consistent with those based on the minimum temperature. The difference between the coefficients ranges only from 0.0002 to 0.0015, which further confirms the robustness of the results. Precipitation still exerts a significant impact on household outmigration in rural areas. In addition, Fig. 6 shows the robustness check results based on standardized monthly minimum temperature data. The results are still robust.

Furthermore, this study finds that low temperatures lead to an increase in rural outmigration. Is this result due to seasonal outmigration? Although we control for seasonal factors through the month fixed effects in Eq. (1), it is still necessary to analyze seasonal outmigration. In rural China, farmers migrate to work during nonagricultural production periods. The main crop in rural China is rice; thus, this study can determine the nonagricultural production period based on the growth cycle of rice. Rice is planted twice a year from April to October. February and March are generally the Chinese Lunar New Year Holiday period, during which no rural outmigration occurs. The period of seasonal outmigration may encompass November, December, and January. This study analyzes the impact of temperature on rural outmigration after excluding the months in which seasonal outmigration may occur. The results are shown in Fig. 7. After excluding the nonagricultural

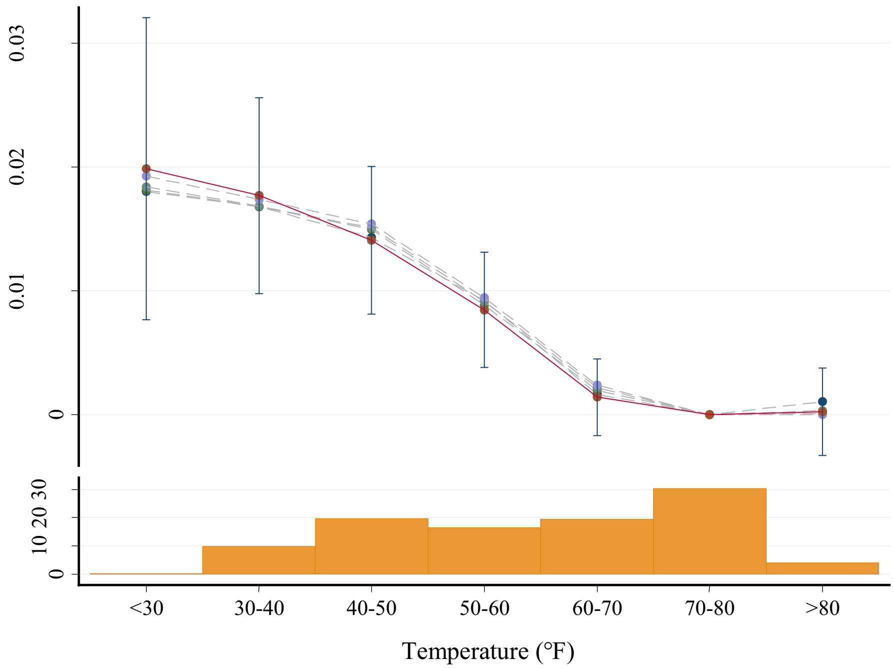

Fig. 6 Robustness check of the impact of temperature on migration based on standardized temperature bins. The red line denotes the influence value of the minimum temperature on population migration, which considers weather and economic factors. This study normalizes the temperature bins to ensure that the sum of the temperature bins equals 30. The dashed line denotes the stepwise regression results, which does not include all the control variables mentioned in this study. The vertical line denotes a 95% confidence interval. The dark orange histogram shows the temperature distribution

production period, this study finds that low temperatures still significantly increase rural outmigration. Therefore, our previous results are robust.

Heterogeneity analysis of the influence of temperature on household outmigration

To identify the heterogeneous effect of temperature on household outmigration in rural areas, this study divides the research sample into regions with low agricultural dependence and regions with high agricultural dependence based on the average value of agricultural production as a threshold (Cai et al., 2016). According to the results in Fig. 4, a minimum temperature below 60 °F could lead to household outmigration. Therefore, this study analyzes the difference in the impact of minimum temperatures below 60 °F on rural outmigration between areas with low and high agricultural dependence. The results are shown in Fig. 8.

According to Fig. 8, the effect of a minimum temperature below 60 °F on low-agricultural dependence areas is 0.0048. This result indicates that one additional day in the < 60 °F range could result in an increase of 0.48% in the outmigration rate, suggesting that 8 out of 10,000 households could exhibit outmigration behavior (the

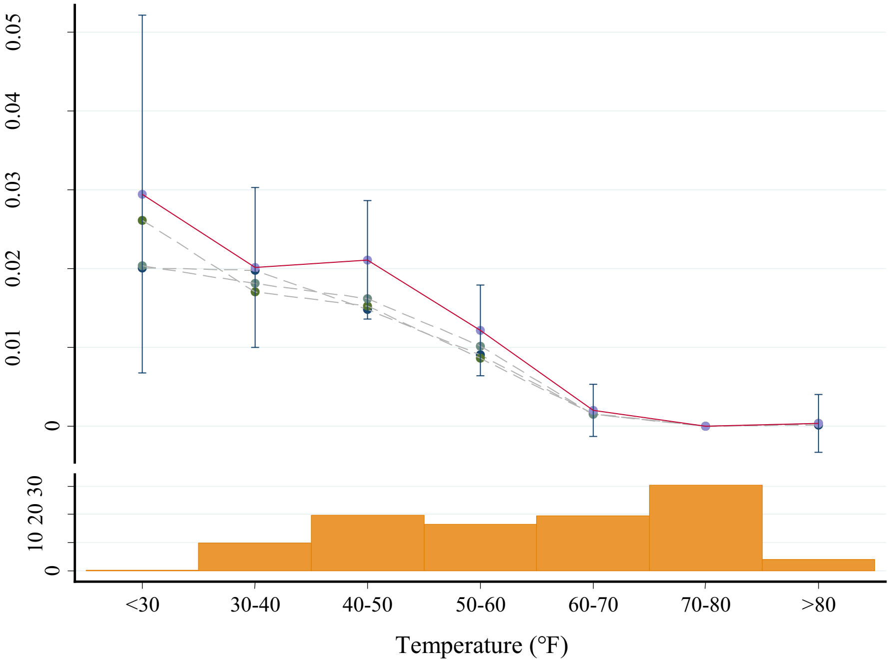

Fig. 7 Impact of temperature on rural outmigration, excluding seasonal outmigration. The red line indicates that the results exclude November, December, and January. The gray dotted line indicates that only 1 month is excluded, i.e., November, December, or January. The dashed line denotes the stepwise regression results, which does not include all the control variables mentioned in this study. The vertical line is a 95% confidence interval. The dark orange histogram shows the temperature distribution

average outmigration rate is 1760 per 10,000 households). The effect of a minimum temperature below 60 °F on household outmigration in high-agricultural dependence areas is 0.0165. This result indicates that one additional day in the < 60 °F range could result in an increase of 1.65% in the outmigration rate, suggesting that 29 out of 10,000 households could exhibit outmigration behavior (the average outmigration rate is 1760 per 10,000 households). The impact of low temperatures on rural outmigration in areas with high agricultural dependence is 3.44 times the impact in areas with low agricultural dependence.[4] Precipitation also significantly impacts rural outmigration in areas with high agricultural dependence. Comparing temperature-induced outmigration between areas with low and high agricultural dependence, we find that the influence of temperature on rural outmigration is obviously heterogeneous. Compared to regions with low agricultural dependence, regions with high agricultural dependence are more greatly affected by temperature, which in turn leads to higher outmigration in these rural areas.

[4] According to the seemingly unrelated regression, the *p* value is 0.0020; thus, the group regression results are comparable.

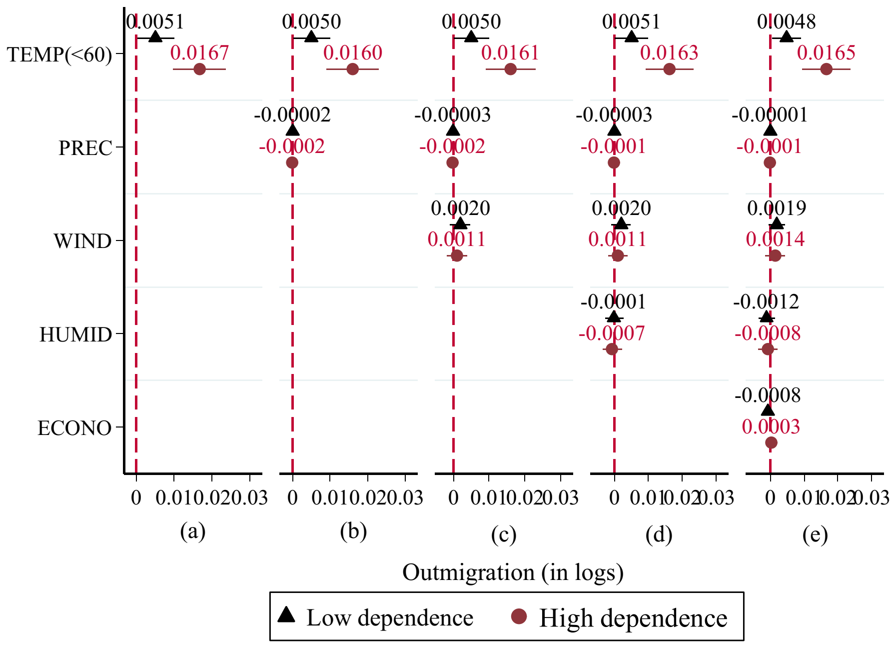

Fig. 8 Role of agricultural dependence in the outmigration effect caused by temperature. **a** shows only the temperature factor. This study gradually adds precipitation, wind velocity, humidity, and economic level to the model. **b** also shows precipitation. **c** shows precipitation and wind velocity as well. **d** shows precipitation, wind velocity, and humidity as well. **e** also shows precipitation, wind velocity, humidity, and economic factors. The horizontal line is a 95% confidence interval

Economic mechanism of the influence of temperature on rural outmigration

According to the analysis above, if the temperature is below 60 °F, rural outmigration significantly increases. This study focuses on analyzing the impact of temperatures below 60 °F on income and agricultural productivity to identify the economic mechanisms through which temperatures trigger rural outmigration. In addition, existing research indicates that the temperature range of [70–75 °F] is associated with the maximum rice yield (Chen & Chen, 2018). Unsuitable temperatures have a significant impact on rice production. Rice is a thermophilic plant, and excessively low temperatures can inhibit its growth and metabolic activity, severely decreasing rice yields and consequently impacting the income of rural residents.

Table 3 shows a summary of the results for the impact of temperature on the income of rural residents based on stepwise regression. For analysis, this study uses the results of column (4) in Table 3, which controls for the main factors affecting rural income. The results show that temperatures below 60 °F significantly reduce the income of rural residents. One additional day in the < 60 °F range could result in a decrease of 6.29 yuan in the income of each rural resident. The consistently significant link between temperature and the income of rural residents suggests a potential economic channel through which temperature may cause rural outmigration. Table 4 shows a summary of the effect of temperature on agricultural productivity.

Table 3 Economic mechanism for the influence of temperature on rural outmigration: rural income

Variable	(1)	(2)	(3)	(4)
TEMP (< 60)	− 9.6389**	− 7.7325**	− 8.0557**	− 6.2912*
	(2.9900)	(2.6605)	(2.6127)	(2.6363)
ECONO		7.9670**	8.1838**	8.7346**
		(0.8686)	(0.8592)	(0.8618)
POPU			− 1.6881**	− 2.6992**
			(0.5311)	(0.7457)
STRUC				− 9.8404
				(5.9104)
Constant	10,550.20**	9429.61**	10,146.98**	10,724.11**
	(535.9649)	(490.8968)	(528.3221)	(584.8572)
N	390	390	390	390
R-squared	0.9943	0.9955	0.9957	0.9958
F	652.0771	819.6634	841.6475	840.2722
p	0.0000	0.0000	0.0000	0.0000

TEMP (< 60) indicates the number of days within the < 60 °F temperature bin; ECONO denotes economic development; POPU is the population; and STRUC indicates the regional industrial structure. Individual and time fixed effects are controlled in all models. The numbers reported in parentheses are standard errors

$^{*}p < 0.05$; $^{**}p < 0.01$

Table 4 Economic mechanism for the influence of temperature on rural outmigration: agricultural productivity

Variable	(1)	(2)	(3)	(4)
TEMP (< 60)	− 0.6986*	− 0.6142*	− 0.6806*	− 0.7154**
	(0.3120)	(0.2880)	(0.2691)	(0.2687)
ECONO		0.7940**	0.5630**	0.5379**
		(0.0605)	(0.0601)	(0.0609)
POPU			0.7024**	0.7215**
			(0.0622)	(0.0625)
STRUC				0.6336*
				(0.2640)
Constant	371.0804**	344.9690**	106.7569	86.6139
	(59.3619)	(54.7992)	(55.3549)	(55.8378)
N	975	975	975	975
R-squared	0.9497	0.9580	0.9634	0.9636
F	190.7866	224.6866	258.4929	257.0592
p	0.0000	0.0000	0.0000	0.0000

TEMP (< 60) indicates the number of days within the < 60 °F temperature bin; ECONO denotes economic development; POPU is the population; and STRUC indicates the regional industrial structure. Individual and time fixed effects are controlled in all models. The numbers reported in parentheses are standard errors

$^{*}p < 0.05$; $^{**}p < 0.01$

The results of column (4) show that temperatures below 60 °F significantly reduce agricultural productivity. One additional day in the < 60 °F range could result in a decrease of 0.72 thousand tons of rice production per county. The results show that reductions in rural income and agricultural productivity are the possible mechanisms through which temperature leads to rural outmigration.

Agriculture is highly sensitive to temperature, and therefore, agricultural productivity is the main channel through which temperature triggers rural outmigration. Rather than high temperatures, low temperatures are an important factor causing rural outmigration in regions with high agricultural dependence. As a thermophilic crop, rice serves as the predominant agricultural product. High temperatures (within a reasonable range) positively increase rice yield, whereas low temperatures exert an obvious negative effect on rice yield. Agricultural production in subtropical regions is primarily hindered by the adverse effects of low temperatures. In tropical countries and regions, extremely high temperatures can seriously impact agricultural production. Our research supplements existing research on the mechanism of outmigration.

Predicted effect of temperature on rural household outmigration

This study further uses Eq. (2) to analyze the impact of temperature on rural household outmigration in the medium and long terms based on the estimation results of Eq. (1). This study uses the daily minimum temperature data of representative concentration pathways 4.5 and 8.5 (RCP 4.5 and RCP 8.5, respectively) for the prediction research. This study uses the minimum temperature from 2016 to 2018 as the baseline to analyze the impact of rural outmigration in the medium term (2041–2060) and the long term (2061–2080). A minimum temperature lower than 60 °F could significantly increase outmigration relative to temperatures between 70 °F and 80 °F; thus, this study predicts the outmigration effect caused by a minimum temperature less than 60 °F. Figure 9 shows the results for the outmigration effects due to medium- and long-term temperature rises based on population weights. Figure 10 also shows the results without considering population weights.

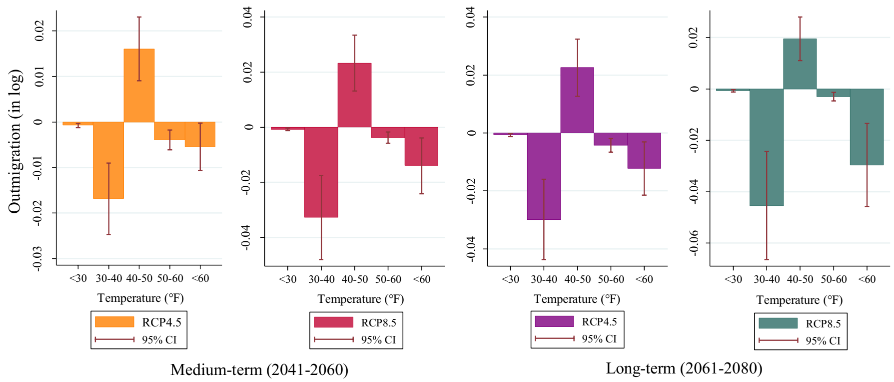

Fig. 9 Prediction of the impact of temperature rise on outmigration based on population weights. The bar denotes the coefficient of the impact of temperature rise on outmigration. The vertical red line denotes a 95% confidence interval

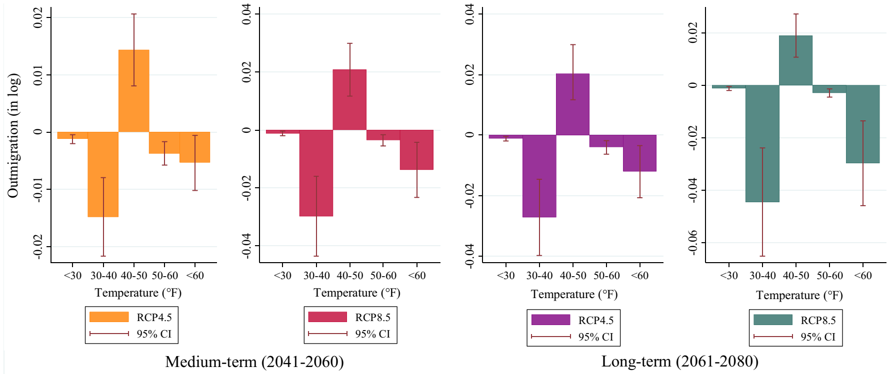

Fig. 10 Prediction of the impact of temperature rise on outmigration without considering population weights. The bar denotes the coefficient of the impact of temperature rise on outmigration. The vertical red line denotes a 95% confidence interval

In the medium term, the number of days with temperatures less than 30 °F, 30–40 °F, and 50–60 °F could decrease, and the number of days with temperatures of 40–50 °F could increase under the two temperature rise scenarios of RCP4.5 and RCP8.5. The total coefficients of influence of low temperatures on rural outmigration under the two temperature rise scenarios (RCP 4.5 and RCP 8.5) are – 0.0055 and – 0.0140, respectively. These results indicate that temperature rise could reduce the annual outmigration rate by 0.55–1.40% in the medium term. Additionally, outmigration could be reduced by 0.96–2.46 households per 10,000 households relative to the 2016–2018 period. In the long term, the total coefficients of influence of low temperatures on rural outmigration under the two temperature rise scenarios (RCP 4.5 and RCP 8.5) are – 0.0123 and – 0.0296, respectively. These results indicate that temperature rise could reduce the annual outmigration rate by 1.23–2.96% in the long term. Furthermore, outmigration could be reduced by 2.16–5.21 households per 10,000 households relative to the 2016–2018 period.

Based on the results above, this study finds that future temperature rise can reduce the rural outmigration caused by low temperatures. A low temperature is an important factor leading to agricultural losses. The main agricultural crop in rural China is rice, which is a thermophilic crop. Future temperature rise could alleviate agricultural losses, which in turn could reduce household outmigration in rural areas. The impact of temperature rise on rural outmigration shown in Fig. 10 is greater than the results shown in Fig. 9. The results indicate that it is necessary to consider population weights; otherwise, the impact of temperature rise could be overestimated.

Conclusions

This study reveals the relationship between temperature and rural outmigration and its underlying mechanisms. This study uses large-scale household smart meter data to identify rural outmigration behavior and to analyze the impact of temperature on rural household outmigration in Jiangxi Province, China. The findings have valuable implications for agriculturally based rural areas with low temperatures.

The conclusions are as follows: first, this study finds that temperature exerts a nonlinear lagged effect on rural household outmigration. An extremely low temperature significantly increases household outmigration in rural areas relative to minimum temperatures between 70 °F and 80 °F. Second, temperature exerts a heterogeneous effect on rural outmigration. The effect of a minimum temperature below 60 °F on household outmigration in areas with high agricultural dependence is 3.44 times the effect in areas with low agricultural dependence. Third, temperature considerably impacts rural residents' income and agricultural productivity, which is an important mechanism through which temperature triggers rural outmigration. Fourth, weather warming can reduce household outmigration caused by low temperatures in the future.

This study has the following implications: temperature is an important factor in rural outmigration, with the main pathway depending on the income of residents and agricultural production. It is necessary to adopt adaptation measures to mitigate the impact of temperature on rural outmigration. In terms of policy support, first, it is necessary to encourage agricultural diversification, reduce the reliance on a single crop, and enhance the resilience to extreme temperature conditions. Second, the government should increase its investment in agricultural technology, improve infrastructure, and promote the application of agricultural technology in rural areas to facilitate the development of agricultural modernization. Third, it is important to improve the agricultural insurance mechanism to enhance the capacity of rural residents to cope with risk. In terms of technological applications, it is important to invest in research and the promotion of cold-resistant crops that can withstand extreme temperatures. In addition, the promotion of technologies such as greenhouse cultivation and geothermal heating can ensure that agricultural production can continue undisturbed even during the winter season.

This study has two limitations. First, the use of smart meter data does not allow us to identify households that abandon one dwelling for a different dwelling locally. Second, when predicting the impact of future temperature changes on population migration, this study assumes that the temperature-response coefficient remains constant. This assumption is a limitation because rural residents may adopt varying adaptive behaviors in the future, leading to changes in the temperature-migration response coefficient. Therefore, in future research, we will improve the accuracy of population migration rate estimation using smart meter data by incorporating micro-level survey data. Additionally, further research will be conducted to explore the adaptive behaviors of rural residents in response to extreme temperatures.

Author contribution Yefei Sun has contributed in all roles as this is a single-authored paper.

Funding This study is supported by the National Natural Science Foundation of China (Grant No. 72304140), the Philosophy and Social Sciences Foundation in Universities of Jiangsu Province (Grant No. 2022SJYB0016), and the Fundamental Research Funds for the Central Universities (Grant No. 30922011206), the Natural Science Foundation of Jiangsu Province (Grant No. BK20220971). The National Natural Science Foundation of China, 72304140, Yefei Sun, The Philosophy and Social

Sciences Foundation in Universities of Jiangsu Province, 2022SJYB0016, Yefei Sun, The Fundamental Research Funds for the Central Universities, 30922011206,Yefei Sun, The Natural Science Foundation of Jiangsu Province, BK20220971, Yefei Sun.

Data availability Weather data is publicly available at http://data.cma.cn. Economic data is publicly available at http://www.epsnet.com.cn. Projected data on temperature rise is publicly available at https://dataserver.nccs.nasa.gov.

Declarations

Conflict of interest The author declares no competing interests.

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