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Assessing the impact of heat stress on technical efficiency in rice production: evidence from Japanese farmers using a stochastic frontier approach

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Background: Climate change and associated heat stress threaten agricultural productivity, particularly rice production. Japan, characterized by its monsoon climate and heavy reliance on rice as a staple food, faces heightened risks from extreme temperatures. These conditions disrupt key physiological processes that are essential for rice yield and production efficiency.

Objective: This study investigates the impact of interannual temperature variability and heat stress on Japanese rice farmers' technical efficiency (TE), emphasizing farm-level dynamics and climatic influences.

Methods: By using panel data from the Kome Seisanhi Chosa Tokei (2008–2016), this study employs a dynamic panel model estimated using System Generalized Method-of-Moments (SYS-GMM). The Heat Stress Index (HSI) is constructed based on cumulative heat exposure and consecutive high-temperature days, whereas the TE is estimated using stochastic frontier analysis (SFA).

Results: The results reveal that heat stress significantly reduces TE, with marginal increases in HSI amplifying its negative effects. Rainfall variability has mixed impacts: abnormal rainfall during heading reduces efficiency, whereas additional rainfall during maturity enhances efficiency.

Conclusion: These findings highlight the need for adaptive measures, such as heat-tolerant rice varieties and optimized resource management, to mitigate climate risks and enhance productivity.

KEYWORDS

climate change, heat stress, technical efficiency, dynamic panel, farm-level data

1 Introduction

Climate change is an important environmental challenge of the 21st century. The Intergovernmental Panel on Climate Change (IPCC) reported in 2023 that human activities have unequivocally caused global warming, with global surface temperature reaching 1.1°C above pre-industrial levels in 2011–2020 [Intergovernmental Panel on Climate Change (IPCC), 2023]. Projections indicate that without significant emission reductions, global warming is likely to exceed 1.5°C in the near future, intensifying the hydrological cycle and leading to more frequent and severe weather extremes, including heavy precipitation, floods, heatwaves, droughts, and precipitation deficits. Notably, 2023 shattered climate records, with the World Meteorological Organization (WMO) confirming it as the warmest year on record, accompanied by extreme weather events that caused widespread devastation [World Meteorological Organization (WMO), 2023]. These developments underscore the urgent need for comprehensive strategies to mitigate and adapt to the escalating impact of climate change.

Human economic activities face both direct and cascading effects of climate change, with considerable economic burdens observed in agriculture and healthcare, often disproportionately affecting certain regions and communities (Tol, 2009). Climate change is driving an increase in extreme weather conditions, including intensified rainfall and snowfall, across most of the globe, even in arid regions. Ocean heatwaves are becoming more frequent and extreme as the climate warms, which is expected to enhance both the amplitude and frequency of climate phenomena, such as eastern Pacific El Niño events, leading to widespread climatic consequences (Tollefson, 2016; Ham, 2018). Extreme weather events have cost approximately USD 140 billion annually between 2000 and 2019, with damages increasing to approximately USD 280 billion in 2022. This significant increase underscores the escalating economic impact of extreme weather, including heatwaves, on various sectors, notably agriculture (Newman and Noy, 2023).

Heat stress considerably impairs plant growth and development, ultimately reducing crop yields, and its effects are expected to worsen with the increasing frequency of heatwaves under climate change scenarios (Sandhu et al., 2018). Heat stress, driven by rising global temperatures, has emerged as a primary cause of global crop yield reduction, considerably impairing key physiological processes essential for plant growth and productivity (Aneja et al., 2022). High-temperature stress has emerged as a critical challenge for rice production in Japan, contributing to a higher incidence of chalky grains, which substantially diminishes both the quality and economic value of rice in the context of a warming climate (Masutomi et al., 2023). The effects of heat stress on key crops exhibit notable spatial variability, with certain regions facing remarkably higher risks owing to climatic conditions (Teixeira et al., 2013). The impact of heat stress on agricultural and worker productivity is profoundly influenced by socioeconomic conditions (Orlov et al., 2021; El Khayat et al., 2022). Thus, micro-level data are crucial for understanding the nuanced responses of farmers to heat stress as they reveal how high temperatures reduce agricultural productivity and drive adjustments in farming practices (Baldoni et al., 2018; Aragón et al., 2021).

Analyzing the impact of heat stress at the micro-level is challenging because of the difficulty in obtaining comprehensive panel data (Chen and Gong, 2021). Such research requires precise farm-level socioeconomic data along with accurate meteorological records, which require detailed farm geolocation and high-resolution weather station data. The complexity of integrating these datasets makes such studies rare and underscores the unique value and significance of the data and findings presented in this study.

This study uses micro-level panel data to examine the impact of extreme weather, specifically heat stress, on the TE of rice production. TE is a crucial indicator for two reasons: it directly influences food security, making it a vital metric in the context of climate change, and it highlights the sustainability of agricultural practices, reflecting the resilience of farming systems [Gaviglio et al., 2021; Food and Agriculture Organization (FAO), 2023]. By focusing on rice, a staple crop essential to global food security, this study provides critical insights into how heat stress affects production efficiency, and contributes to the understanding of sustainable agriculture under changing climatic conditions.

This study uses micro-level panel data from *Kome Seisanhi Chosa Tokei* (Production Cost Statistics of Rice), conducted by Japan's Ministry of Agriculture, Forestry, and Fisheries (2008–2016). These data are highly reliable and comprehensive, and capture detailed farm-level socioeconomic information. Climate variables are sourced from the Japan Meteorological Agency (JMA), which is known for its extensive coverage and accuracy across all prefectures. By using these datasets, a dynamic panel model is estimated using the system-generalized method of moments (SYS-GMM) to investigate the impact of heat stress on rice technical efficiency, incorporating both farm-level characteristics and climate variability.

Japan is an ideal subject for studying the impacts of climate variability and heat stress, particularly on rice production and consumption, which play a crucial role in the country's food security and agricultural economy, accounting for a per capita rice consumption of 50.9 kilograms in 2022 and 40% of the annual staple food intake (Ministry of Agriculture, Forestry, and Fisheries, 2023). Furthermore, situated in a monsoonal climate zone prone to heat stress due to seasonal temperature fluctuations and high humidity (Gosling et al., 2007; Fu et al., 2018; Pickson et al., 2022), Japan faces heightened vulnerability to this growing threat under climate change. The country's geographical diversity, spanning over 3,000 kilometers from the cold northern regions of Hokkaido to the subtropical climate of Okinawa, has resulted in significant climatic heterogeneity. Additionally, distinct differences in weather patterns between the Pacific Ocean and Sea of Japan sides further highlight regional variability. These factors, combined with the cultural and economic significance of rice, make it an excellent case for analyzing the effects of heat stress and understanding the broader implications for monsoonal agricultural systems.

This paper is structured as follows. Section 2 provides a literature review of the analysis. Section 3 outlines the data sources and methodology, including the specifications and estimation of the empirical model. Section 4 presents the findings and explores their policy implications. Finally, Section 5 presents the concluding remarks.

2 Background

2.1 Climate change and heat stress

Climate change has significantly increased the global frequency of record-breaking high-temperature events, particularly since the 1970s (Coumou et al., 2013). The increasing frequency of high-temperature events has posed a significant threat to global food security by reducing major crop yields (Lobell and Gourdji, 2012). Climate change-induced heat stress exhibits significant regional variability in frequency, duration, and intensity (Hansen and Sato, 2016; Perkins-Kirkpatrick and Gibson, 2017). Heat stress events in East Asia are projected to increase remarkably in both frequency and intensity under 1.5°C and 2.0°C global warming scenarios, emphasizing the profound regional impacts of climate change (Lee and Min, 2018). In Japan, the annual average temperature has been rising at a rate of 1.19°C per century, with a notable increase in extreme high-temperature events since the 1990s, highlighting the intensifying heat stress caused by climate change (Ministry of the Environment, 2020).

Recent reports indicate that Asia has experienced record-breaking extreme heat events, with Japan enduring the hottest summer on record, further demonstrating the severe impact of climate change-induced heat stress on the region [World Meteorological Organization (WMO), 2023].

2.2 Metrics and measurement approaches for heat stress

Heat stress refers to the physiological and environmental strains resulting from high temperatures, humidity, and radiation (Rachid and Qureshi, 2023), affecting both human health and agricultural productivity.

For human health, heat stress is commonly measured using indices such as the Wet-Bulb Globe Temperature (WBGT) and Universal Thermal Climate Index (UTCI), which incorporate temperature, humidity, wind speed, and solar radiation (Copernicus Climate Change Service, 2024). Aduna-Sánchez et al. (2023) developed a low-cost monitoring system to assess heat stress using real-time environmental data in urban environments. Gao et al. (2018) highlighted WBGT and Predicted Heat Strain (PHS) as effective tools for evaluating heat exposure and protecting workers in occupational settings. In studies on the impact of heat stress on human health, measurements have consistently been based on various indices.

However, agricultural production is uniquely influenced by seasonality, perishability, and weather conditions, which affect the supply and pricing dynamics (Zhang and Donaldson, 2008). To evaluate heat stress in cereal crops, such as maize, wheat, and rice, various methods have been developed to quantify its impact on growth and yield. Canopy temperature depression (CTD) and membrane thermostability are widely used indicators of heat stress in wheat (Lepekhov, 2022). Yield reductions are estimated by scaling the final yield based on the accumulated thermal time above the critical temperature thresholds during sensitive periods (Teixeira et al., 2013; Challinor et al., 2005). Daily changes in the harvest index are adjusted proportionally to temperature exceedances during heat-sensitive growth stages (Rezaei et al., 2015). Specific physiological processes, such as photosynthesis and grain filling, are directly modeled to capture nonlinear yield responses to heat stress (Sage and Kubien, 2007).

By building on the existing research, this study focuses on calculating the heat stress index (HSI) for rice by considering Japan's specific climatic conditions and rice growth characteristics. Using the accumulated thermal time data and the number of consecutive high-temperature days during the heading and maturity stages, a logistic curve is applied to model rice growth dynamics, providing a quantitative assessment of the impact of heat stress on rice production.

2.3 Climate change, heat stress, and agricultural production

Table 1 provides an overview of the existing literature on the impact of climate change and heat stress on technical efficiency (TE) and total factor productivity (TFP) across various agricultural contexts. Climate change negatively affects agricultural productivity, with significant declines in total factor productivity (TFP) reported at the global level, including an estimated reduction of less than 0.1% in TFP growth due to climate change (Letta and Tol, 2018). Regional studies on Japanese rice production have also identified reductions in productivity due to climate variability, particularly in response to heavy rainfall and other climate-related factors. For example, benchmark model estimates indicating that a 3°C temperature increase could lead to an 8% reduction in farm revenue due to rice quality deterioration, despite a 3.4% increase in revenue owing to higher yields (Kawasaki and Uchida, 2016).

TABLE 1 Literature on the impact of climate change and heat stress on TE/TFP.

Authors	Period	Sector	Level	Topic	Source/ model	TE/TFP	Relationship
Aragón et al. (2021)	2007–2015	Peruvian agriculture	Farm	Heat stress	Econometric model (panel)	TFP	Negative
Auci et al. (2021)	2007–2017	European agriculture	Farm	High temperatures	Stochastic Frontier Analysis (SFA)	TE/Econ	Positive
Kawasaki and Uchida (2016)	1976–2010	Japanese rice	Prefecture	Climate change	Production	-	Negative
Kunimitsu and Kudo (2015)	1979–2011	Japanese rice	Prefecture	Heavy rainfall	Index Number Methods	TFP	Negative
Kunimitsu et al. (2016)	1979–2010	Japanese rice	Prefecture	Climate change	DEA-Malmquist	TFP	Negative
Letta and Tol (2018)	1960–2006	Global agriculture	Country	Climate change	Penn World Table	TFP	Negative
Ogundari and Onyeaghala (2021)	1981–2010	African agriculture	Country	Climate change	USDA-ERS	TFP	Negative
Ortiz-Bobea et al. (2021)	1961–2010	Global agriculture	Country	Climate change	Econometric model (panel)	TFP	Negative
Tokunaga et al. (2015)	1995–2006	Japanese agriculture	Prefecture	Climate change	Production	-	Negative
Wang et al. (2017)	Historical	U.S. agriculture	State	Heat stress	Stochastic Frontier Analysis (SFA)	TE/TFP	Negative

Heat stress is a specific manifestation of climate change and has been found to significantly reduce productivity in both Peruvian and U.S. agriculture, highlighting its adverse effects on efficiency and output, with an average 1°C temperature increase causing production efficiency to decrease by 0.38% in the Pacific region and 1.31% in the Delta region (Wang et al., 2017). However, in European agriculture, high temperatures have encouraged farmers to adopt innovative adaptive strategies that indirectly improve technical efficiency (Auci et al., 2021). This suggests that regional differences in adaptive capacity and policy environments play crucial roles in mitigating the negative effects of climate change.

Despite extensive research, several gaps remain in the literature. Studies on Japanese agriculture predominantly rely on prefecture-level data and focus on TFP, overlooking the micro-level dynamics of farm-level technical efficiency and the localized impacts of heat stress. Moreover, most analyses use static models that fail to capture the dynamic nature of climatic variability and its interactions with critical crop growth stages. These gaps are not unique to Japan. For example, Zuniga-Gonzalez (2023) analyzed post-COVID-19 changes in total factor productivity in bio-based agricultural economies across six global regions, identifying region-specific declines in technical efficiency, particularly in North America and Western Europe, using a DEA-Malmquist approach.

This study aims to address these gaps by utilizing farm-level panel data to analyze the impact of heat stress on the TE of Japanese rice production. By focusing on critical phenological stages and employing dynamic panel models, this study provides a more nuanced understanding of how climate change affects farm-level efficiency and offers insights for targeted policy interventions and climate adaptation strategies.

3 Data and methodology

3.1 Data

Figure 1 presents the methodological steps of this study. A dynamic panel model for analyzing the technical efficiency (TE) of rice farmers is constructed and estimated using the SYS-GMM method based on the calculation of the Heat Stress Index (HSI) and stochastic frontier analysis (SFA) for estimating TE. The dataset employed in this study has significant strengths. To obtain detailed data on rice production and management practices, this study utilizes the *Kome Seisanhi Chosa Tokei* (Production Cost Statistics of Rice) conducted by Japan's Ministry of Agriculture, one of Japan's most authoritative sources of agricultural microdata. This survey is known for its rigor and consistency, which makes it highly reliable for longitudinal analyses. However, accessing balanced panel data poses considerable challenges due to the comprehensive nature of data collection and the need to ensure continuity across multiple years. The final dataset comprises production and management data from 124 rice farmers over a nine-year period (2008–2016), yielding 1,116 observations (microdata). These farmers are distributed across seven major agricultural regions of Japan, as follows: Hokkaido (16 farmers), Tohoku (24), Kanto (17), Chubu (22), Kinki (15), Chugoku-Shikoku (11), and Kyushu (19), ensuring broad regional coverage and spatial representativeness. These farmers were selected based on data completeness and logical consistency. A small number of farms were excluded due to implausible values (e.g., negative output or zero input use). All theoretically relevant and available farm-level variables were retained in the analysis. The difficulty of securing a robust and continuous dataset further highlights the value of this paper's empirical approach. To link farm-level data with localized climate conditions, this study uses daily meteorological observations from the Japan Meteorological Agency (JMA). Each farm's village location, as recorded in the production survey, is matched with the nearest JMA weather station, with most located within 20 km of the farm site. This ensures a high level of spatial precision in associating temperature and precipitation data with individual farmers' production environments.

3.2 Definition and calculation of the heat stress index (step 1)

Building on the methodologies proposed by Rane and Nagarajan (2004), Ishigooka et al. (2017), and Hasegawa et al. (2011), we employ logistic regression curves to quantify the impact of high temperatures on rice growth. The choice of the logistic model is driven by the nature of the response of rice yield and quality to accumulated heat, which typically exhibits an S-shaped curve akin to the logistic function. This approach provides a nuanced understanding of the effect of temperature on rice growth at various stages.

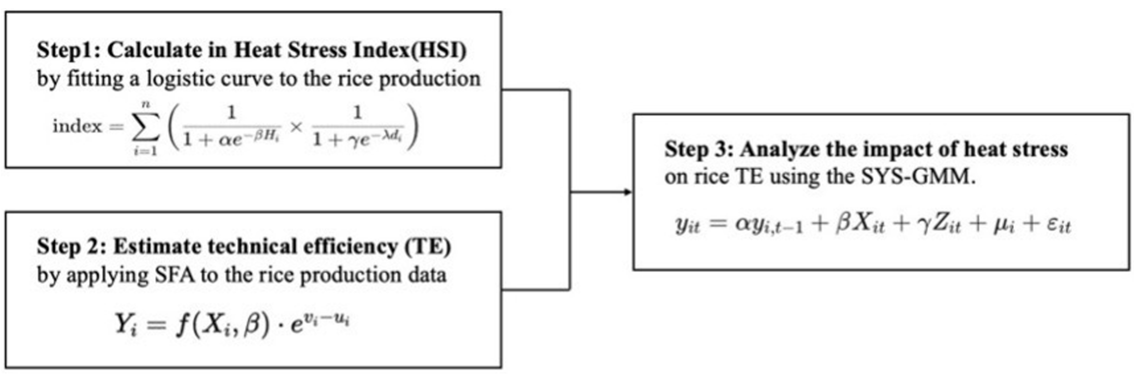

FIGURE 1
Methodological steps.

$$index = \sum_{i=1}^{n}\left(\frac{1}{1+\alpha e^{-\beta H_i}} \times \frac{1}{1+\gamma e^{-\lambda d_i}}\right) \tag{1}$$

Where

- H_i represents the accumulated temperature exceeding a 27°C threshold, capturing the cumulative heat exposure,
- d_i denotes the consecutive days the temperature threshold is exceeded, and α, β, γ, and λ are parameters describing the logistic growth response to temperature and duration of exposure.[1]

Equation 1 effectively integrates the intensity and duration of heat stress, and reflects its dual impact on crop physiology.

To calibrate this model, parameters α, β, γ, and λ are estimated using empirical data from growth experiments on rice conducted in Japan. These experiments provide detailed records of temperature fluctuations and their corresponding effects on rice growth, allowing for the precise modeling of heat stress impacts. The results are formulated as shown in Equation 2.

Where

- The temperature threshold values (H_i) are set at 20 and 60, representing mild and severe heat stress conditions, respectively.
- The duration parameters (d_i) are set at 5 and 7 days to reflect short-term and prolonged exposure, respectively.

$$index = \sum_{i=1}^{n}\left(\frac{1}{1+15.48 e^{-0.0685 H_i}} \times \frac{1}{1+3707.55 e^{-1.37 d_i}}\right) \tag{2}$$

3.3 Estimation of rice productivity technical efficiency (step 2)

This study estimates the TE of rice production using a Stochastic Frontier Analysis (SFA) model. The SFA model is particularly effective in capturing the effects of unpredictable environmental variables, such as temperature and precipitation, on agricultural outputs. A translog production function is specified to allow for flexible interactions and nonlinearities among production inputs. The formula for the model is presented below.

This study estimates the technical efficiency of rice production using a Stochastic Frontier Analysis (SFA) model, which effectively captures in capturing the effects of unpredictable environmental variables, such as temperature and precipitation, on agricultural outputs. A translog production function is specified to allow for flexible interactions and nonlinearities among production inputs. Following Zuniga-Gonzalez et al. (2024), SFA is especially well-suited for evaluating efficiency in agricultural and bioeconomic contexts because it decomposes deviations from the production frontier into two parts: statistical noise (e.g., measurement errors, weather fluctuations) and true technical inefficiency. This distinction is critical for accurately assessing productivity in the presence of unobserved heterogeneity and environmental shocks—factors that are especially prevalent in rice farming systems. Unlike traditional estimation methods such as Ordinary Least Squares (OLS), which attribute all deviations to random errors, SFA enables more precise efficiency measurement by isolating inefficiency effects from stochastic disturbances (Battese and Coelli, 1995; Zuniga-Gonzalez et al., 2024). The translog functional form used in the SFA model is presented in Equation 3 below.

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{5}\beta_j \ln X_{j,it} + \sum_{j=1}^{5}\beta_{jj}\left(\ln X_{j,it}\right)^2 + \sum_{j=1}^{4}\sum_{k=j+1}^{5}\beta_{jk} \ln X_{j,it} \ln X_{k,it} + v_{it} - \mu_{it} \tag{3}$$

Where.

- Y_{it} is the observed rice output for the i-th farmer at time t.
- $X_{j,it}$ shows that inputs ($j = 1, 2, 3, 4, 5$) represent labor (L), fertilizer (F), seed (S), chemicals (C), and machinery (M).
- v_{it} represents random error te4rm accounting for measurement errors and stochastic effects.
- μ_{it} is the inefficiency term representing deviations from the production frontier.

$$TE_i = \exp\left(-u_i\right) \tag{4}$$

Equation 4 implies that when $\mu_{it} = 0$, $\mathrm{TE}_i = 1$, thus indicating full technical efficiency, whereas any $\mu_{it} > 0$, results in $\mathrm{TE}_i < 1$, reflecting a departure from full efficiency.

The variables used in the SFA model are summarized in Table 2.

3.4 Assessing the impact of heat stress on technical efficiency (step 3)

The generalized method of moments (GMM) is a robust estimator for dynamic panel data models that addresses the key limitations of fixed- and random-effects models. Traditional methods often yield biased estimates when explanatory variables are correlated with an error term (Arellano and Bond, 1991). By employing lagged values as instruments, GMM effectively mitigates endogeneity. The System GMM estimator further enhances efficiency, particularly for

TABLE 2 Description of variables in SFA.

Variables	Obs	Mean	Std. Dev.	Min	Max
Rice yield (kg, Y)	1,116	19,558	29,200	566	319,761
Labor (hours, L)	1,116	763	904	23	8,436
Fertilizer cost (JPY, F)	1,116	335,000	520,000	0	7,410,000
Seedling cost (JPY, S)	1,116	90,457	129,000	0	1,340,000
Chemicals cost (JPY, C)	1,116	274,000	375,000	2,498	3,790,000
Machinery cost (JPY, M)	1,116	890,000	1,180,000	0	9,550,000

[a] The price data was adjusted using the "Agricultural Production Materials Price Index".

1 This paper focuses on the high-temperature environment during the heading and maturity stages of rice, which vary according to the farmers' regions (prefecture) and the rice varieties they cultivate.

datasets with short time dimensions or persistent variables, by combining the level and difference equations to strengthen the instrument matrix (Blundell and Bond, 1998). These advantages make GMM superior for obtaining consistent and reliable estimates in panel data analyses.

The estimated dynamic model in this study can be formally represented as shown in Equation 5 below:

$$TE_{it} = \beta_1 TE_{i,t-1} + \beta_2 HI_{it} + \beta_3 R_{it}^{heading} + \beta_4 T_{it}^{heading} + \beta_5 R_{it}^{maturity} + \beta_6 T_{it}^{maturity} + \beta_7 LI_{it} + \beta_8 FI_{it} + \beta_9 BI_{it} + \beta_{10} MI_{it} + \sum_{j=1}^{8} \gamma_j Year_j + \varepsilon_{it} \quad (5)$$

The variables employed in the GMM model are detailed in Table 3. This table outlines the definitions and calculation methods of the key variables used in the dynamic panel estimation, providing a clear reference for interpreting the model results.

4 Results and discussion

4.1 Analysis of datasets

The spatial distribution of the Heat Stress Index (HSI) across Japan, as shown in Figure 2, reveals significant regional disparities. Eastern Japan generally experiences lower levels of heat stress than western Japan, likely because of differences in climatic patterns and topographical features. Additionally, prefectures along the Sea of Japan exhibit consistently lower HSI values than those along the Pacific Ocean side, possibly because of the cooling effects of ocean currents and sea breezes. These patterns suggest that regions in the western and Pacific-facing areas are more vulnerable to heat stress, which may have pronounced implications for agricultural productivity. In processing temperature data, varietal differences were also considered by aligning the heat stress index calculation with region-specific rice growth periods based on local cropping calendars. These observations underscore the importance of geographically tailored climate adaptation strategies to effectively address these disparities.

The temporal trends of HSI and TE from 2008 to 2016, shown in Figure 3, suggest fluctuations but no clear linear pattern. Although years like 2010 and 2013 show high HSI and relatively low TE, statistical tests using annual averages do not indicate a significant correlation. To better assess this relationship, we rely on panel-based regression, which reveals a significant negative impact of HSI on TE after controlling for other factors. Over nine years, the regional TE of Japanese rice farmers, as shown in Figure 4, exhibits notable disparities. Small-scale farming regions generally demonstrate lower efficiency, whereas Hokkaido, which is characterized by large-scale farming practices, consistently outperforms other regions with significantly higher TE. This disparity likely stemmed from economies of scale, where larger operations in Hokkaido benefit from more efficient input utilization, better access to advanced technologies, and superior management practices.

TABLE 3 Description of variables in GMM.

Variable	Description
TE_{it}	Technical efficiency of farm *i* in year *t*.
$TE_{i,t-1}$	Lagged technical efficiency of farm *i* in year $t - 1$.
HI_{it}	Heat stress index for farm *i* in year *t*.
R heding it	Precipitation deviation during the heading stage for farm *i* in year *t*.
T heding it	Temperature deviation during the heading stage for farm *i* in year *t*.
R maturity it	Precipitation deviation during the maturity stage for farm *i* in year *t*.
T maturity it	Temperature deviation during the maturity stage for farm *i* in year *t*.
LI_{it}	Labor input intensity for farm *i* in year *t*.
FI_{it}	Fertilizer input intensity for farm *i* in year *t*.
BI_{it}	Biological input intensity (e.g., seeds and fertilizers) for farm *i* in year *t*.
MI_{it}	Machinery input intensity for farm *i* in year *t*.
$YEAR_j$	Year-specific fixed effects to control for time-specific unobserved heterogeneity.
ε_{it}	Error term.

[a] Input intensity was calculated by dividing the input expenditure by the planting area. [b] Due to the large value of the input intensity, we applied Min-Max normalization to avoid scaling issues (Singh and Singh, 2020).

4.2 Analysis of SFA

The estimation results of the stochastic frontier analysis (SFA) are presented in Table 4. The results of the time-varying inefficiency model indicate a strong overall fit, with a Wald chi-square value (3012.81) significant at the 1% level, confirming the robustness of the model. The variance ratio ($\gamma = 0.916$) shows that 91.61% of the variance in the composite error term is attributable to inefficiency rather than random noise, supporting the use of the stochastic frontier model.

Among the input variables, the quadratic terms for fertilizer (*ln_fertilizer*^{2}) and seed (*lnseed*^{2}) show significant positive effects, suggesting that these inputs contribute to efficiency improvements within certain thresholds. Conversely, the interaction terms between fertilizer and seed (*lnfertilizer_seed*) exhibit significant negative effects, indicating potential inefficiencies from unbalanced or excessive input combinations.

The negative coefficient of time (*t*) suggests a declining trend in TE during the study period, possibly reflecting cumulative environmental and operational challenges. However, the positive coefficient of the squared time term (t^2) implies that some degree of adaptation or recovery occurred over time, highlighting the dynamic nature of efficiency trends.

Overall, these results underscore the critical need for balanced input management and adaptive practices to sustain TE in rice production, particularly under the pressures of evolving climatic and resource conditions.

4.3 Model's estimation and policy implications

4.3.1 Robustness and stability of results

To further validate the robustness of our system GMM (SYS-GMM) findings, we conducted complementary estimations using

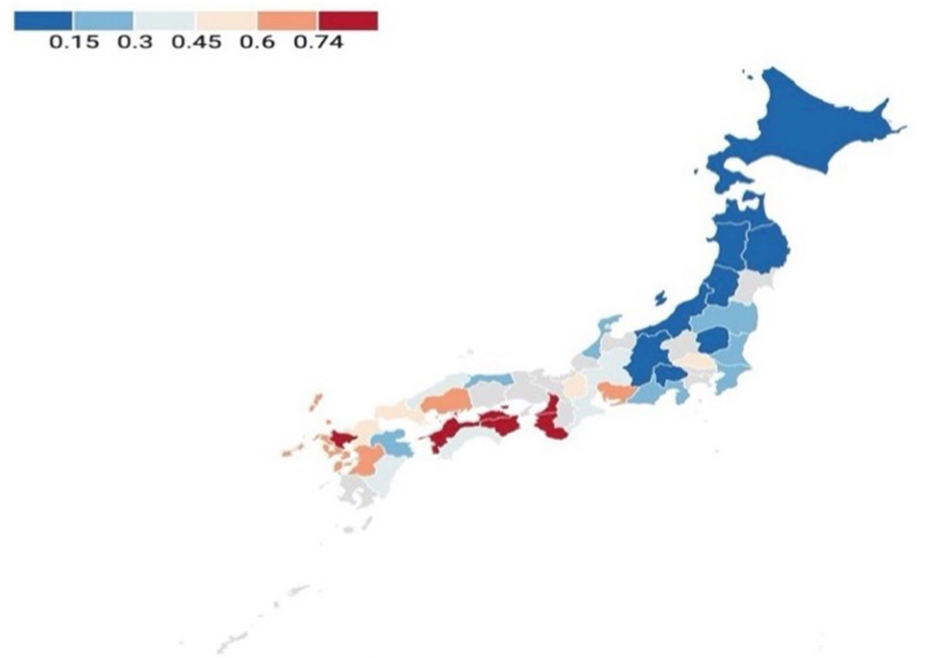

FIGURE 2
Average heat stress index, experienced by each prefecture.

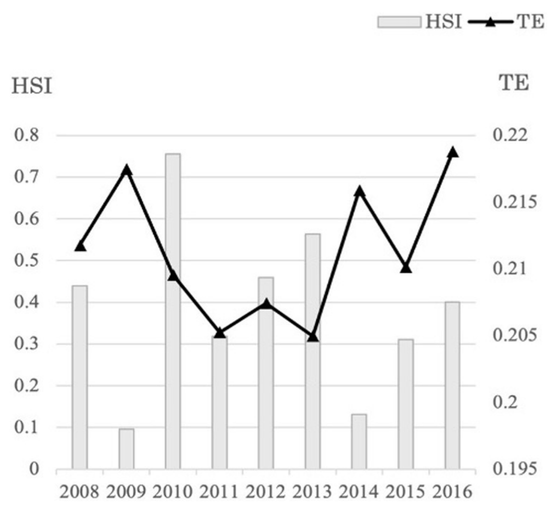

FIGURE 3
Temporal trends of heat stress index (HSI) and technical efficiency (TE) in rice production.

ordinary least squares (OLS) methods with both linear and nonlinear specifications of the heat stress index (*HI*). The results of the dynamic SYS-GMM and OLS model estimations are presented in Table 5. The SYS-GMM approach is widely used to address potential dynamic panel biases and endogeneity issues (Arellano and Bover, 1995; Blundell and Bond, 1998). Complementary estimates that do not rely on GMM assumptions enhance the robustness of the conclusions.

First, we re-estimated the model by replacing *HI* with its logarithmic transformation (*Ln HI*) under a fixed-effects (FE) OLS specification. This approach reduces the skewness of the distribution and captures the elasticity effects. The FE regression controlling for year fixed effects and clustering standard errors at the farm level yielded a statistically significant negative coefficient for *Ln HI*, implying that increases in heat stress are associated with lower technical efficiency (*TE*). Although this OLS model inevitably leads to a slight reduction in sample size due to missing values from the log transformation, the resulting negative and significant effect closely aligns with the direction and significance levels found in the SYS-GMM estimates.

Second, we tested a quadratic specification of *HI*—including HI^2—to probe potential nonlinearity. This flexible model allows for the possibility that the marginal impact of heat stress on TE changes as exposure intensifies. The results confirm a nonlinear relationship; the linear term of *HI* is positive and significant, whereas the squared term is negative and significant. This pattern suggests an inverted U-shaped relationship, where mild heat stress may not severely harm efficiency but further intensification of heat stress clearly diminishes technical performance. This result is in line with the agricultural and climate economics literature, indicating that moderate changes in temperature may not be detrimental until thresholds are crossed (Deschênes and Greenstone, 2007).

Crucially, these OLS-based robustness checks do not contradict our core conclusion derived from the SYS-GMM. Instead, they reinforce this by showing that even under more restrictive or alternative assumptions, such as no dynamic specification or nonlinearity, the adverse impact of heat stress on TE remains evident. Although SYS-GMM estimations are preferred because of their superior ability to handle endogeneity and dynamic panel aspects, presenting these OLS estimates strengthens the argument that the negative association between *HI* and *TE* is not merely an artifact of the chosen method.

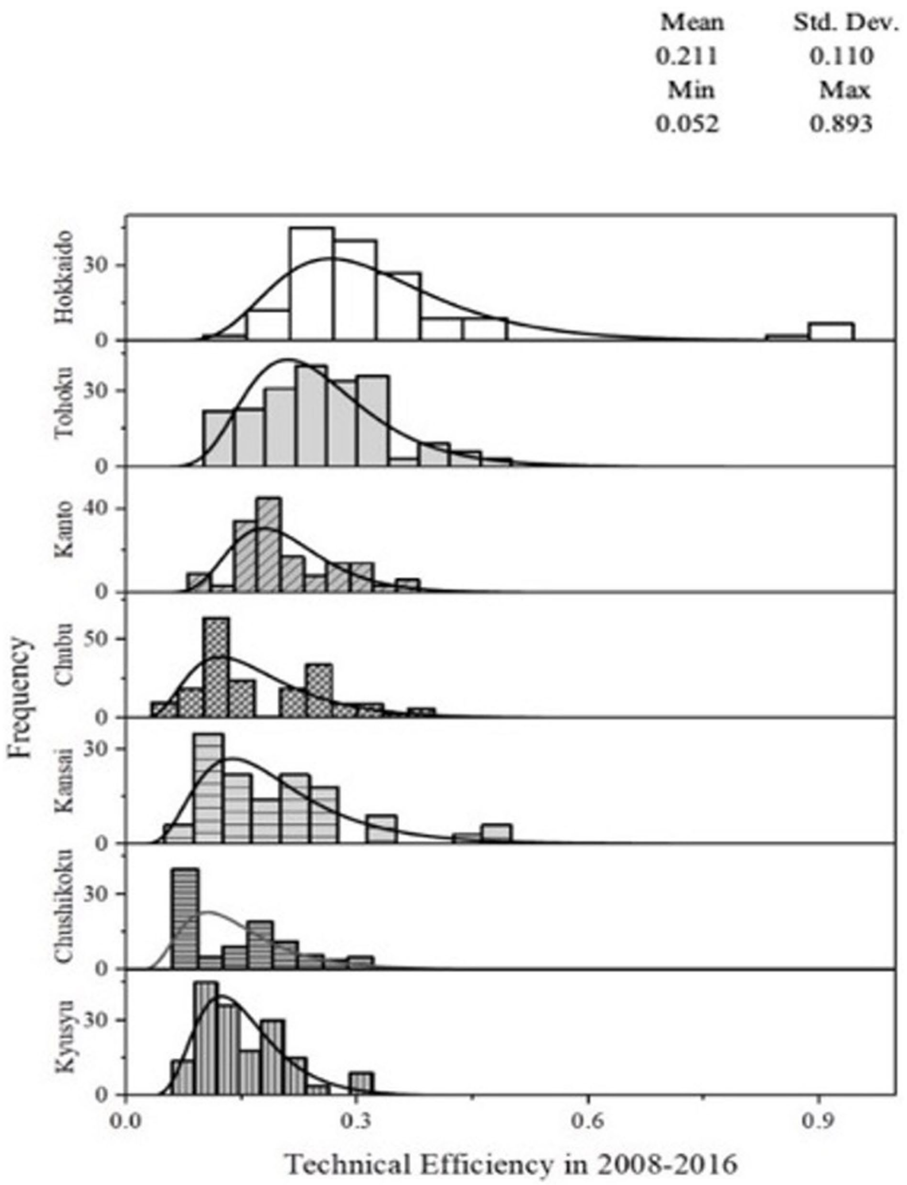

FIGURE 4
Technical efficiency of Japanese rice farmers by region.

In summary, the complementary OLS analyses, both with a log transformation of hi and a quadratic term, corroborate the negative effect of heat stress on TE, previously identified by the SYS-GMM approach. This convergence across methodologies enhances the credibility and robustness of our empirical findings, as advocated in the existing literature, where multiple model specifications bolster confidence in the reported results (Wooldridge, 2002).

4.3.2 Estimation of SYS-GMM

Several diagnostic tests and robustness checks are conducted to ensure reliability of the results. The Arellano-Bond test for autocorrelation in the first-differenced residuals is performed to assess the validity of the moment conditions. The test results indicate the presence of a first-order autocorrelation (AR (1) $z = -2.54$, $p = 0.011$), which was expected because of the transformation process in the dynamic panel models. Importantly, the second-order autocorrelation test is not significant (AR (2) $z = -0.42$, $p = 0.676$), suggesting that the instruments used were valid and that the model was correctly specified (Arellano and Bond, 1991).

The Hansen test of overidentifying restrictions yields a p-value of 0.969, indicating that we cannot reject the null hypothesis that the instruments are valid and uncorrelated with the error term. This high p-value suggests that the instruments are appropriate for the model. However, an excessively high p-value may also indicate instrument proliferation or weak instruments (Roodman, 2009). To address this, care was taken to limit the number of instruments relative to the number of groups, ensuring that the instrument count did not exceed the number of cross-sectional units; this helped mitigate potential overfitting and weak identification issues.

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TABLE 4 Estimation results of SFA.

Variable	Coefficient	Robust SE	Variable	Coefficient	Robust SE
lnlabor	0.425*	0.232	*lnpesticedes_ machine*	−0.022**	0.010
lnfertilizer	0.027	0.144	*t_ lnlabor*	−0.005	0.004
lnseed	0.011	0.109	*t_ lnfertilizer*	0.002	0.004
lnpesticedes	−0.144	0.172	*t_ lnseed*	−0.003**	0.002
lnmachine	−0.061	0.074	*t_ lnpesticedes*	0.003	0.004
lnlabor2	0.334	0.026	*t_ lnmachine*	0.005***	0.002
lnfertilizer2	0.109***	0.003	t	−0.082***	0.030
lnseed2	0.014***	0.002	t^2	0.002**	0.001
lnpesticedes2	0.009	0.015	*cons*	5.301***	1.041
lnmachine2	0.002*	0.001	γ	0.916***	0.018
lnlabor_ fertilizer	−0.056**	0.027	μ	0.576***	0.099
lnlabor_ seed	0.015	0.018	σ^2	0.211***	0.438
lnlabor_ pesticedes	0.005	0.029	$\sigma_v{}^2$	0.193***	0.178
lnlabor_ machine	0.006	0.013	$\sigma_u{}^2$	0.017***	0.001
lnfertilizer_ seed	−0.033***	0.011			
lnfertilizer_ pesticedes	0.009	0.016	*WALD TEST*	3,012.81	
lnfertilizer_ machine	0.034***	0.012			
lnseed_ pesticedes	0.027*	0.014	*N*	1,116	
lnseed_ machine	−0.015**	0.006			

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

TABLE 5 Dynamic SYS-GMM & OLS model estimations.

Variables	Name	(1) SYS-GMM		(2) Linear model (log of *HI*)		(3) Quadratic model (*HI* & HI^2)	
		Value	St.d	Value	St.d	Value	St.d
Main vars.	*TEt-1*	0.994797***	0.0006	-	-	-	-
	Ln HI	-	-	−0.0000864**	0.0000411	-	-
	HI	−0.000057**	0.0000259	-	-	0.0015023***	0.0004834
	HI^2	-	-	-	-	−0.0009033***	0.0003365
Climate vars.	$R_{heading}$	0.000097***	0.0000373	−0.0001408	0.0001759	−0.0002539	0.0001785
	$T_{heading}$	3.91E-06	0.000011	−0.00006	0.0001186	−0.0005499***	0.0001603
	$R_{maturity}$	0.000038**	0.074	−0.000386	0.0002261	−0.0001302	0.0002024
	$T_{maturity}$	−0.0000284	0.026	−0.0007105***	0.0002163	−0.0009647***	0.0002015
Other controls	*LI*	0.0009389	0.003	1.57E-06	2.05E-06	1.24E-06	2.33E-06
	FI	−0.0005471**	0.002	−4.58E-09	2.84E-09	−4.09E-09	2.56E-09
	BI	−0.0001274	0.015	4.91E-09	2.81E-09	4.89E-09	2.50E-09
	MI	−0.0002454**	0.001	−8.23e-10*	4.16E-10	−9.89e-10**	4.24E-10
Specification	*Hansen test (Chi2)*	-	9.9	-	-	-	-
	AR(1)	-	−2.54**	-	-	-	-
	AR(2)	-	−0.42	-	-	-	-
Fixed effects	*Year FE*	-	-	Yes	-	Yes	-
	Farm FE	-	-	Yes	-	Yes	-
	Observations	1,116	-	891	-	1,116	-
	Number of Farms	123	-	118	-	124	-
	R-squared (within)	-	-	0.9704	-	0.9702	-

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

The estimation results from the dynamic panel data analysis reveal several significant insights into the factors affecting the TE of rice production among Japanese farmers from 2008 to 2016. The lagged technical efficiency variable (TE_{t-1}) exhibits a strong positive effect, indicating a high persistence in efficiency levels over time. This suggests that past performance is a crucial determinant of current efficiency, aligning with the notion that learning and adaptation in farming practices contribute to sustained productivity (Kumbhakar, 1991).

The heat stress index (HI), our core variable of interest, shows a negative and statistically significant impact on technical efficiency, suggesting that high temperatures during critical growth phases impair physiological processes such as photosynthesis and grain filling, which directly reduce yield potential and efficiency (Jagadish et al., 2007). These results are also consistent with findings by Aragón et al. (2021), who identified a significant decline in productivity under high heat exposure, though our micro-level analysis reveals more nuanced effects across production regions. This finding highlights the detrimental effects of heat stress on rice production. Although the coefficient of the heat stress index appears relatively small, its explanatory power is substantial when considering its relationship with the accumulated temperature. By taking the partial derivative of accumulated temperature with respect to the heat stress index, the theoretical result indicates that under certain conditions, a marginal increase in the heat stress index—infinitesimally small in theory—would correspond to an increase in accumulated temperature approximately 114.6 times[2] the marginal increment. This significant multiplier highlights the sensitivity of accumulated temperature to changes in the heat stress index, emphasizing the profound implications of even minor increases in heat stress during a single high-temperature event. These findings align with the existing literature, which emphasizes the critical role of heat stress in impairing physiological processes such as photosynthesis and grain filling under high-temperature conditions (Jagadish et al., 2007). They further underscore the urgency of developing adaptive measures, such as heat-tolerant rice varieties and optimized agronomic practices, to mitigate the adverse effects of rising temperatures on TE. It is important to clarify that this multiplier effect is derived from the theoretical relationship between HSI and accumulated temperature, based on the functional form of the index. While this does not always directly manifest in year-level trends—such as during the 2010–2013/14 period—the model captures the underlying sensitivity of TE to marginal increases in heat stress, especially when controlling for other factors. This supports the theoretical concern that even small heat stress increments may have disproportionately large impacts on rice physiology and efficiency.

Among the climatic variables, rainfall deviation during the heading stage ($R_{heading}$) negatively affects TE. This suggests that abnormal rainfall patterns during this critical growth phase can hinder crop development, possibly through water stress or increased susceptibility to diseases. Conversely, rainfall deviation during the maturity stage ($R_{maturity}$) has a significant positive effect on efficiency, indicating that additional rainfall during this period may enhance grain filling and final yield. Temperature deviations during the heading and maturity stages ($T_{heading}$ & $T_{maturity}$) do not exhibit statistically significant effects, which may imply that rice crops in the studied regions are less sensitive to temperature fluctuations during these stages or that farmers have already adapted their practices to mitigate potential adverse impacts.

The input intensity variables yield mixed results. Fertilizer intensity (*FI*) has a negative and significant relationship with TE, which appears counterintuitive at first glance. However, this outcome aligns with those of other studies suggesting that excessive fertilizer use can lead to diminishing returns, environmental degradation, and increased production costs without proportional yield benefits (Zhang et al., 2013). Overfertilization may also cause nutrient imbalances and soil degradation, ultimately reducing efficiency. Similarly, mechanical intensity (*MI*) negatively impacts efficiency. This could reflect inefficiencies associated with machinery use, such as underutilization owing to small farm sizes, lack of skilled operators, and maintenance issues (Rahman and Rahman, 2009). In contrast, labor intensity (*LI*) and seed input intensity (*BI*) do not have statistically significant effects, suggesting that variations in these inputs did not significantly influence efficiency within the context of this study.

Overall, these findings emphasize the critical role of environmental factors, particularly heat stress and rainfall variability, in shaping the TE of rice production. The negative impact of the heat injury index underscores the need for targeted adaptation strategies to address the challenges posed by climate change. Developing and promoting heat-tolerant rice varieties, adjusting planting dates, and improving irrigation practices are potential measures for mitigating the effects of heat stress (Yang et al., 2022). The counterintuitive negative effects of fertilizer and mechanical intensities suggest that optimizing input use is essential for enhancing efficiency. This could involve providing farmers with better access to information and training on efficient resource management and encouraging sustainable agricultural practices that balance productivity with environmental stewardship.

These insights contribute to a deeper understanding of the influence of climatic and managerial factors on the TE of rice production. They offer valuable guidance to policymakers and stakeholders who aim to improve agricultural productivity and sustainability in the face of evolving environmental challenges.

5 Conclusion

This study examines the impact of heat stress and other environmental and managerial factors on the technical efficiency (TE) of rice production in Japan between 2008 and 2016. Using a stochastic frontier analysis (SFA) model and a dynamic SYS-GMM framework, this study reveals significant insights into how climatic and input variables interact to influence efficiency.

The findings show that heat stress, measured using the Heat Stress Index (HSI), has a statistically significant negative impact on TE, as revealed through panel-based estimation (SYS-GMM, Linear Model and Quadratic Model). While visual trends may not show a direct correlation, the empirical model results confirm this conditional relationship after controlling for confounding factors. High temperatures, particularly during critical growth stages such as the reproductive and ripening phases, significantly reduce efficiency due to physiological impairments such as reduced photosynthesis and

2 Approved in the Appendix.

poor grain filling. However, the impact of heat stress may not be uniform across all regions. While Figure 2 suggests that southern Japan experiences higher heat stress levels, the current analysis does not fully establish a causal link between these stress conditions and efficiency losses. Further region-specific regression analyses are needed to substantiate such claims. Such regional disparities in the effects of heat stress suggest the need for location-specific adaptation strategies, including the development of heat-tolerant rice varieties and adjustments to planting schedules.

In addition to heat stress, rainfall variability also plays a crucial role in shaping efficiency. Abnormal rainfall during the heading stage is associated with a decline in efficiency, likely due to water stress or heightened susceptibility to diseases. However, increased rainfall during the maturity stage enhances efficiency by supporting grain filling and yield. These findings highlight the importance of targeted water management practices tailored to specific growth stages to enable farmers to mitigate the adverse effects of rainfall variability while maximizing their potential benefits.

Managerial factors, such as input intensities, present mixed results. Fertilizer intensity shows a counterintuitive negative relationship with TE, suggesting that excessive fertilizer use can lead to nutrient imbalances, soil degradation, and diminishing returns. Similarly, mechanical intensity negatively affects efficiency, reflecting the inefficiencies associated with machinery use, such as underutilization or lack of skilled operation. These results highlight the importance of optimizing input use and providing farmers with better training and resources to improve resource management and efficiency.

In addition to these empirical findings, this study makes several contributions to the existing literature on TE in agriculture. First, this study integrates farm-level panel data with a phenology-based heat stress index, providing a more biologically meaningful measure of climate exposure. Second, the application of a dynamic SYS-GMM model allows for the identification of temporal persistence in efficiency and addresses potential endogeneity, which is often overlooked in previous studies. Third, this research offers new micro-level evidence from Japan, a country that has received limited attention in TE studies despite its unique climate and farming practices. These contributions enhance the understanding of climate impacts on rice production efficiency and offer methodological insights for future research.

Compared with previous studies that primarily relied on aggregated data or static models (e.g., Aragón et al., 2021; Auci et al., 2021), this study provides novel micro-level evidence that reveals spatial and temporal variations in how heat stress affects technical efficiency across Japan. By integrating a phenology-based heat stress index and SYS-GMM estimation, it contributes to the methodological advancement in analyzing climate-agriculture linkages. These insights are particularly valuable in the Japanese context, where regional climatic diversity and aging farm populations pose unique challenges to resilience and adaptation. The identification of nonlinear impacts further informs policymakers that moderate heat may be manageable, but beyond critical thresholds, productivity drops sharply—underscoring the urgency of proactive climate risk management.

Practically, our findings suggest that adaptation efforts should not only promote technological improvements such as heat-resilient cultivars but also enhance farmers' decision-making capacity through targeted extension services. Particularly in small-scale or labor-constrained farms, support mechanisms should prioritize input optimization rather than intensification. These implications resonate with broader efforts to balance climate resilience with sustainable resource use in agriculture.

Overall, this study underscores the complex relationships between climate stressors, managerial practices, and TE in rice production. The findings emphasize the urgency of implementing adaptive strategies to combat the challenges posed by heat stress and rainfall variability. Policymakers should prioritize the promotion of sustainable agricultural practices, development of innovative technologies, and tailored support for farmers to enhance resilience and productivity in the face of climate change. Future research should expand on these findings by applying similar frameworks to other crops and regions to offer broader insights into the global implications of environmental stressors on agricultural efficiency. That said, this study has several limitations. The dataset covers a relatively small number of rice farms over a nine-year period, which may limit the generalizability of the findings. Moreover, while the heat stress index effectively captures thermal exposure, it does not fully account for all physiological and behavioral responses of crops. Future studies could enhance this framework by incorporating additional crops, extending the time span, and exploring regional heterogeneity using spatial econometric approaches.

Data availability statement

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

Author contributions

RX: Conceptualization, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. AM: Conceptualization, Methodology, Project administration, Supervision, Writing – review & editing. SK: Funding acquisition, Investigation, Writing – review & editing.

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Conflict of interest

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

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025.1586506/full#supplementary-material

References

Aduna-Sánchez, À., Correcher, A., Alfonso-Solar, D., and Vargas-Salgado, C. (2023). Measuring heat stress for human health in cities: a low-cost prototype tested in a district of Valencia, Spain. *Sensors (Basel)* 23:9285. doi: 10.3390/s23229285

Aneja, P., Dwivedi, A., and Ranjan, A. (2022). "Physiology of crop yield under heat stress" in Thermotolerance in crop plants. eds. R. R. Kumar, S. Praveen and G. K. Rai (Singapore: Springer Nature), 45–79.

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

Arellano, M., and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* 58, 277–297. doi: 10.2307/2297968

Arellano, M., and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *J. Econom.* 68, 29–51. doi: 10.1016/0304-4076(94)01642-D

Auci, S., Barbieri, N., Coromaldi, M., and Vignani, D. (2021). Innovation for climate change adaptation and technical efficiency: an empirical analysis in the European agricultural sector. *Econ. Polit.* 38, 597–623. doi: 10.1007/s40888-020-00182-9

Baldoni, E., Coderoni, S., and Esposti, R. (2018). The complex farm-level relationship between environmental performance and productivity: the case of carbon footprint of Lombardy farms. *Environ. Sci. Pol.* 89, 73–82. doi: 10.1016/j.envsci.2018.07.010

Battese, G. E., and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empir. Econ.* 20, 325–332. doi: 10.1007/BF01205442

Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *J. Econ.* 87, 115–143. doi: 10.1016/S0304-4076(98)00009-8

Challinor, A. J., Wheeler, T. R., Craufurd, P. Q., and Slingo, J. M. (2005). Simulation of the impact of high temperature stress on annual crop yields. *Agric. For. Meteorol.* 135, 180–189. doi: 10.1016/j.agrformet.2005.11.015

Chen, S., and Gong, B. (2021). Response and adaptation of agriculture to climate change: evidence from China. *J. Dev. Econ.* 148:102557. doi: 10.1016/j.jdeveco.2020.102557

Copernicus Climate Change Service. (2024). Heat stress: what is it and how is it measured? Available online at: https://climate.copernicus.eu/heat-stress-what-it-and-how-it-measured [Accessed 26 Nov 2024].

Coumou, D., Robinson, A., and Rahmstorf, S. (2013). Global increase in record-breaking monthly-mean temperatures. *Clim. Chang.* 118, 771–782. doi: 10.1007/s10584-012-0668-1

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

El Khayat, M., Halwani, D. A., Hneiny, L., Alameddine, I., Haidar, M. A., and Habib, R. R. (2022). Impacts of climate change and heat stress on farmworkers' health: a scoping review. *Front. Public Health* 10:782811. doi: 10.3389/fpubh.2022.782811

Food and Agriculture Organization (FAO). (2023). The agricultural technical efficiency and food security nexus. FAO agricultural development economics working paper. Available online at: https://openknowledge.fao.org/bitstreams/39c66f1e-44db-4a0d-8805-bf9c06be55c1/download (Accessed November 26, 2024).

Fu, S. H., Gasparrini, A., Rodriguez, P. S., and Jha, P. (2018). Mortality attributable to hot and cold ambient temperatures in India: a nationally representative case-crossover study. *PLoS Med.* 15:e1002619. doi: 10.1371/journal.pmed.1002619

Gao, C., Kuklane, K., Östergren, P.-O., and Kjellstrom, T. (2018). Occupational heat stress assessment and protective strategies in the context of climate change. *Int. J. Biometeorol.* 62, 359–371. doi: 10.1007/s00484-017-1352-y

Gaviglio, A., Filippini, R., Madau, F. A., Marescotti, M. E., and Demartini, E. (2021). Technical efficiency and productivity of farms: a periurban case study analysis. *Agric. Food Econ.* 9. doi: 10.1186/s40100-021-00181-9

Gosling, S. N., McGregor, G. R., and Páldy, A. (2007). Climate change and heat-related mortality in six cities part 1: model construction and validation. *Int. J. Biometeorol.* 51, 525–540. doi: 10.1007/s00484-007-0092-9

Ham, Y. G. (2018). El Niño events will intensify under global warming. *Nature* 564, 192–193. doi: 10.1038/d41586-018-07638-w

Hansen, J., and Sato, M. (2016). Regional climate change and national responsibilities. *Environ. Res. Lett.* 11:034009. doi: 10.1088/1748-9326/11/3/034009

Hasegawa, T., Ishimaru, T., Kondo, M., Kuwagata, T., Yoshimoto, M., and Fukuoka, M. (2011). Spikelet sterility of rice observed in the record hot summer of 2007 and the factors associated with its variation. *J. Agric. Meteorol.* 67, 225–232. doi: 10.2480/agrmet.67.4.3

Intergovernmental Panel on Climate Change (IPCC). (2023). 2023: synthesis report. Climate change. IPCC, Geneva. Available online at: https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_LongerReport.pdf [Accessed 26 Nov 2024].

Ishigooka, Y., Fukui, S., Hasegawa, T., Kuwagata, T., Nishimori, M., and Kondo, M. (2017). Large-scale evaluation of the effects of adaptation to climate change by shifting transplanting date on rice production and quality in Japan. *J. Agric. Meteorol.* 73, 156–173. doi: 10.2480/agrmet.D-16-00024

Jagadish, S. V. K., Craufurd, P. Q., and Wheeler, T. R. (2007). High temperature stress and spikelet fertility in rice (*Oryza sativa* L.). *J. Exp. Bot.* 58, 1627–1635. doi: 10.1093/jxb/erm003

Kawasaki, K., and Uchida, S. (2016). Quality matters more than quantity: asymmetric temperature effects on crop yield and quality grade. *Am. J. Agric. Econ.* 98, 1195–1209. doi: 10.1093/ajae/aaw036

Kumbhakar, S. C. (1991). Estimation of technical inefficiency in panel data models with firm- and time-specific effects. *Econ. Lett.* 36, 43–48. doi: 10.1016/0165-1765(91)90053-N

Kunimitsu, Y., and Kudo, R. (2015). Fluctuations in rice productivity caused by long and heavy rain under climate change in Japan: evidence from panel data regression analysis. *Jpn. Agric. Res. Q.* 49, 159–172. doi: 10.6090/jarq.49.159

Kunimitsu, Y., Kudo, R., Iizumi, T., and Yokozawa, M. (2016). Technological spillover in Japanese rice productivity under long-term climate change: evidence from the spatial econometric model. *Paddy Water Environ.* 14, 131–144. doi: 10.1007/s10333-015-0485-z

Lee, S.-M., and Min, S.-K. (2018). Heat stress changes over East Asia under 1.5° and 2.0°C global warming targets. *J. Clim.* 31, 2819–2831. doi: 10.1175/JCLI-D-17-0449.1

Lepekhov, S. B. (2022). Canopy temperature depression for drought- and heat stress tolerance in wheat breeding. *Vavilovskii Zhurnal Genet. Selektsii* 26, 196–201. doi: 10.18699/VJGB-22-24

Letta, M., and Tol, R. S. J. (2018). Weather, climate and total factor productivity. *Environ. Resour. Econ.* 73, 283–305. doi: 10.1007/s10640-018-0262-8

Lobell, D. B., and Gourdji, S. M. (2012). The influence of climate change on global crop productivity. *Plant Physiol.* 160, 1686–1697. doi: 10.1104/pp.112.208298

Masutomi, Y., Takimoto, T., Manabe, T., Imai, Y., Tamura, M., and Kobayashi, K. (2023). Breeding targets for heat-tolerant rice varieties in Japan in a warming climate. *Mitig. Adapt. Strateg. Glob. Change* 28. doi: 10.1007/s11027-022-10027-4

Ministry of Agriculture, Forestry, and Fisheries. (2008–2016). Kome Seisanhi Chosa Tokei. Available online at: https://www.maff.go.jp/j/tokei/kouhyou/noukei/seisanhi_nousan/ (Accessed October 24, 2024).

Ministry of Agriculture, Forestry, and Fisheries. (2023). Syokuseikatsu Lifestyle chosa. Available online at: https://www.maff.go.jp/j/press/kanbo/anpo/attach/pdf/230331-1.pdf [Accessed November 27, 2024].

Ministry of the Environment. (2020). Climate change in Japan and its impacts. Available online at: https://www.env.go.jp/content/900449807.pdf [Accessed November 27, 2024].

Newman, R., and Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. *Nat. Commun.* 14:6103. doi: 10.1038/s41467-023-41888-1

Ogundari, K., and Onyeaghala, R. (2021). The effects of climate change on African agricultural productivity growth revisited. *Environ. Sci. Pollut. Res. Int.* 28, 30035–30045. doi: 10.1007/s11356-021-12684-5

Orlov, A., Daloz, A. S., Sillmann, J., Thiery, W., Douzal, C., Lejeune, Q., et al. (2021). Global economic responses to heat stress impacts on worker productivity in crop production. *Econ. Disasters Clim. Change* 5, 367–390. doi: 10.1007/s41885-021-00091-6

Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., and Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nat. Clim. Chang.* 11, 306–312. doi: 10.1038/s41558-021-01000-1

Perkins-Kirkpatrick, S. E., and Gibson, P. B. (2017). Changes in regional heatwave characteristics as a function of increasing global temperature. *Sci. Rep.* 7:12256. doi: 10.1038/s41598-017-12520-2

Pickson, R. B., He, G., and Boateng, E. (2022). Impacts of climate change on rice production: evidence from 30 Chinese provinces. *Environ. Dev. Sustain.* 24, 3907–3925. doi: 10.1007/s10668-021-01594-8

Rachid, A., and Qureshi, A. M. (2023). Sensitivity analysis of heat stress indices. *Climate* 11:181. doi: 10.3390/cli11090181

Rahman, S., and Rahman, M. (2009). Impact of land fragmentation and resource ownership on productivity and efficiency: the case of rice producers in Bangladesh. *Land Use Policy* 26, 95–103. doi: 10.1016/j.landusepol.2008.01.003

Rane, J., and Nagarajan, S. (2004). High temperature index—for field evaluation of heat tolerance in wheat varieties. *Agric. Syst.* 79, 243–255. doi: 10.1016/S0308-521X(03)00075-1

Rezaei, E. E., Webber, H., Gaiser, T., Naab, J., and Ewert, F. (2015). Heat stress in cereals: mechanisms and modelling. *Eur. J. Agron.* 64, 98–113. doi: 10.1016/j.eja.2014.10.003

Roodman, D. (2009). How to do Xtabond2: an introduction to difference and system GMM in Stata. *Stata J.* 9, 86–136. doi: 10.1177/1536867X0900900106

Sage, R. F., and Kubien, D. S. (2007). The temperature response of C(3) and C(4) photosynthesis. *Plant Cell Environ.* 30, 1086–1106. doi: 10.1111/j.1365-3040.2007.01682.x

Sandhu, S. S., Singh, J., Kaur, P., and Gill, K. K. (2018). "Heat stress in field crops: impact and management approaches" in eds. S. K. Bal, J. Mukherjee, B. U. Choudhury and A. K. Dhawan. Advances in crop environment interaction, Singapore: Springer. 181–204. doi: 10.1007/978-981-13-1861-0_7

Singh, D., and Singh, B. (2020). Investigating the impact of data normalization on classification performance. *Appl. Soft Comput.* 97:105524. doi: 10.1016/j.asoc.2019.105524

Teixeira, E. I., Fischer, G., van Velthuizen, H., Walter, C., and Ewert, F. (2013). Global hot-spots of heat stress on agricultural crops due to climate change. *Agric. Forest Meteorol.* 170, 206–215. doi: 10.1016/j.agrformet.2011.09.002

Tokunaga, S., Okiyama, M., and Ikegawa, M. (2015). Dynamic panel data analysis of the impacts of climate change on agricultural production in Japan. *JPN. Agric. Res. Q.* 49, 149–157. doi: 10.6090/jarq.49.149

Tol, R. S. J. (2009). The economic effects of climate change. *J. Econ. Perspect.* 23, 29–51. doi: 10.1257/jep.23.2.29

Tollefson, J. (2016). Global warming already driving increases in rainfall extremes. *Nature*. doi: 10.1038/nature.2016.19508

Wang, S. L., Ball, E., Nehring, R., Williams, R., and Chau, T. (2017). Impacts of climate change and extreme weather on U.S. agricultural productivity: Evidence and projection. National Bureau of economic research, working paper no. 23533. Avaialble online at: http://www.nber.org/papers/w23533

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data. Cambridge, MA: MIT Press.

World Meteorological Organization (WMO). (2023). 2023 shatters climate records: major impacts confirmed. Available online at: https://wmo.int/media/news/2023-shatters-climate-records-major-impacts-0 [Accessed 11 October 2024].

Yang, Y., Yu, J., Qian, Q., and Shang, L. (2022). Enhancement of heat and drought stress tolerance in rice by genetic manipulation: a systematic review. *Rice (N. Y.).* 15:67. doi: 10.1186/s12284-022-00614-z

Zhang, Q. F., and Donaldson, J. A. (2008). The rise of agrarian capitalism with Chinese characteristics: agricultural modernization, agribusiness, and collective land rights. *China J.* 60, 25–47. doi: 10.1086/tcj.60.20647987

Zhang, W. F., Dou, Z. X., He, P., Ju, X. T., and Zhang, F. S. (2013). New technologies reduce greenhouse gas emissions from nitrogenous fertilizer in China. *Proc. Natl. Acad. Sci. USA* 110, 8375–8380. doi: 10.1073/pnas.1210447110

Zuniga-Gonzalez, C. A. (2023). TFP bioeconomy impact post Covid-19 on the agricultural economy. *PLoS One* 18:e0288885. doi: 10.1371/journal.pone.0288885

Zuniga-Gonzalez, C. A., Quiroga-Canaviri, J. L., Brambila-Paz, J. J., Ceballos-Pérez, S. G., and Rojas-Rojas, M. M. (2024). Formulation of an innovative model for the bioeconomy. *PLoS One* 19:e0309358. doi: 10.1371/journal.pone.0309358