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Determinants of Sustainable Productivity Growth in Thai Rice Farming

Supawat Rungsuriyawiboon and Piyawong Punjataewakupt

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Determinants of Sustainable Productivity Growth in Thai Rice Farming

Supawat Rungsuriyawiboon[1] and Piyawong Punjataewakupt[2]

Abstract

This study provides a comprehensive assessment of rice production performance across Thailand's 76 provinces during the period 1997–2018, with a particular focus on contrasting the main rice season and the second rice season. Employing the Malmquist Productivity Index (MPI) within the Data Envelopment Analysis (DEA) framework, the study decomposes total factor productivity (TFP) growth into its core components. A spatial econometric model is subsequently applied to identify the determinants of TFP growth, explicitly accounting for spatial dependence and other influential factors. The empirical findings indicate that the overall productivity of rice cultivation has experienced only marginal improvement over the study period. Decomposition results reveal that the sluggish TFP growth in the main rice season is primarily attributable to limited technological adoption and persistent inefficiencies in farm management. For second-season rice, stagnation in TFP is linked to even slower technological uptake and a lack of significant improvements in managerial practices. Moreover, the analysis uncovers significant spatial interdependence in TFP growth among provinces, suggesting the presence of technology diffusion and performance spillover effects. The policy implications of these findings highlight the importance of leveraging spatial spillovers in the short term to enhance production efficiency. In the long term, a strategic re-evaluation of the role of rice cultivation is warranted—one that prioritizes climate resilience, national food security, and the economic sustainability of rice-farming households.

Keywords: DEA, Malmquist Productivity index, Rice production, Spatial panel model, TFP growth

JEL: C13, D24, Q18

[1] Corresponding author, Professor, Faculty of Economics, Thammasat University, Bangkok, Thailand, Email: supawat@econ.tu.ac.th. [ORCID 0000-0002-1119-7801]

[2] Assistant Professor, Faculty of Economics, Thammasat University (piyawong@econ.tu.ac.th). [ORCID 0009-0008-5323-2928]

The views and interpretations expressed in this paper are solely those of the authors and do not necessarily reflect those of the Faculty of Economics, Thammasat University.

1. Introduction

Rice is one of the most important staple foods globally, particularly in Asia where it constitutes a central component of the daily diet. In Thailand, the rice industry is a key economic sector, serving both as the main staple food for the population and as a critical source of income for rural communities. As a result, Thailand has long been recognized as one of the world's leading rice producers and exporters. Beyond its economic importance, rice production in Thailand plays a vital role in ensuring national food security and in meeting the growing global demand for rice. To sustainably develop and enhance the country's rice production capacity in alignment with these objectives, it is essential to establish comprehensive indicators that accurately reflect the potential and productivity of rice cultivation in Thailand.

Despite Thailand's strong position in global rice trade, its rice yield remains relatively low compared to other major rice-producing countries. According to data from FAOSTAT, published by the Food and Agriculture Organization (FAO) of the United Nations, Thailand recorded the lowest rice yield among the top six rice-exporting countries in 2019. The country's average yield was 29,188 hectograms per hectare (Hg/Ha), considerably lower than that of China (70,601 Hg/Ha), Vietnam (58,165 Hg/Ha), India (40,577 Hg/Ha), Myanmar (37,957 Hg/Ha), and Pakistan (36,637 Hg/Ha). Furthermore, Thailand's yield also falls significantly below the global average rice yield of 46,618 Hg/Ha. This disparity underscores the need for targeted efforts to improve productivity and strengthen the long-term sustainability of Thailand's rice sector.

Rice production in Thailand exhibits substantial regional variation, primarily due to differences in geographical features, climatic conditions, and the availability of irrigation infrastructure. Rice cultivation in the country can be broadly classified into two main types: the main rice season (*Khao Na Pi*) and the second rice season (*Khao Na Prang*). The main rice season corresponds with the monsoon period and relies predominantly on rainfall. It is cultivated across all regions of the country, with the largest concentration found in the northeastern region, followed by the northern, central, and southern regions, respectively. In contrast, the second rice season takes place outside the rainy season and is therefore highly dependent on irrigation systems. As a result, this type of rice is primarily cultivated in the central region and the lower northern region, where the availability of large- and medium-scale irrigation infrastructure is significantly higher compared to other areas. Beyond regional and irrigation-related factors, differences in rice varieties and cultivation practices across regions also play a critical role in determining yield outcomes. These factors collectively contribute to the spatial heterogeneity of rice productivity within the country.

Understanding rice production performance across different regions of Thailand is a critically important research issue, as it provides valuable insights for policymakers aiming to promote the sustainable development of the country's rice sector. A number of studies have investigated rice production efficiency in Thailand, including those by Sriboonchitta and Wiboonpongse (2001), Rahman et al. (2009), Sansri et al. (2014), Ebers et al. (2016), and Panpluem et al. (2019). However, these studies typically focus on household-level data within specific provinces or regions, rather than offering a comprehensive analysis at the national or provincial level.

With regard to rice productivity, the majority of prior research has concentrated on partial productivity measures, such as land productivity or labor productivity. While useful, these measures may fail to capture the broader efficiency with which all inputs are used collectively in the production process. In contrast, TFP offers a more comprehensive metric by accounting for multiple inputs simultaneously. Only a limited number of studies have examined the TFP growth of rice cultivation in Thailand. Notably, Suphannachart (2013; 2018) investigated TFP at the national and provincial levels, albeit over a limited number of years. These studies revealed notable regional disparities in TFP growth, with second-season rice demonstrating significantly higher TFP growth rates than main-season rice. Key factors positively associated with TFP growth included the adoption of high-yielding rice varieties and the proportion of cultivated areas under irrigation, while regional rainfall was found to have a negative association with TFP. Furthermore, evidence of spatial dependence in rice TFP was observed across provinces during the study periods (2004, 2006, 2008, 2010, and 2012), suggesting that productivity performance in one province may influence that of neighboring provinces.

As highlighted in previous studies, there remains a significant gap in the literature regarding the measurement of production efficiency and TFP growth in rice production at the provincial level in Thailand. In particular, few studies have examined these dimensions disaggregated by growing season and over a sufficiently long time span to capture meaningful trends and structural changes. To address these gaps, the objective of this study is to assess the technical efficiency (TE) and TFP growth of rice production in Thailand using provincial-level data spanning from 1997 to 2020. In the second stage of the analysis, TFP growth will be further examined through a TFP determinant model, incorporating spatial effects and other relevant factors that may influence TFP dynamics. The findings from this study are expected to offer valuable insights for policymakers seeking to formulate targeted and effective policies aimed at enhancing TFP growth and ensuring the sustainable development of rice cultivation in Thailand.

The remainder of this paper is structured as follows. The next section outlines the methodological framework employed to measure TE and TFP growth. This is followed by a detailed description of the data set and the definitions of all variables used in the analysis. The subsequent section presents and discusses the empirical results. Finally, the paper concludes with a summary of the main findings and their policy implications.

2. Methodology

2.1 Models

The analysis in this study is conducted in two stages. In the first stage, the MPI is employed to measure TE and TFP growth and to decompose this growth into its underlying components. This decomposition allows for the identification of the sources contributing to productivity changes over time. In the second stage, the TFP growth estimates obtained from the MPI are used in a regression framework to investigate the factors influencing rice TFP across provinces, with particular attention given to spatial spillover effects arising from technological adoption or other regional improvements.

2.1.1 The Malmquist Productivity Index

Following the approach of Caves, Christensen, and Diewert (1982), the Malmquist TFP change index defines productivity change as the geometric mean of two productivity indices, each evaluated with respect to a different time period's technology. Specifically, the Malmquist TFP change index measures how much a production unit's performance changes between two time periods, considering both efficiency change and technological change. The index is expressed as follows:

$$\begin{aligned} M_{t,t+1}^{o}(x_t,y_t,x_{t+1},y_{t+1}) &= [M_t^o(x_t,y_t,x_{t+1},y_{t+1})M_{t+1}^o(x_t,y_t,x_{t+1},y_{t+1})]^{1/2} \\ &= \left[\frac{D_t^o(x_{t+1},y_{t+1})}{D_t^o(x_t,y_t)} \times \frac{D_{t+1}^o(x_{t+1},y_{t+1})}{D_{t+1}^o(x_t,y_t)}\right]^{1/2} \\ &= \frac{D_{t+1}^o(x_{t+1},y_{t+1})}{D_t^o(x_t,y_t)}\left[\frac{D_t^o(x_{t+1},y_{t+1})}{D_{t+1}^o(x_{t+1},y_{t+1})} \times \frac{D_t^o(x_t,y_t)}{D_{t+1}^o(x_t,y_t)}\right]^{1/2} \end{aligned} \quad (1)$$

where $M_{t,t+1}^{o}$ is the changes of TFP or TFP growth (TFPC) from period t to $t+1$; D_t^o and D_{t+1}^o is the output distance function measures based on production technology at period t and $t+1$ given observed input and output data at period t and $t+1$, respectively.

Assuming a constant returns to scale (CRS) technology, TFP growth can be decomposed into two components; (1) Technical efficiency change (TEC): This component reflects the ability of a decision-making unit (DMU) to improve its technical efficiency over time, i.e., to "catch up" to the frontier. It is measured as $\frac{D_{t+1}^o(x_{t+1},y_{t+1})}{D_t^o(x_t,y_t)}$, (2) Technical change: This component captures shifts in the production frontier over time, reflecting improvements in technology. It represents the ability of producers (e.g., farmers) to adopt new technologies that expand the production possibility set. The TC is typically computed as the geometric mean of the shift in the frontier between periods t and $t+1$, $\left[\frac{D_t^o(x_{t+1},y_{t+1})}{D_{t+1}^o(x_{t+1},y_{t+1})} \times \frac{D_t^o(x_t,y_t)}{D_{t+1}^o(x_t,y_t)}\right]^{1/2}$. Together, TEC and TC explain the sources of TFP growth, enabling a more nuanced understanding of whether improvements arise from increased efficiency or technological progress.

The four output distance functions in Equation (1) can be calculated using linear programming techniques. Following the seminal work of Charnes, Cooper, and Rhodes (1978), the output-oriented DEA model under the assumption of CRS can be applied to evaluate the relative efficiency of each DMU. Consider a production system involving K inputs and M outputs for each of the N provinces in Thailand at time t. The output distance function for the i^{th} DMU is derived by solving the following linear programming problem (Coelli et al., 2005):

$$max_{\theta,\lambda}\ \theta_i^t,$$

Subject to

$$\begin{aligned} \theta y_i^t &\le Y^t\lambda^t, \\ X^t\lambda^t &\le x_i^t, \\ \lambda^t &\ge 0 \end{aligned}$$

(2)

where x_i^t and y_i^t denote the input and output vectors, respectively, for province i at time t. The matrices X^t and Y^t represent the input and output data for all N provinces at time t, with dimensions $K \times \mathrm{N}$ and $M \times \mathrm{N}$, respectively. The vector λ^t is an $N \times 1$ vector of intensity variables, which assign weights to the reference provinces used in constructing the efficient production frontier for province i. Accordingly, $Y^t\lambda^t$ and $X^t\lambda^t$ define the boundaries of the output and input sets, respectively. The scalar θ_i^t, where $1 \leq \theta_i^t \leq \infty$, represents the proportion by which outputs can be radially expanded, holding inputs constant. TE score for province i is defined as the inverse of θ_i^t, such that: $TE_i^t = 1/\theta_i^t$. This value also corresponds to the output distance function for province i. A TE score equal to 1 indicates full technical efficiency, while scores less than 1 suggest the presence of inefficiency and room for proportional output expansion.

TE score (TE_i^t) for province i in period t is interpreted as follows: if $TE_i^t < 1$, it indicates that the province is technically inefficient during that time. In such a case, the province has the potential to increase its output by $(1 - TE_i^t) \times 100\%$ while maintaining the same level of input usage in order to achieve full technical efficiency, which is indicated by $TE_i^t = 1$.

2.1.2 TFP Determinant Model

TFP growth reflects improvements in output that are not solely explained by increases in input usage. Identifying the determinants of TFP growth is therefore essential for understanding the underlying drivers of productivity enhancements. In this study, six explanatory variables are considered in relation to TFP growth in rice production in Thailand: irrigation availability ($Irrig$), gross provincial product (GPP), adoption rate of high-yielding rice varieties (HYS), average surface temperature ($skinT$), total precipitation ($Tpre$), and a natural factor (NF), which proxies for extreme weather-related damages through the share of damaged planted areas. For clarity in interpretation, both HYS and NF are expressed in percentage terms.

A basic approach to examining the relationship between these factors and TFP growth is to estimate a pooled Ordinary Least Squares (OLS) regression model, specified as follows:

$$TFP\ growth_{it} = Irrig_{it} + GPP_{it} + HYS_{it} + \ln(skinT_{it}) + \ln(Tpre_{it}) + NF_{it} + \varepsilon_{it} \tag{3}$$

However, the objective at this stage is also to identify spatial influences within the panel data framework. Following the formulation of Anselin, Gallo, and Jayet (2008), the full specification of the spatial panel data model in its stacked form can be expressed as:

$$\begin{gathered} \boldsymbol{y} = \rho(\boldsymbol{I}_T \otimes \boldsymbol{W}_N)\boldsymbol{y} + (\iota_{\boldsymbol{T}} \otimes \boldsymbol{\alpha}) + \boldsymbol{X\beta} + \boldsymbol{\varepsilon}, \\ \boldsymbol{\varepsilon} = (\iota_{\boldsymbol{T}} \otimes \boldsymbol{I}_N)\boldsymbol{\mu} + \left(\boldsymbol{I_T} \otimes \boldsymbol{B_N^{-1}}\right)\boldsymbol{u}, \\ B_N = \boldsymbol{I}_N - \lambda\boldsymbol{W}_N \end{gathered} \tag{4}$$

Let $\boldsymbol{y}$ denote the NT×1 vector of the dependent variable, where N represents the number of cross-sectional units (provinces) and T is the total number of time periods. The matrix $\boldsymbol{X}$ is the NT×K matrix of explanatory variables, where K denotes the number of explanatory variables. In this study, six explanatory variables are included to explain TFP growth in the rice sector. The parameter vector $\boldsymbol{\beta}$ is of dimension $K\times1$, representing the coefficients associated with the explanatory variables.

Let $\iota_{\boldsymbol{T}}$ be a $T\times1$ vector of ones. $\boldsymbol{I_T}$ and $\boldsymbol{I_N}$ are identity matrices of dimensions $T\times T$ and $N\times N$, respectively. $\boldsymbol{W_N}$ is the spatial weights matrix of size N×N, representing the spatial relationship among provinces. The vector $\boldsymbol{\alpha}$ is an $N\times1$ vector of individual fixed effects (FE), with the constraint $\boldsymbol{\alpha}'\iota_{\boldsymbol{N}} = 0$, ensuring identifiability. $\boldsymbol{\mu}$ denotes the $N\times1$ vector of random effects (RE). The parameters $\boldsymbol{\rho}$ and $\boldsymbol{\lambda}$ are the spatial autoregressive parameters corresponding to the spatial lag and spatial error components, respectively. Finally, $\boldsymbol{u}$ is the $NT\times1$vector of idiosyncratic error terms.

The specification of the model depends on the inclusion or exclusion of the parameters $\rho, \boldsymbol{\alpha}, \boldsymbol{\mu},$ and λ. When all parameters are set to zero, the model reduces to a pooled OLS estimator. If only ρ is non-zero, the model becomes a pooled spatial lag model. If only λ is non-zero, it corresponds to a pooled spatial error model. When both ρ and $\boldsymbol{\alpha}$ are non-zero, the model is specified as a FE spatial lag model; if ρ and $\boldsymbol{\mu}$ are non-zero, it becomes a RE spatial lag model. Similarly, the combination of non-zero λ and $\boldsymbol{\alpha}$ indicates a FE spatial error model, while non-zero λ and $\boldsymbol{\mu}$ specify a RE spatial error model.

In this study, the spatial panel models are estimated using the spml package in R, developed by Millo and Piras (2012).

2.2 Data

The empirical analysis in this study focuses on rice cultivation in Thailand, which is categorized into two cropping seasons: the main rice season and the second rice season. The dataset comprises provincial-level aggregate data covering the period from 1997 to 2018. Due to the limitations of irrigation infrastructure, the number of provinces included differs between the two seasons. Specifically, data for the main rice season includes all 77 provinces, while the second rice season includes 71 provinces, as certain provinces lack irrigation systems suitable for off-season rice cultivation.

In the first stage of the analysis, secondary data on input and output variables related to rice production were obtained from the Office of Agricultural Economics (OAE). The production technology is represented by a single output variable—paddy rice—and four input variables: land, labor, seed, and fertilizer.

The output variable is defined as the total quantity of paddy rice (unmilled rice) produced, measured in metric tons. The input variables are grouped into two categories: traditional inputs and a modern input. Traditional inputs include:

1. Land, measured as the rice-planted area in rai (1 rai = 0.16 hectare).
2. Labor, proxied by the number of rice-farming households.
3. Seed, measured as the total amount of rice seed used in production (metric tons).

The modern input is:

4. Fertilizer, measured as the amount of chemical fertilizer used in production (metric tons), and considered to be a proxy for technological input.

All input and output data are compiled separately for the main and second rice seasons across provinces, ensuring accurate reflection of the seasonal production processes. The dataset spans 22 years (1997–2018), with the final analysis including 76 provinces due to missing data in one province. It is important to note that each input and output variable was collected distinctly by season and province, providing a detailed dataset for season-specific productivity and efficiency analysis.

Preliminary observations suggest significant variation in both production volume and input utilization across regions and cropping seasons. For the main rice season, the northeastern region consistently records the highest production volume and input usage. In contrast, for the second rice season, the northern region leads in both production and input utilization, followed by the central, northeastern, and southern regions, respectively. These regional patterns highlight the influence of agro-ecological and infrastructural factors, such as the availability of irrigation, on rice production performance across Thailand.

In the second stage of the analysis, additional data are compiled from multiple sources to investigate the determinants of TFP growth. The dependent variable in this stage is the TFP index calculated from the first stage using the MPI. The explanatory variables include: irrigation availability ($Irrig$), adoption rate of high-yielding rice varieties (HYS), a natural factor (NF), gross provincial product (GPP), average surface temperature ($skinT$) and total precipitation ($Tpre$), and Consistent with the first stage, these variables are collected separately for the main rice season and the second rice season at the provincial level. The variable $Irrig$ is defined as the ratio of irrigated area to the total rice-planted area in each province, capturing the degree of irrigation infrastructure support. HYS represents the adoption of high-yielding rice varieties and is calculated as the ratio of the area planted with high-yielding varieties to the total rice-planted area, reflecting the penetration of improved seed technology. NF, or the natural factor, is measured as the proportion of rice-planted area that was damaged and could not be harvested. This variable serves as a proxy for natural and weather-related shocks—such as droughts, floods, or pest infestations—that adversely impact rice production. These three variables are sourced from the Office of Agricultural Economics (OAE). GPP refers to the Gross Provincial Product, measured in chained values (billion baht), and is used as a proxy for the level of economic development in each province. GPP data are obtained from the Office of the National Economic and Social Development Council (NESDC). The final two variables, $skinT$ (average surface temperature) and $Tpre$ (total precipitation), are derived from satellite data using the ERA5-Land dataset accessed via Google Earth Engine. Average surface temperature ($skinT$) is expressed in degrees Celsius, while total precipitation ($Tpre$) is expressed in meters of water depth uniformly distributed over the area. These variables collectively capture key environmental, technological, and economic factors hypothesized to influence TFP growth in rice production across provinces and over time.

3. Result And Discussion

3.1 Efficiency and TFP growth of Thai rice production

This section sketches a picture about rice production performance across different regions in Thailand. Table 1 reports the weighted average values of provincial-level TE scores by region for both main and second rice crops. The overall weighted average TE is 0.7788 for the main rice season and 0.8003 for the second rice season. These results indicate that, on average, Thai rice farmers did not operate at full TE. Specifically, they could have increased rice output by approximately 22.12% during the main rice season and 19.97% during the second rice season using the same level of inputs, indicating substantial potential for efficiency improvements. The results reveal that second rice cultivation tends to be more efficient than main rice cultivation, with the exception of the northern and southern regions.

The central and northern regions show relatively higher TE scores for both cropping seasons (see Figure 1). These findings align with those reported by Nunti et al. (2019), who found that rice cultivation in the central and northern regions demonstrated the highest efficiency. However, their analysis did not disaggregate efficiency by cropping season.

An important observation from this study is that the TE scores derived from provincial-level data tend to be higher than those obtained from household-level analyses. Previous studies using household-level data have typically reported average TE scores below 0.750 (Champhech, 2003; Krasachat, 2004; Sriboonchitta & Wiboonpongse, 2005; Chaovanapoonphol, Battese, & Chang, 2005; Songsrirote & Singhapreecha, 2007; Rahman et al., 2009; Taraka et al., 2010; Srisompun & Isvilanonda, 2012; Sansri et al., 2014; Osti, 2016; Ebers et al., 2017; Panpluem et al., 2019; Jirarud & Suwanmaneepong, 2020). This discrepancy may be attributed to data aggregation, which can smooth out individual inefficiencies and lead to upward bias in efficiency estimates.

Differences in TE scores between cropping seasons and across regions can be attributed to several factors. First, rice farming during the main rice season—particularly in provinces within the northeastern region—may involve production at such a large scale that it has reached the stage of decreasing returns to scale, whereas second-season rice production has not yet encountered this constraint. Second, rice cultivation in the second cropping season, especially in provinces located in the central and northern regions, tends to involve more intensive input use compared to the main season. Another contributing factor may be the development of irrigation infrastructure. Large-scale irrigation projects are predominantly concentrated in the central and lower-northern regions, where higher TE scores are observed. Provinces in these regions consistently demonstrate superior TE scores for both main and second rice crops. These findings suggest that large-scale irrigation systems may enhance farmers' ability to manage production more effectively, leading to improved technical efficiency.

Table 1 also presents the weighted average of TFP growth and its decomposition into TEC and TC. A positive TEC reflects a "catching-up" effect, indicating improvements in efficiency relative to the frontier, while a positive TC represents a "frontier-shift" effect, capturing technological progress or innovation. The results suggest a rather pessimistic outlook for the productivity dynamics of rice cultivation in Thailand over the past two decades. Although the overall weighted average TFP growth is positive, it remains relatively modest for main rice, at only 0.19%. In contrast, second rice exhibits a negative TFP growth rate of -0.18%, indicating a decline in productivity over the study period. Among the regions, the central region exhibits comparatively stronger productivity performance, characterized by positive growth in TFP. In contrast, the northeastern region experiences consistent TFP regressions across both the main and second rice cropping seasons (see Figure 2). The observed decline in TFP in the northeastern region can be largely attributed to the frequent occurrence of natural disasters, which have adversely impacted agricultural productivity in rice cultivation. When compared with earlier studies, the findings are broadly consistent yet indicate some divergence. Suphannachart (2013, 2018), using different methodologies and covering different time periods, reported that the average annual TFP growth rate across all provinces was 0.34% for main-season rice (1995–2011) and -0.30% for second-season rice (1998–2011). These results, while methodologically distinct, similarly highlight the stagnation or decline in productivity growth in certain segments of rice cultivation in Thailand.

The decomposition analysis further reveals that the relatively low overall TFP growth rate observed for main rice has primarily been driven by TC, while TEC has exerted a negative influence. Specifically, TEC for main-season rice declined at an average annual rate of 0.02%, suggesting that TFP growth could have been 0.02% higher in the absence of efficiency deterioration. This implies that falling efficiency levels have partially offset gains from technological progress. The northeastern region emerges as a significant contributor to the observed TFP regression, particularly through negative TEC. A key factor underlying this decline is the limited access to reliable irrigation systems. Many rice farms in the northeastern region operate outside areas covered by formal irrigation infrastructure, which has negatively impacted their ability to maintain or improve efficiency levels. This finding supports the view that consistent access to water is a critical determinant of TE in rice cultivation. In addition, the decline in TEC may also be attributed to challenges related to farm management. Specifically, the relatively larger scale of main rice farms, compared to second rice farms, may introduce complexity in farm operations and increase the likelihood of inefficiencies. Issues such as labor shortages, mismanagement, or suboptimal input use may disproportionately affect larger-scale farms, thereby contributing to the observed efficiency regress.

The decomposition of TFP growth also provides insight into the role of technological progress in rice cultivation in Thailand. The results indicate that TC, which reflects shifts in the production frontier due to technological improvements, was positive but modest for main rice. Specifically, TC increased at an average annual rate of 0.21%, suggesting gradual but limited technological advancement. The adoption of improved rice varieties and incremental innovations in cultivation practices contributed to this frontier expansion, pushing up productivity by approximately 0.21% annually for main rice. In contrast, second-season rice exhibited a negative TC of -0.52% per year, indicating technological regress during the study period. This suggests a stagnation or decline in the adoption of new technologies for second rice farm, which may reflect a lack of innovation or insufficient diffusion of existing technologies among farmers cultivating this crop.

Overall, the findings highlight that the pace of technological adoption in Thai rice farming remains relatively slow. Contributing factors may include farmers' risk-averse behavior, particularly in the face of uncertain outcomes from new practices or unfamiliar technologies, as well as the high upfront costs associated with technological investment. These barriers can discourage timely adoption and limit the potential productivity gains from innovations in rice production.

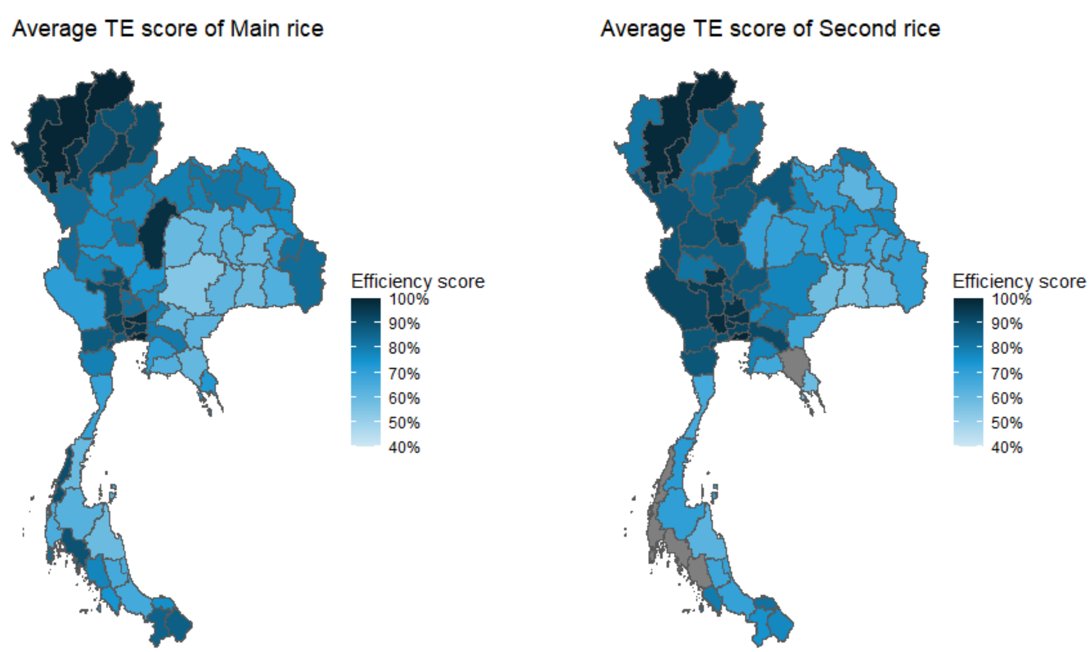
Table 1: Weighted average TE scores and TFP growth decomposition over the study period by regions

	Main rice				Second rice			
Province	TE[a]	TFPC[b] (%)	TEC[b] (%)	TC[b] (%)	TE[a]	TFPC[b] (%)	TEC[b] (%)	TC[b] (%)
Central	0.8055	1.05	0.44	0.61	0.8604	0.37	0.49	-0.12
Northeastern	0.7012	-0.91	-0.95	0.04	0.7026	-0.73	0.14	-0.87

	Main rice				Second rice			
Province	TE[a]	TFPC[b] (%)	TEC[b] (%)	TC[b] (%)	TE[a]	TFPC[b] (%)	TEC[b] (%)	TC[b] (%)
Northern	0.8729	0.13	0.20	-0.06	0.8774	-0.45	0.11	-0.57
Southern	0.7371	0.23	0.20	0.03	0.7247	0.21	0.95	-0.74
Whole country	0.7788	0.19	-0.02	0.21	0.8003	-0.18	0.33	-0.52

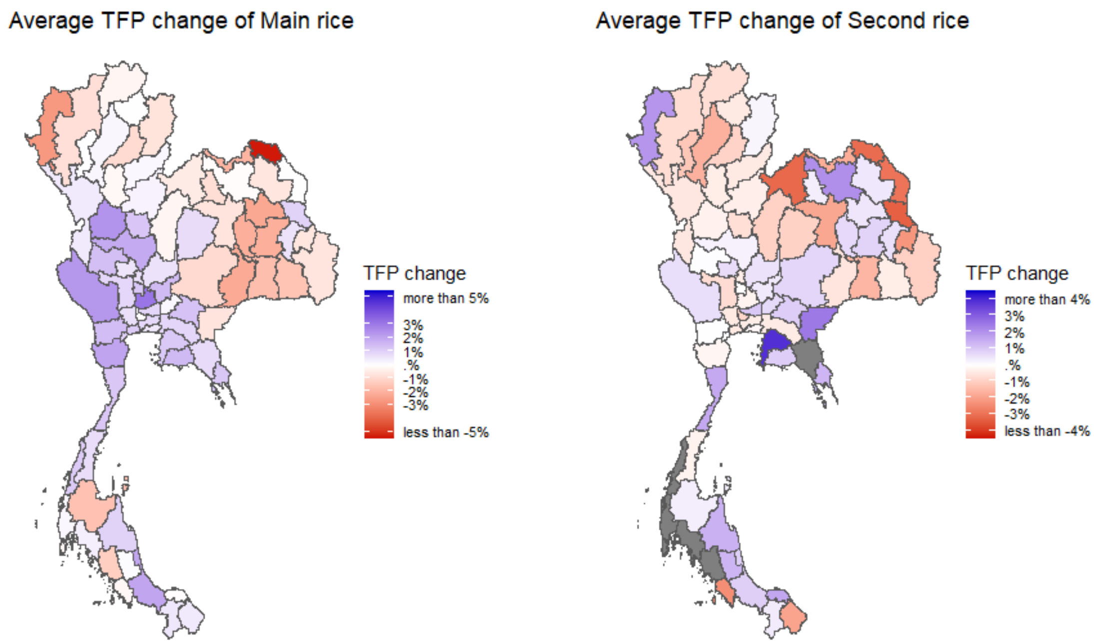
Source: Research finding
Note: average value at the regional level and whole country is the geometric mean of provinces in that region or of all provinces in Thailand.
[a] average value is the geometric mean of the value from 1997 to 2018.
[b] average value is the geometric mean of the value from 1998 to 2018.

Figure 1: Average TE scores of main and second rice by province during 1997-2018



Source: Research finding

Figure 2: Average TFP growth of main and second rice by province during 1998-2018



Source: Research finding

3.2 Determinants of TFP Growth and Spatial Dependence in Thai Rice Production

This section investigates the factors influencing TFP and spatial dependence in rice farming across Thailand by applying the TFP growth determination model outlined in Section 2.1.2. The empirical analysis begins with the estimation of several model specifications, including the pooled OLS model, as well as pooled and FE spatial lag and spatial error models, for both main-season and second-season rice production. Subsequently, a series of specification tests are performed to assess the adequacy of each model and to determine the most appropriate framework for capturing the determinants of TFP growth. These tests help identify the presence of spatial dependence, individual effects, and model fit for each case.

The results of the model specification tests for both main and second rice are summarized in Table 2. The Hausman tests [1] and [2] are first employed to examine the appropriateness of FE versus RE models, excluding spatial components. The results indicate no statistically significant difference between these effects and the pooled OLS model, suggesting that neither FE nor RE are preferred in the absence of spatial considerations.

However, relying solely on the pooled OLS model may lead to biased coefficient estimates if spatial dependence exists among provincial TFP growth. To test for this, Moran's I test [3] is conducted on the residuals of the pooled OLS model to detect spatial autocorrelation. The results confirm the presence of significant spatial autocorrelation in both the main and second rice models, indicating that the pooled OLS specification is inappropriate. In such cases, spatial lag or spatial error models are more suitable.

To further explore spatial dependence and spatial heterogeneity, Lagrange Multiplier (LM) tests are applied: the LM-lag test [4] for spatial dependence and the LM-error test [5] for spatial error correlation. Both tests yield statistically significant results for the main and second rice models, supporting the adoption of either the pooled spatial lag or pooled spatial error model.

In addition, panel data-specific LM tests [6]–[10], as proposed by Baltagi et al. (2003), are employed to assess spatial dependence and heterogeneity relative to the pooled OLS model, as well as to evaluate the presence of RE—with and without spatial components. These tests further confirm significant spatial dependence and heterogeneity, and also suggest that RE models incorporating spatial terms may be appropriate.

Finally, to determine whether a spatial FE or a spatial RE model is more suitable, the spatial Hausman test, as extended by Mutl and Pfaffermayr (2011), is employed [11] and [12]. The results clearly indicate that the spatial FE model is preferred over the spatial RE model for both main-season and second-season rice. Based on these findings, subsequent interpretations and discussions will focus exclusively on the FE spatial model specifications.

Table 3 and 4 presents the estimated coefficients from the various TFP determinant models for both the main and second rice production seasons, respectively. The models include FE spatial lag and spatial error specifications, capturing both the direct and spatially correlated influences of explanatory variables on TFP growth. The FE spatial lag model for the main rice season reveals a statistically significant spatial dependence parameter (ρ), indicating that TFP growth in one province is positively influenced by TFP growth in neighboring provinces. This spatial interdependence implies that productivity improvements in one region can spill over to adjacent areas, reflecting shared resources, farming practices, and environmental conditions. However, due to the presence of spatial feedback effects, the estimated coefficients of the explanatory variables in the spatial lag model cannot be directly interpreted as marginal effects. The explanatory variables impact the TFP growth of a given province and, through spatial interactions, influence neighboring provinces, thereby generating feedback loops that complicate direct interpretation. By contrast, the spatial error model does not suffer from these feedback complications. Therefore, the coefficients in the FE spatial error model can be interpreted as the marginal effects of explanatory variables on TFP growth. The spatial error coefficient (λ) is statistically significant, suggesting that unobserved factors affecting TFP growth are spatially correlated. This highlights the possibility of omitted variables whose effects extend across provincial boundaries.

The results from the spatial error model indicate that the proportion of high-yielding varieties planted is positively and significantly associated with TFP growth in the main rice season: a 1% increase in HYS leads to a 0.116% increase in TFP growth. In contrast, surface temperature and the proportion of damaged area to total planted area exhibit statistically significant negative effects. Specifically, a 1% increase in surface temperature results in a 0.6328% reduction in TFP growth, while a 1% increase in damaged area is associated with a 0.759% decline in TFP growth. Other factors, including irrigation area, total precipitation, and gross provincial product, do not exhibit statistically significant relationships with TFP growth for main rice.

For the second rice season, both the spatial lag and spatial error parameters are statistically significant, albeit with lower magnitudes compared to the main rice season. According to the FE spatial error model, irrigation area per planted area, surface temperature, total precipitation, and damaged area are significant determinants of TFP growth. Specifically, a one-unit increase in irrigation area per planted area leads to a 0.0138% increase in TFP growth, while a 1% increase in total precipitation contributes to a 0.04% increase in productivity. On the other hand, a 1% rise in surface temperature results in a 0.6422% decline in TFP growth, and a 1% increase in damaged area corresponds to a 1.042% reduction. Unlike the main rice season, HYS and GPP are not statistically significant for second rice. Irrigation plays a crucial role in second rice TFP growth but not in the main rice season. This finding is consistent with Suphannachart (2013, 2018), who also observed a positive effect of irrigation on second rice. This disparity can be attributed to the seasonality of rice cultivation. The second rice season is typically grown during the dry season and is thus more dependent on irrigated water. The positive effect of both irrigation and precipitation for second rice suggests that even with irrigation, the natural rainfall during the off-season may be insufficient, and any additional precipitation enhances productivity. Conversely, the main rice season coincides with the rainy season, where rainfall is generally sufficient for crop growth. Consequently, increases in irrigation area or rainfall do not significantly improve, and may sometimes hinder, productivity due to potential flooding. This is further supported by the negative but statistically insignificant coefficient of total precipitation in the main rice model.

Technological advancement, often proxied by research expenditure or investment, could not be directly measured due to lack of provincial-level data. Therefore, the HYS was used as a proxy for technological change. A significant positive effect of HYS on TFP growth was found for the main rice season, supporting the view that adoption of improved varieties enhances productivity. For second rice, however, the effect was positive but not statistically significant.

Temperature and natural damage were found to have negative impacts on TFP growth across both seasons. These findings are consistent with Kunimitsu et al. (2014, 2016), who reported that temperature increases tend to reduce productivity in regions with already high baseline temperatures. Zhong et al. (2019) also documented asymmetric effects of climate change on agricultural TFP, finding negative effects in southern China and positive effects in the north. In Thailand, a tropical country, further increases in temperature are more likely to harm rice productivity. Pakeechay et al. (2020) similarly found that higher temperatures not only reduce average yields in central Thailand but also increase production variance and downside risk.

The negative effect of the damaged area ratio on TFP growth further underscores the vulnerability of rice production to climate-related shocks such as droughts, floods, and pest outbreaks. This variable also captures some of the stochastic variation and measurement error inherent in the non-parametric estimation of TFP.

Together, the evidence suggests that climate change—manifested through rising temperatures and increased frequency of natural disasters—poses a significant threat to rice productivity in Thailand. Moreover, spatial dependence patterns highlight the importance of regionally coordinated adaptation strategies and the need to account for spillover effects in agricultural policy design. The results also stress the need for improved data on technological investments to better understand their spatial and productivity dynamics.

The significance of the spatial dependence parameter in the spatial lag model for both rice seasons highlights the presence of spatial spillover effects. One possible explanation is that agricultural innovations or efficiency-enhancing techniques in one province can disseminate to neighboring areas through informal knowledge sharing or market mechanisms. Alternatively, provinces in close proximity may inherently share similar agroecological conditions—such as soil quality, climate, rice varieties, or farming practices—resulting in correlated productivity levels. At the same time, widespread adverse events such as floods or droughts often impact multiple provinces simultaneously, reinforcing spatial dependence in negative productivity shocks.

Table 2: Testing for model specification

Test	Main rice model	Second rice model
[1] LM test for RE H_a: RE	-3.0739 (0.9989)	-3.6274 (0.9999)
[2] F test for individual effects H_a: significant FE	0.82501 (0.8556)	0.71475 (0.9622)
[3] Moran's I statistics H_a: significant spatial effects	11.987 (0.000001)	5.3263 (0.000001)
[4] LM test for ρ (χ^2)	132.68 (0.000001)	26.306 (0.000001)
[5] LM test for λ (χ^2)	138.89 (0.000001)	26.796 (0.000001)
[6] Marginal LM test for H_0: $\sigma_\mu^2 = 0$ (assuming $\lambda = 0$)	-3.0585 (1.998)	-2.3399 (1.981)
[7] Marginal LM test for H_0: $\lambda = 0$ (assuming $\sigma_\mu^2 = 0$)	11.825 (0.000001)	5.4253 (0.000001)
[8] One-side joint LM test for H_0: $\lambda = \sigma_\mu^2 = 0$	139.82 (0.000001)	29.434 (0.000001)
[9] Conditional LM test for H_0: $\lambda = 0$ (assuming $\sigma_\mu^2 \geq 0$)	11.494 (0.000001)	5.9926 (0.000001)
[10] Conditional LM test for H_0: $\sigma_\mu^2 = 0$ (assuming $\lambda \geq 0$)	3.0696 (0.002144)	2.8049 (0.005033)
[11] Spatial Hausman test (χ^2) FE vs RE spatial lag H_a: FE spatial lag	42.756 (0.000001)	45.311 (0.000001)
[12] Spatial Hausman test (χ^2) FE vs RE spatial error H_a: FE spatial error	52.271 (0.000001)	59.632 (0.000001)

Source: Research finding

Note: the table shows the test score of each test and the p-value are in parenthesis.

Table 3: Estimated results of TFP growth determinant models for the main rice

Variables	Pooled OLS	Pooled spatial lag	Pooled spatial error	FE spatial lag	FE spatial error
High-yielding shared ($\boldsymbol{HYS}$)	0.014 (0.012)	0.015 (0.012)	0.022 (0.014)	0.096** (0.03)	0.116*** (0.033)
Irrigation area per planted area ($\boldsymbol{Irrig}$)	-0.007 (0.023)	-0.004 (0.022)	0.0002 (0.024)	-0.056 (0.034)	-0.055 (0.037)
ln(Surface temperature) ($\boldsymbol{Tpre}$)	9.33 (6.97)	7.999 (6.571)	8.677 (8.215)	-50.749* (21.41)	-63.278* (31.239)
ln(Total precipitation) ($\boldsymbol{skinT}$)	0.826 (1.612)	1.249 (1.519)	1.455 (1.858)	-1.321 (2.584)	-3.215 (3.522)
Damaged area ($\boldsymbol{NF}$)	-0.593*** (0.053)	-0.499*** (0.05)	-0.582*** (0.057)	-0.672*** (0.059)	-0.759*** (0.064)
Gross provincial product ($\boldsymbol{GPP}$)	-0.001 (0.001)	-0.0003 (0.0009)	0.0004 (0.0009)	0.0005 (0.004)	0.0004 (0.004)
Constant	-25.441 (20.498)	-20.347 (19.323)	-21.906 (24.34)		
Spatial lag parameter ($\boldsymbol{\rho}$)		0.343*** (0.031)		0.33*** (0.032)	
Spatial error parameter ($\boldsymbol{\lambda}$)			0.358*** (0.032)		0.35*** (0.033)

Source: Research finding
Note: *** means significant at 0.1%, ** means significant at 1%, * means significant at 5%, $^{+}$ means significant at 10%. Standard errors of estimated coefficients are in parenthesis

Table 4: Estimated results of TFP growth determinant models for the second rice

Variables	Pooled OLS	Pooled spatial lag	Pooled spatial error	FE spatial lag	FE spatial error
High-yielding shared ($\boldsymbol{HYS}$)	0.002 (0.017)	-0.01 (0.016)	-0.006 (0.017)	0.02 (0.023)	0.024 (0.024)
Irrigation area per planted area ($\boldsymbol{Irrig}$)	0.004** (0.001)	0.012*** (0.002)	0.012*** (0.002)	0.014*** (0.002)	0.014*** (0.002)
ln(Surface temperature) ($\boldsymbol{Tpre}$)	-9.94^{+} (5.387)	-5.772 (5.043)	-6.421 (5.605)	-53.33** (17.43)	-64.216** (19.709)
ln(Total precipitation) ($\boldsymbol{skinT}$)	2.196** (0.713)	3.228*** (0.745)	3.607*** (0.871)	3.785** (1.385)	4.01* (1.57)
Damaged area ($\boldsymbol{NF}$)	-0.686*** (0.104)	-0.92*** (0.099)	-0.948*** (0.101)	-1.018*** (0.103)	-1.042*** (0.105)
Gross provincial product ($\boldsymbol{GPP}$)	0.0002 (0.001)	-0.0001 (0.001)	-0.0001 (0.001)	-0.0009 (0.004)	-0.0006 (0.004)

Variables	Pooled OLS	Pooled spatial lag	Pooled spatial error	FE spatial lag	FE spatial error
Constant	44.522* (17.333)	36.866* (15.974)	40.786* (17.853)		
Spatial lag parameter ($\boldsymbol{\rho}$)		0.165*** (0.034)		0.132*** (0.036)	
Spatial error parameter ($\boldsymbol{\lambda}$)			0.171*** (0.035)		0.143*** (0.037)

Source: Research finding
Note: *** means significant at 0.1%, ** means significant at 1%, * means significant at 5%, + means significant at 10%. Standard errors of estimated coefficients are in parenthesis

4. Conclusions

Rice production in Thailand plays a crucial role in ensuring national food security and contributing to the global rice supply. Despite this importance, Thailand's average rice yield remains lower than that of many major rice-exporting countries and below the global average. To address this discrepancy and support effective policy design, it is essential to establish comprehensive indicators that accurately capture the productivity potential of rice cultivation in Thailand. This study seeks to provide a comprehensive assessment of rice production performance across Thailand, with a particular focus on identifying spatial patterns and regional disparities. The analysis employs the MPI based on the DEA approach to estimate TE and to decompose TFP growth into its constituent components. Subsequently, a spatial econometric model is applied to investigate the determinants of TFP growth, incorporating spatial dependence and other relevant explanatory factors. The study distinguishes between the main rice and second rice cropping seasons and utilizes the most recent data from the OAE, covering all 76 provinces over the period 1997–2018.

The findings of this study reveal substantial variation in TE scores across provinces and between rice cropping seasons in Thailand. Overall, Thai farmers are not operating at optimal efficiency, indicating considerable room for improvement in resource management and agricultural practices. The second rice farming demonstrates relatively higher efficiency than main rice farming, with farms in the central and northern regions typically outperforming those in other parts of the country. TE scores are positively correlated with the presence of large-scale irrigation infrastructure and areas designated as suitable for rice cultivation by the Land Development Department. The productivity assessment presents compelling evidence that rice cultivation in Thailand has experienced limited improvement over the past two decades. The annual average TFP growth rate was merely 0.19% for main rice and -0.18% for second rice over the period of analysis (1997–2018), indicating stagnation and even regression in productivity for certain regions and seasons.

The decomposition of TFP growth highlights that the modest progress in main rice TFP was primarily due to the slow adoption of new technologies and inefficiencies in farm management. Conversely, the TFP regression in second rice cultivation is attributed to an even slower technological adoption and inadequate changes in management practices across provinces. The TFP determinant model further confirms the presence of spatial spillover effects in productivity growth across provinces. Neighboring provinces tend to exhibit similar levels of performance due to shared agroecological conditions—such as soil quality, climatic patterns, rice varieties, and farming techniques—which contribute to spatial autocorrelation in TFP outcomes. Technological adoption, particularly the increased share of high-yielding rice varieties, plays a crucial role in enhancing TFP growth. Additionally, irrigation infrastructure, as a form of technological advancement, positively influences productivity, particularly in second rice cultivation, which is more reliant on controlled water supply during the off-season. However, the study also finds that climate change poses a significant threat to rice productivity in Thailand. Rising average temperatures and increasing frequency and severity of natural shocks—such as floods, droughts, and pest outbreaks—have a negative impact on TFP growth. These adverse effects are expected to intensify under current climate change trajectories.

The findings of this study offer several key policy implications for enhancing the productivity and sustainability of rice production in Thailand. First, the low TE scores observed across provinces suggest that there is considerable room for improving production efficiency through better managerial practices. Farmers could benefit from adopting more efficient input use strategies by learning from provinces with similar agroecological conditions but higher efficiency scores. The results further indicate that the scale of main rice production—particularly in the northeastern region—may be too large and operating under decreasing returns to scale. In such cases, reducing the size of rice farming and shifting to alternative crops better suited to local weather and soil conditions may enhance agricultural performance, increase resilience, and diversify farmers' income sources beyond rice cultivation. Second, the decline in TE during the main rice season has been identified as the primary factor contributing to the sluggish TFP growth in Thailand's rice cultivation. This suggests that several provinces are struggling to converge toward the efficiency frontier. To address this issue, policy interventions are needed to promote the diffusion of best practices from high-performing (frontier) provinces to those that are lagging behind. In addition, the observed declines in TE may be further exacerbated by exogenous natural shocks, including floods and droughts. Such environmental disruptions can hinder production performance and widen regional efficiency gaps. Accordingly, policy measures that enhance farmers' resilience—such as the implementation of crop insurance schemes, the development of early warning systems, and the promotion of climate-adaptive agricultural practices—are critical to sustaining long-term TFP growth in the rice sector. Third, the negative trend in technical change, especially in second rice production, reveals a gap in the adoption of new technologies across provinces. While some progress has been made in main rice production, the pace of innovation remains modest compared to leading rice-producing countries. The government should prioritize policies that promote the adoption of modern agricultural technologies, such as precision farming systems, mechanization, and agricultural drones. Given the high capital costs of such technologies, targeted subsidies and financial support for smallholder farmers are critical. Furthermore, shared use of equipment—such as community-owned drones for sowing, fertilization, pest control, and field monitoring—can facilitate technology diffusion and reduce individual investment burdens. These technologies not only enhance productivity but can also create new rural employment opportunities. Fourth, the significant spatial dependence observed in TFP growth across rice-producing provinces suggests the existence of regional spillover effects. Enhancements in TFP or technological progress in one province are likely to generate positive externalities for neighboring provinces through mechanisms such as imitation, knowledge diffusion, and shared agro-environmental conditions. This spatial interdependence presents an opportunity for policymakers to strategically target interventions in selected pilot provinces—those with high potential for innovation and adoption—thereby maximizing the regional propagation of improved production practices and technologies. Lastly, climate change poses a serious threat to the long-term productivity of rice in Thailand by raising average temperatures and increasing the frequency and severity of weather-related shocks. Policymakers must prioritize adaptation strategies that strengthen the resilience of rice farming systems. These include developing and disseminating new rice varieties that are tolerant to heat, drought, floods, and pests. In some regions, transitioning to alternative crops more suitable for changing climatic conditions may be necessary. Furthermore, investments in research and development, infrastructure, and climate-smart agriculture will be key to mitigating the adverse impacts of climate change.

In conclusion, enhancing the productivity and sustainability of rice production in Thailand requires a comprehensive and multi-dimensional policy approach. This should encompass sustained investment in the research and development of high-yielding and climate-resilient rice varieties, the widespread dissemination and adoption of advanced agricultural technologies, and the strategic exploitation of spatial spillover effects to maximize regional productivity gains. In the short term, these measures are critical for narrowing the yield gap relative to international standards. In the long term, it is imperative to undertake a broader structural reassessment of the role of rice cultivation within the national agricultural framework—one that reconciles objectives of food security, economic viability, and climate adaptability. Such an approach will be central to improving the welfare of rice farming households and fostering inclusive and sustainable rural development.

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