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Impact of Climate Change on Paddy Productivity in Malaysia's Granary Areas: A Markov Chain Monte Carlo Analysis

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ABSTRACT

Objective - This study simulates paddy productivity across Malaysia's granary areas over a 10-year period, with a focus on the non-linear effects of climate change, particularly rainfall and temperature variability. This study examines how each granary area evolves and reaches its optimal point as climate variability risks increase over time.

Methodology/Technique - Using a Markov Chain Monte Carlo (MCMC) approach, the analysis estimates the impact of these climate factors on paddy yields. The findings reveal that rainfall has a positive effect on productivity in areas with low rainfall, such as IADA BLS, IADA PP, and MADA, while excessive rainfall has a detrimental, non-linear impact across all regions. Temperature variability has mixed effects, enhancing productivity in IADA PP and IADA KETARA but negatively affecting areas such as IADA MADA and IADA SEM.

Findings - A key finding from the simulation is that each granary area reaches its optimal productivity at different times. IADA PP is projected to achieve the highest yield (6.47 tonnes/hectare) in the 10th year, whereas IADA KER is expected to reach the lowest maximum productivity (5.45 tonnes/hectare) in the 5th year. Notably, IADA BLS and IADA KER achieve peak productivity within just 5 years, faster than other regions.

Novelty - IADA KEM exhibits the largest improvement, with a 58.7% increase in productivity over a 10-year period, despite its vulnerability to climate variability. These findings highlight the diverse impacts of climate change on paddy yields and the need for region-specific adaptive strategies.

Type of Paper: Empirical

JEL Classification: Q51, Q54.

Keywords: Climate change, Granary areas, Markov Chain Monte Carlo, Paddy Productivity

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1. Introduction

Paddy production systems are subjected to unique ecological and climatic conditions. This crop is cultivated in rainfed and irrigated lowlands, uplands, and deep-water areas. In general, this crop can grow in areas with temperatures between 20 °C– 35 °C, rainfall of 1000-2000mm/year, and a water level of 10–15cm (De Silva et al., 2007) (Oh et al., 2023) (Ratnayake et al., 2023).

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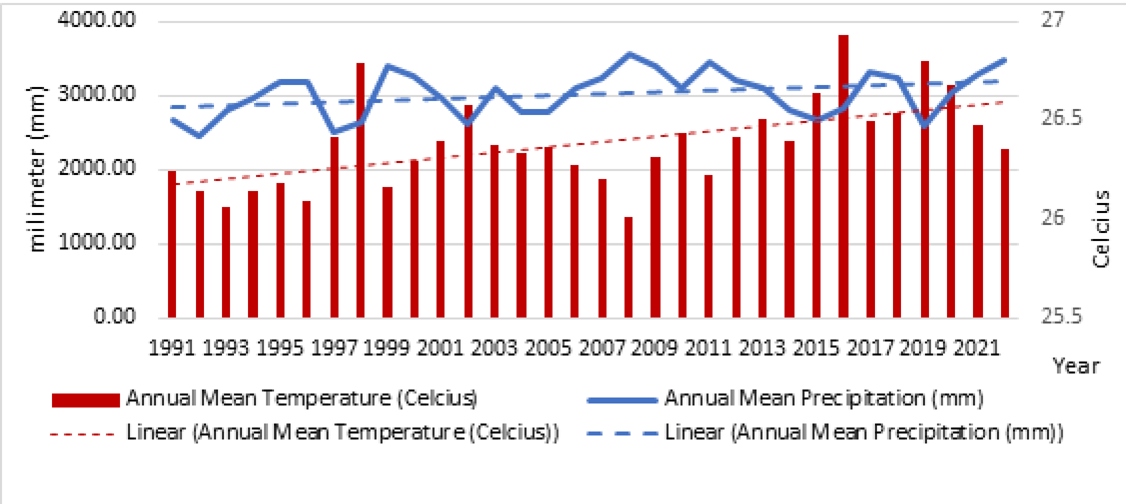
Most of the world's paddy is produced in irrigated lowland rice systems, which account for approximately 75% of the worldwide paddy crop, covering around 93 million hectares. Conversely, 19% of the world's paddy production comes from 52 million hectares of rainfed lowlands (Almanac, 2013). Specifically in Malaysia, paddy is planted twice annually in two separate cropping seasons. The main season, characterized by humid weather from August to February, is based on a non-irrigation-dependent system, whereas the off-season, marked by dry weather from March to July, requires an irrigation system. Mostly, paddy production is coming from granary areas. There are 12 paddy granary areas in Malaysia: Muda Agricultural Development Authority (MADA), Kemubu Agricultural Development Authority (KADA), Integrated Agricultural Development Area (IADA) KETARA, IADA Barat Laut Selangor (BLS), IADA Kerian (KER), IADA Seberang Perak (SP), IADA Pulau Pinang (PP), IADA Kemasin (KEM), IADA Rompin, IADA Pekan, IADA Kota Belud and IADA Batang Lupar.

There are many factors affecting the paddy productivity in these granary areas. Among these factors is climate change. Figure 1 shows that the annual mean temperature has increased over the last two decades, reaching its maximum level in 2016 (26.93 °C). Meanwhile, average precipitation shows fluctuations with a slow upward trend over the years. This scenario could have a potentially detrimental impact on paddy productivity over time. As suggested by (Zahid Zainal et al., 2014) the optimal temperature for paddy growth is very sensitive to temperature changes. Paddy yield is found to decline steeply as the mean temperature exceeds 28 °C. Meanwhile, rainfall variability is attributed to the poor amount and distribution of rainfall, as well as soil properties such as water-holding capacities and poor fertility. This is the reason why paddy is not cultivated during the off-season. It is expected that in Malaysia, the increasing temperature and rainfall during the main and offseason will decrease paddy yield by 12 percent and 31.3 percent, respectively, in 20 years (Vaghefi et al., 2016). In this respect, climate change could have a significant effect on paddy productivity across these granary areas.



Source: World Bank (2023)

Figure 1: Annual Trend of Mean Temperature and Precipitation in Malaysia, 1991 – 2022

The impact of climate change variables on paddy yield can be pronounced in a non-linear relationship. A moderate increase in rainfall or temperature can promote paddy yield but an extreme in rainfall or temperature could deteriorate paddy yield (Wang et al., 2016) (Amaratunga et al., 2020). This means that beyond a certain point, temperature, precipitation, or rainfall can reduce paddy yield, which explains the non-linear response of climate change on paddy productivity. Previous studies suggested on this non linearity relationship such as in China, (Wang et al., 2016);

continents (D. Liu et al., 2020); Nigeria (Oguntunde et al., 2018); selected countries (Feng et al., 2021) the Philippines (Stuecker et al., 2018), Global (Ray et al., 2015) and Taiwan (Chen et al., 2023) by using various technique of analysis. However, it found a lack of evidence examining the non-linear relationship between climate change and paddy productivity specifically, across paddy granary areas in Malaysia. Moreover, this study differs from the previous one in terms of methodology. A Monte Carlo Markov Chain simulation will be used to project the trend of paddy productivity over the next 10 years, with respect to the annual temperature transition for each of the granary areas. These findings are crucial, as they will provide tailored policy recommendations for each granary area. This will enable region-specific strategies rather than relying on a general approach to increase paddy productivity.

2. Literature Review

Climate change could have a significant impact on the agricultural sector, as it can directly influence agricultural yields. Environmental factors, including soil moisture and temperature, influence plant systems. (Adams et al., 1998) and (Malhi et al., 2021) argued that the combined effect of warming, precipitation change, and CO2 concentration on crop yield is expected to vary. Climate change factors are expected to affect agricultural productivity and crop yields by changing precipitation patterns, changes in planting and harvesting dates, and quality and quantity of yield (Solaymani, 2023). For example, an increase in temperature decreases crop yield as the evapotranspiration rate increases and deteriorates land moisture, whereas increases in precipitation can support land moisture and increase crop yield. However, crops are directly affected by changes in climatic factors such as the frequency and severity of extreme events like drought, floods, and wind storms (Adams et al., 1998) Such extreme precipitation phenomena, either heavy rainfall or drought, are dependent on a region’s geography. Extreme precipitation is predicted to increase river flows due to prolonged heavy rainfall, which can disrupt the agricultural system and reduce crop yields, including those of rice, wheat, and maize. (Herath et al., 2020). Meanwhile, extreme temperature levels cause prolonged drought, resulting in a shortage of water availability

The complex interaction of temperature, CO2 levels, and precipitation on paddy production may result in a non-linear relationship among these variables. For instance, the elevated CO2 level resulting from fertilization has a positive impact on paddy productivity, enhancing photosynthesis and water–use efficiency. However, this positive effect is diminished as elevated CO2 levels increase further, leading to higher temperatures, a shorter growth period, and reduced paddy yields in tropical and temperate climate zones. (Kim et al., 2013). On the other hand, (Iizumi et al., 2011) highlighted the uncertainty in the combination of temperature and rainfall could shape a non-linear effect of climate change on paddy productivity. Zones with cooler temperatures are more likely to benefit from an increase in paddy yield, whereas warmer areas with the combined stress of heat and unpredictable rainfall show a high probability of reduced yield.

Numerous studies have examined the impact of climate change variables on paddy productivity, particularly in Malaysia. Some studies have performed simulations on paddy productivity in relation to climate change. For example, (Felkner et al., 2009) evaluated crop yield impact from climate change for Southeast Asia countries by using DSSAT Simulation. It predicted a decrease in aggregate yield compared to normal condition simulation for the high emission scenario (high temperature and less rain) and the low emission scenario (moderate temperature and more rain. The results suggested that the low-emission scenario causes more damage to paddy yields due to higher rainfall during the paddy's maturity and harvesting periods. Concerning the loss in paddy production, Vaghefi et al. (2011) estimated the potential impact of climate change on rice production in Malaysia by using the crop model ORZYA 2000 to simulate rice yield across eight granary areas. The model predicted a reduction in rice yield under a scenario of increasing temperature and CO2 at a specific level. (Zahid Zainal et al., 2014) investigated the economic impact of climate change variables (temperature and rainfall variability) on paddy production in Malaysia from 1980 to 2010 based on a modified Ricardian model, where the results signify that temperature and rainfall variability had a negative impact on production.

In a different technique, (Ibrahim & Alam, 2016) Employed multiple log-linear ordinary least squares on the Cobb-Douglas production function model, found that the climatic changes variable does influence paddy production at MADA areas in Malaysia. Rainfall and the number of rainy days are positively and significantly associated with paddy production, whereas temperature has a negative influence on paddy production. With the same view, (Alam et al., 2014) used a log-linear OLS regression model to discuss the impact of rainfall and temperatures on the paddy sector at IADA North West Selangor granary area in Malaysia from 1992 to 2007. This result found that both temperature and rainfall have a negative and significant impact on paddy production. Similarly, (Firdaus et al., 2020) explored the impact of climate change on rice production and food security in Malaysia from 2016 to 2020 by using Mann–Kendall and Sen's slope. This result suggests that there has been an increase in both minimum and maximum temperatures in the granary area, as well as an increase in precipitation in the same area. This result poses a threat to paddy production. Additionally, Tan et al. (2021) examined the impact of climate change, including maximum and minimum temperatures and precipitation, on rice yields in eight granary areas of Malaysia. The regression results indicate that precipitation was not significantly affected by paddy yield during the main and off-seasons. In contrast, maximum temperature had a negative effect on yield during the off-season, while minimum temperature showed a positive effect in both seasons. For a dynamic perspective, (Herath et al., 2020) studied the impact of climate change on paddy production in Malaysia by utilizing the autoregressive distributed lag (ARDL) model at the national and state levels. The result indicates that an increase in temperature ultimately reduces paddy production. Paddy production in Kedah state is affected by rainfall, which ultimately reduces paddy output. Similarly, (Solaymani, 2023) used the dynamic ARDL simulation method to estimate the long-run and short-run relationship between climate change variables and paddy production. The results indicated that temperature could reduce rice yield in both the long and short term. However, the effect of precipitation and carbon emissions on rice production is not significant.

3. Methodology

In general, the quadratic functional form is more reasonable in examining the nonlinear effect of climate change on paddy yield (Gay et al., 2006) (Eboh et al., 2012); (Sassi & Cardaci, 2013); (Esteve et al., 2015). Thus, the model of this study utilized the function of yield response to climate variables of rain, fed, which can be specified as (Javadi et al., 2024):

$$y_{z,t} = \alpha + \beta_1 RF_{z,t} + \beta_2 RF^{\,2}_{z,t} + \beta_3 SDTem_{z,t} + \mu_{z,t} \qquad (1)$$

where z and t are suffixes for granary areas (1,2, …8) and time (from 1994 - 2023), respectively. Meanwhile, y, RF, RF^2, SDTem and μ are paddy productivity (tonne/ hectare), rainfall (mm), squared rainfall (mm), standard deviation of mean temperature (Celsius), and error term, respectively. These climatic data are from nearby weather stations serving the respective granary areas, compiled on the MyMetdata website. Due to data availability constraints on paddy productivity, this study only focuses on eight granary areas.

The methodology is based on two-step techniques. The first step is to estimate the coefficient of climate variables on paddy productivity for each granary area by using Seemingly Unrelated Regression (SUR). It captures the efficiency of coefficients by considering the correlation of the disturbances across individual equations. Suppose the error term of granary area k is correlated with the error term of granary area j, which is shown in Equation (2)

$$\text{cov}(\varepsilon_{k,t}, \varepsilon_{j,t}) = \sigma_{k,j} \quad \sigma_{k,j} \neq 0 \tag{2}$$

The coefficient of $\varepsilon_{k,t}$ and $\varepsilon_{j,t}$ might be correlated in Equation (2). SUR will estimate Zs, granary areas equations jointly for the fact that variances of error terms are different for each Z equation, and accounting for contemporaneous correlation between errors of Zs equations (Hill et al., 2018). Although each granary area demonstrates a unique climatic change, it suggests there are interconnected effects of shared climate factors across regions, such as common temperature changes, which have caused a decline in productivity across multiple zones. (Gupta & Mishra, 2019); the impacts of extreme weather or climatic stressors can be extended to other regions as well (L. Liu et al., 2013) (Arshad et al., 2018). These interconnected effects will be captured by contemporaneous correlation in SUR estimation.

The next step is to run a simulation of Markov Chain Monte Carlo (MCMC) based on the transition probability distribution. MCMC simulation is a general method based on a sequence of random variables $\theta^1, \theta^2, \ldots$, for which, for any t, the distribution θ^t given all previous θ's depends only on the most recent value, θ^{t-1} (Gelman et al., 1995). The transition probability distributions must be constructed so that the Markov chain converges to a unique stationary distribution that is the posterior distribution $p(\theta|y)$. Let $p_{ij}(n)$ denote the conditional probability that the system will be in state j after exactly n transitions, given that it is presently in state i (Ibe, 2013). With the transition probability for all $0 < r < n$, the transition distribution of a Markov chain (or transition kernel) is denoted by

$$p_{ij}(n) = \sum_k p_k(r) p_{ik}(n-r) \tag{3}$$

It can be shown that $p_{ij}(n)$ is the ith row and jth column in the matrix P^n. This study constructed transitional probability matrices based on the threshold of the standard deviation of temperature, which represent "low", "medium", and "high" states for each area. The simulation is initialized with a particular state of SDTemp for each of the granary areas. The simulation will repeat the process for 1,000 iterations for 10 10-year periods to generate a random process based on the transitional probability. Each iteration updates the productivity value for year t based on the estimated SUR coefficients' values. After productivity is calculated for the current year, the Markov Chain decides the next state. The current state's transition probabilities are used to randomly choose the next state.

4. Result

Table 1 presents a descriptive analysis of climate change variables and paddy productivity for each granary area. It suggests that the average productivity (1994–2023) for IADA BLS is the highest, followed by IADA PP, whereas IADA KEM has the lowest productivity among the granary areas. For climate variables, the IADA Barat Laut Selangor area received the lowest rainfall among the granary areas; however, the lowest standard deviation of rainfall indicates a consistent (low variation) rainfall pattern in the area. The highest rainfall is recorded in IADA KEM, with the highest standard deviation, highlighting that this area is particularly vulnerable to extreme weather events, such as flood disasters. In terms of temperature, IADA KER posits the lowest average temperature, accompanied by a high standard deviation. The highest temperature is IADA PP, accompanied by a high standard deviation of temperature, suggesting this area could be exposed to extreme drought seasons

Table 1: Descriptive Analysis on paddy productivity and climate change variables

(1994-2023)

Paddy Granary Areas	Average annual mean temperature (ºC)	Standard deviation of mean temperature (ºC)	Average rainfall (mm)	Standard deviation of rainfall (mm)	Average paddy productivity (tonne/ hectare)	Standard deviation of paddy productivity (tonne/ hectare)
MADA	27.648	0.311	2155.931	279.913	4.578	0.418
KADA	27.307	0.271	2757.000	571.589	3.650	0.576
IADA KEM	26.820	0.347	2801.878	594.557	3.035	0.715
IADA PP	27.910	1.326	2272.431	339.381	4.783	0.841
IADA KETARA	27.355	0.347	2721.371	582.617	4.526	0.988
IADA BLS	27.879	0.386	1859.033	287.762	5.058	0.673
IADA KER	26.674	1.249	2064.689	311.676	3.629	0.691
IADA SP	27.178	1.290	2452.537	426.444	3.797	0.695

Source: author's calculation

Table 2 presents the transition probability distributions for each respective granary area, which ultimately form the transition probability matrices. These matrices signify a unique transition in the standard deviation of temperature from one state to another for each granary area. The MCMC simulation would be built upon these transition probabilities. Table 3 presents the result of SUR estimation on paddy yield response to climate change.

Table 2: The Transition Probability in the Standard deviation of temperature for each granary Area

Granary Areas	From (Previous state)	To (New State)		
		Low	Medium	High
MADA	Low	0.50	0.30	0.20
	Medium	0.11	0.44	0.44
	High	0.30	0.30	0.40
KADA	Low	0.40	0.40	0.20
	Medium	0.40	0.20	0.40
	High	0.11	0.44	0.44
IADA KEM	Low	0.80	0.20	0.00
	Medium	0.10	0.60	0.30
	High	0.11	0.11	0.78
IADA PP	Low	0.60	0.20	0.20
	Medium	0.10	0.40	0.50
	High	0.22	0.44	0.33
IADA KETARA	Low	0.60	0.30	0.10
	Medium	0.20	0.50	0.30
	High	0.11	0.22	0.67
IADA BLS	Low	0.60	0.30	0.10
	Medium	0.22	0.33	0.44
	High	0.10	0.40	0.50
IADA KER	Low	0.60	0.10	0.30
	Medium	0.11	0.56	0.33
	High	0.20	0.40	0.40
IADA SP	Low	0.50	0.30	0.20
	Medium	0.20	0.60	0.20
	High	0.22	0.11	0.67

Source: author's calculation

Table 3: SUR estimation result of paddy yield response to climate changes

Variables	Areas							
	MADA	KADA	KEM	PP	KETARA	BLS	KER	SP
Constant	4.613*** (0.020)	3.648*** (0.009)	3.037*** (0.006)	4.777*** (0.026)	4.523*** (0.011)	5.073*** (0.038)	3.624*** (0.020)	3.794*** (0.015)
RF	0.183*** (0.048)	0.002 (0.012)	-0.000 (0.002)	0.228*** (0.039)	-0.001 (0.006)	0.099*** (0.034)	-0.020 (0.020)	0.040* (0.024)
RF^2	- 0.869*** (0.048)	-1.003*** (0.011)	-1.000*** (0.002)	-0.778*** (0.040)	-0.995*** (0.006)	-0.917*** (0.049)	-1.018*** (0.021)	-0.991*** (0.023)
Sdtem	-0.302** (0.121)	-0.003 (0.053)	-0.040** (0.019)	0.014*** (0.003)	0.060*** (0.019)	-0.058 (0.150)	0.000 (0.002)	0.000 (0.002)
Adj. R^2	0.956	0.993	0.998	0.969	0.996	0.934	0.973	0.986

Note: ***, **, and * are significant at 1, 5, and 10 percent level, respectively

Table 3 presents the result of SUR estimation on paddy yield response to climate change. The estimation result shows a significant and positive impact of rainfall on paddy productivity, especially in areas with low rainfall, such as IADA BLS, IADA PP, and MADA. This emphasizes that rainfall helps maintain the water level in the irrigation system, which supports paddy growth in these respective areas. On the contrary, the rest of the granary areas showed no significant impact on paddy productivity due to rainfall. This result is consistent with Tafoughalti et al. (2018), who found that the different impacts of rainfall on crop productivity are due to varying rainfall variability across the zones.

Meanwhile, RF^2 is found to be significant for all granary areas at a 1% significance level. This means that an increase in squared rainfall could deteriorate paddy productivity across the granary areas, lending support to the non-linear relationship between rainfall and paddy productivity. It is consistent with the findings of (Mitra, 2014), (Feng et al., 2018) and (Ranasinghe et al., 2022) Suggested that rainfall at extreme points contributes a significant decrease in paddy productivity. The standard deviation of temperature is found to significantly increase paddy productivity in IADA PP and IADA KETARA. It is suggested that crop yield increases when temperature variability is maintained within a certain optimal range, which can accelerate plant development and stimulate photosynthesis. (Wheeler et al., 2000). However, IADA MADA and IADA Sem found that to be negatively associated with paddy productivity. (Rahman et al., 2017) implied that rising temperatures, especially in minimum temperatures, pose significant risks to rice productivity across different ecosystems, especially for rainfed rice, emphasizing the detrimental effects of temperature variability.

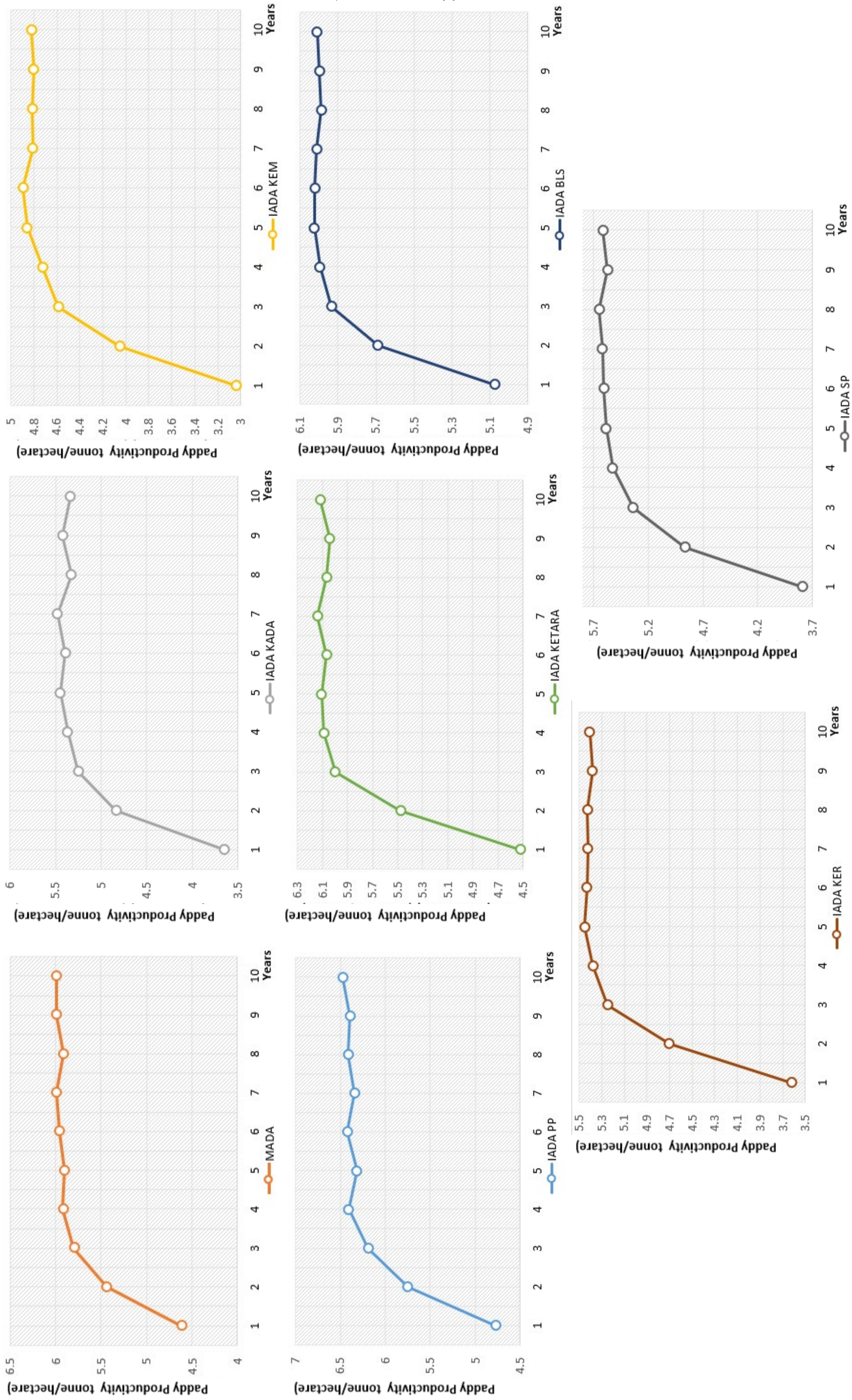


Figure 2: The MCMC simulation result of paddy productivity across granary areas in Malaysia

Source: Author’s calculation

Figure 2 presents the simulation results of paddy productivity for 10 years based on the transition probability distribution. It shows that all granary areas achieve different optimal paddy productivity levels within 10 years, as shown in Table 4.

Table 4: Optimal paddy productivity in eight granary areas

Paddy Granary Areas	Maximum Paddy Productivity (tonne/hectare)	Optimal Years	Changes in Productivity, (1st year to 10th year) (%)
MADA	5.994	7	29.919
KADA	5.478	7	46.213
IADA KEM	4.894	6	58.739
IADA PP	6.473	10	35.524
IADA KETARA	6.137	7	35.312
IADA BLS	6.024	5	18.446
IADA KER	5.451	5	49.136
IADA SP	5.647	8	47.970

Note: The Author's calculation

With respect to the transition probability distribution, IADA PP achieves the highest maximum paddy productivity in the 10th year (6.4 tonne/hectare), in contrast to IADA KER, which achieves the lowest maximum paddy productivity (5.4 tonne/hectare) in the 5th year. Meanwhile, the most significant granary area, MADA, achieves its maximum paddy productivity in the 7th year. Meanwhile, IADA BLS and IADA KER achieve maximum paddy productivity in only 5 years, which is faster than other regions. In terms of productivity change over 10 years, IADA KEM experienced the most significant increase in productivity, with a 58.7 percent increase, highlighting its improvement from a low average paddy productivity (see Table 2), despite its vulnerability to climate change. To sum up, their simulation results show a non-linear trend in paddy productivity, where, at a certain point, each granary area reaches its maximum productivity before the trend curve flattens out across the time horizon.

5. Conclusions and Policy Recommendations

The analysis of the impacts of climate change on paddy yields in Malaysia's granary areas, using the Markov Chain Monte Carlo approach, highlights several critical findings. First, rainfall plays a crucial role in promoting paddy productivity in regions with lower rainfall, such as IADA BLS, IADA PP, and MADA. However, squared rain could have a detrimental effect on paddy productivity across the granary areas, suggesting a non-linear impact of rainfall and paddy yields. Second, temperature variability, represented by the standard deviation in temperature, shows a mixed effect. Temperature variability could enhance paddy productivity in IADA PP and IADA KETARA, but it decreases paddy productivity in IADA MADA and IADA SEM, suggesting different yield responses to temperature variation. Finally, the simulation results over the next 10 years show that each granary area achieves its optimal productivity at various points in time. It is projected that paddy productivity for all granary areas will reach its optimal point, ranging from 4.8 to 6.4 tons per hectare, over the next 10 years. Notably, the results indicate a non-linear relationship between climate change variables and paddy yield. During the early years of the simulation, moderate temperature deviations and optimal rainfall levels may initially enhance yields. However, as time increases, an optimal point is reached. Beyond this point, climate change does not cause further increases in paddy productivity. These findings offer crucial insights for policymakers seeking to achieve sustainability in Malaysia's rice production in the future. By identifying an optimal point in the non-linear relationship between climate change and paddy productivity, this study suggests that intervention measures such as the development and deployment of drought-resistant rice varieties, the enhancement of irrigation infrastructure, and the implementation of region-specific climate mitigation strategies are essential to sustain paddy production in Malaysia's key granary areas.

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