Unlocking the future of rice production for food security in Southeast Asia amid climate change concerns: Arima forecasting

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Abstract. Southeast Asia is a region with a tropical climate suitable for rice farming. Several Southeast Asian countries are experiencing problems in dealing with climate change, which disrupts rice productivity as a staple food for the community. The purpose of this study is to determine the mapping of average temperature and precipitation as a sign of climate change and to predict how rice productivity will be in the next decade. The Geo-map Orange Data Mining approach is used for mapping and ARIMA models for predicting Southeast Asian rice productivity in the future. This study found that temperature and precipitation have the potential to shorten the plant growth cycle, increase the rate of evaporation, and cause heat stress, which can cause floods and droughts that disrupt rice plant productivity. Although the ARIMA prediction results for countries such as Cambodia and the Philippines have significant coefficients in the ARIMA model, they still show unpredictable spikes due to high environmental pressure. This suggests that climate variation, particularly temperature and precipitation, plays a significant role in shaping the long-term dynamics of rice production. Policies regarding food security, particularly rice productivity, need to address climate factors by developing climate-resilient varieties, managing irrigation, and educating farmers on climate-smart agricultural practices.

Keywords: precipitation, production, rice, Southeast Asia, temperature.

1 Introduction

The world needs rice as a staple food, increasing every year. The increasing global population growth has caused changes in consumption patterns and the need for staple foods to increase. This drives countries to produce staple food crops to increase their productivity and meet world needs. In the agricultural sector, food crops are very important crops that must be produced. Food security threats in one sector can have devastating impacts on many other

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sectors [1]. Along with the increasing need for staple foods accompanied by the challenges of climate change and limited land, it becomes a serious obstacle in efforts to meet these needs. Climate change is one of the significant external factors that have a direct impact on the rice farming sector in Southeast Asia [2]. Rising global temperatures, changes in precipitation patterns, higher frequency of natural disasters such as floods and droughts, and rising sea levels are signs of climate change. Drought resulting from a lack of precipitation poses a significant threat to agricultural production, depending on the complex influence of various factors. These problems can worsen the ability of agricultural productivity in Southeast Asian countries with tropical climates. Staple food crop farming such as rice, sorghum and corn has fluctuating yields and must be improved in adapting to climate change [3].

Important foodstuffs consumed by the world community are rice, wheat, and corn. Rice is the main commodity and the main food ingredient for the world's people [4]. International rice trade is also growing rapidly, reaching around 48 million tons per year. The volatility of rice prices, influenced by geopolitical factors, trade policies, and extreme weather conditions, has encouraged many countries to strengthen their national rice reserves. The strategies and policies related to the rice supply chain system that focus on controlling the rate of price transmission. This is done as an anticipatory step against possible market shocks in the future. The Southeast Asian climate supports the growth of rice plants, which makes several Southeast Asian countries plant rice as the staple crop of their population. Southeast Asian countries that are rice producers include the Philippines, Indonesia, Cambodia, Laos, Malaysia, Myanmar, Thailand, and Vietnam. Almost all Southeast Asian countries have rice farming land except Brunei and Singapore, which have little agricultural land.

The degradation of agricultural land that is increasingly being displaced by the housing and industrial sectors is an obstacle to food productivity. Urban economic development has led to a decline in the level of food security and food diversity needed by urban communities who depend on agriculture in other areas [5]. The problem of these obstacles is making global food security increasingly complex, including the obstacles to the target of sustainable development goals, namely ending hunger, achieving food security, improving community nutrition, and encouraging sustainable agriculture. Countries must prioritize food self-sufficiency to overcome hunger and food security. Countries in Southeast Asia are also rice-exporting countries in several countries worldwide. The potential future rice shortage will be a significant obstacle to food security. It is essential to understand how these issues will affect Southeast Asian rice productivity in the future. This is because Southeast Asian countries are also major rice exporters to several countries worldwide.

Rice farming in Southeast Asia faces complex structural and environmental challenges. One of the main issues is the vulnerability of the agricultural sector to climate change, which can disrupt food productivity. Southeast Asian countries face challenges in regional market integration, where imbalances in productivity between countries can create food dependency and price vulnerability. Stable prices of staple foods, especially rice, help prevent poverty in poor and developing countries.

Climate change adds pressure to their agricultural systems. Farmers' ability to adapt to climate change can contribute to food security. Disruptive problems include unpredictable weather patterns, droughts, and floods that have the potential to disrupt production stability. Governments in Southeast Asian countries must create a food security strategy with a comprehensive transformation in the global agricultural and food system. A found that programs that contribute to food security are needed to maintain macroeconomic stability. The government needs to analyse rice productivity predictions in the future to estimate the fulfilment of community food needs. Knowledge of estimated community food needs is needed to create a strategy that balances increased productivity with sustainable agricultural practices, such as variety diversification, ecosystem-based resource management, application

of environmentally friendly technologies, and strengthening farmers adaptive capacity. The purpose of this study is to examine the impact of future rice productivity in Southeast Asia on global food security.

2 Material and Methods

2.1 Geo-map Analysis

A geo-map was used before analysing how to predict rice productivity in the future; an analysis is needed to determine the spatial distribution, which was analysed using Orange Data Mining Geo-Map mapping[6]. This analysis is to assess regional dominance in Southeast Asia, namely in the signs of climate change in temperature and precipitation. With this Geo-map analysis, it will be more visible how climate change in Southeast Asia relates to rice productivity. Geo Map will visualize geospatial data on a map. This widget works on a dataset containing latitude and longitude variables in WGS 84 format.

2.2 Auto-Regressive Integrated Moving Average

This study uses annual time series data of rice production from 2012 to 2022 in eight Southeast Asian countries. There are 11 countries in Southeast Asia, but not all countries have rice farming. Countries in Southeast Asia that have rice farming productivity are the Philippines, Indonesia, Cambodia, Laos, Malaysia, Myanmar, Thailand, and Vietnam. In analysing and forecasting rice production during this period, an appropriate modelling approach is used, one of which is the Box and Jenkins method or, known as ARIMA modelling. This method was first developed by Box [7] and was widely introduced through their work in 1976. However, Granger and Newbold in 1973 stated that the ARIMA model has limitations in long-term forecasting and seasonal data. This technique combines two specifications in one equation: the Autoregressive Process (AR) and the Moving Average Process (MA). The general structure of the ARIMA model is expressed in the form ARIMA (p, d, q), where 'p' denotes the order of the autoregressive process, 'q' represents the order of the moving average process, and 'd' is the degree of differentiation required to make the data stationary. The mathematical form of the ARIMA (p, d, q) model describes the relationship between past values and previous forecast errors in determining current values.

$$Yt = C + (F1\ Yt\text{-}1 + ... + Fp\ Yt\text{-}p) - (\theta 1\ et\text{-}1 + ... + \theta q\ et\text{-}q) + et \quad (1)$$

where, C is a constant, Yt-1, ..., Yt-p is a lag, θ1 is a parameter of the equation, and et is a random error.
However, the p-sequence AR model is:

$$Yt = C + (F1\ Yt\text{-}1 + ... + Fp\ Yt\text{-}p) + et \quad (2)$$

Similarly, the structure of the Q-sequence MA is:

$$Yt = et - (\theta 1\ et\text{-}1 + ... + \theta q\ et\text{-}q) \quad (3)$$

The forecasting process using the ARIMA model involves several important stages, namely: (i) model identification or specification, (ii) parameter estimation, and (iii) model diagnostics. The initial step in the modelling process is to check the stationarity of the time series data because the estimation procedure in the ARIMA model can only be applied to stationary data. Stationarity testing is generally carried out using the Augmented Dickey-Fuller (ADF) test, as introduced by Dickey and refined [8]. If the original data is non-stationary, the first step that must be taken is to make it stationary through an appropriate

differentiation process. After the ARIMA model parameters (p, d, q) have been successfully identified, the next step is to fit the model to the data that has been differentiated. The selection of parameters 'p' and 'q' is based on significant patterns of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). At the estimation stage, various model parameters are then calculated and evaluated. The final stage is a diagnostic test to test the model's suitability to the data. One of the tools used in this stage is the Akaike Information Criteria (AIC), developed by Akaike in 1979. AIC functions to select the best model by considering the balance between the level of model complexity and the level of suitability to the data.

In the final stage of ARIMA modelling, a diagnostic test is performed to assess the suitability of the model to the data. One method used is the Akaike Information Criteria (AIC), which was introduced by Akaike in 1979. AIC is calculated using the formula:

$$AIC = -2 \log L + 2n \quad (4)$$

L is the likelihood function, and n is the number of parameters estimated from the model. In addition to AIC, another alternative often used is the Schwarz-Bayesian Information Criteria (SBIC), also known as the Bayesian Information Criteria (BIC), which was developed by Schwarz in 1978. The formula for SBIC is:

$$SBIC = -2 \log L + n \log T \quad (5)$$

Where T is the total nsumber of observations, the lower the AIC or SBIC value, the better the model fits the data. In addition to these two criteria, the coefficient of determination (R^2) is also used to evaluate the level of model fit. After the appropriate ARIMA model is successfully obtained, the next step is to test the goodness of fit through the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the model residuals. The results of this analysis are the basis for making accurate forecasts.

3 Results

3.1. Climate Change Indicator in Agriculture

Mapping using geo-map analysis in understanding the dynamics of climate change and its impact on a particular region, visually and measurably. The use of spatial data enables the description of the geographical distribution patterns and temporal trends that occur in a particular region. The results of the Southeast Asian geo-map mapping reveal significant variations in temperature increases and precipitation intensity between countries, especially for rice producers. Geographical conditions, urbanization levels, and proximity to sea masses are factors in changes in temperature and precipitation.

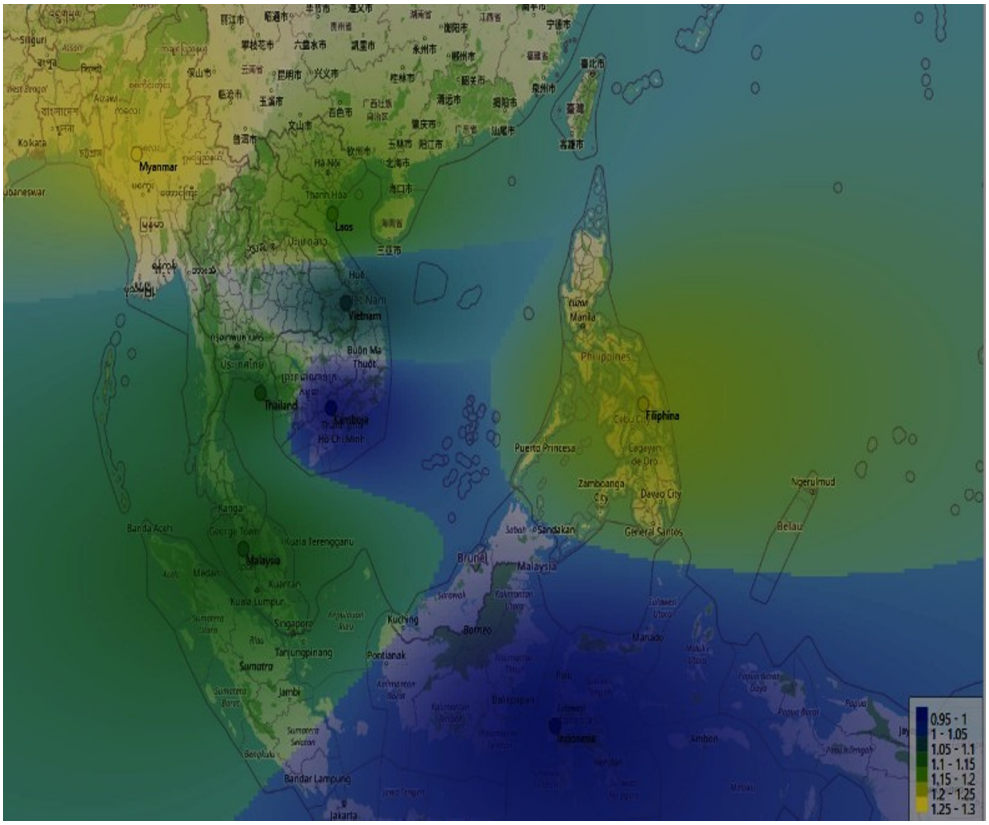

Fig. 1 Map of Average Temperature Rise

Fig. 1 explains that there has been an average temperature increase of around 1.12°C in Southeast Asian rice-producing countries over the past 11 years. Myanmar and the Philippines recorded the highest increase since 2012. The phenomenon of global warming comes from heat energy, which worsens climate phenomena. A country's activities in increasing economic activity with industrialization can increase greenhouse gas emissions and deforestation, leading to global warming. Meanwhile, Indonesia and Cambodia experienced a lower temperature increase, namely an average temperature of less than 1°. According to Chen [9], industrial activity and urbanization in a country are not evenly distributed, causing lower carbon emission intensity in aggregate than in other regions. Sun [10] explain that regional phenomena such as El Nino, Monsoon, and wind circulation patterns affect temperature variations.

This increase in temperature is a real indicator of the impact of climate change that is starting to be felt in the agricultural sector, especially in rice cultivation, which is highly dependent on climate stability. The increase in temperature has an impact on reducing rice plant productivity. High temperatures can disrupt the flowering and grain filling process of rice and cause crop failure. Extreme temperature changes can worsen drought and disrupt precipitation, which is a basic need for rice field irrigation in the agricultural sector.

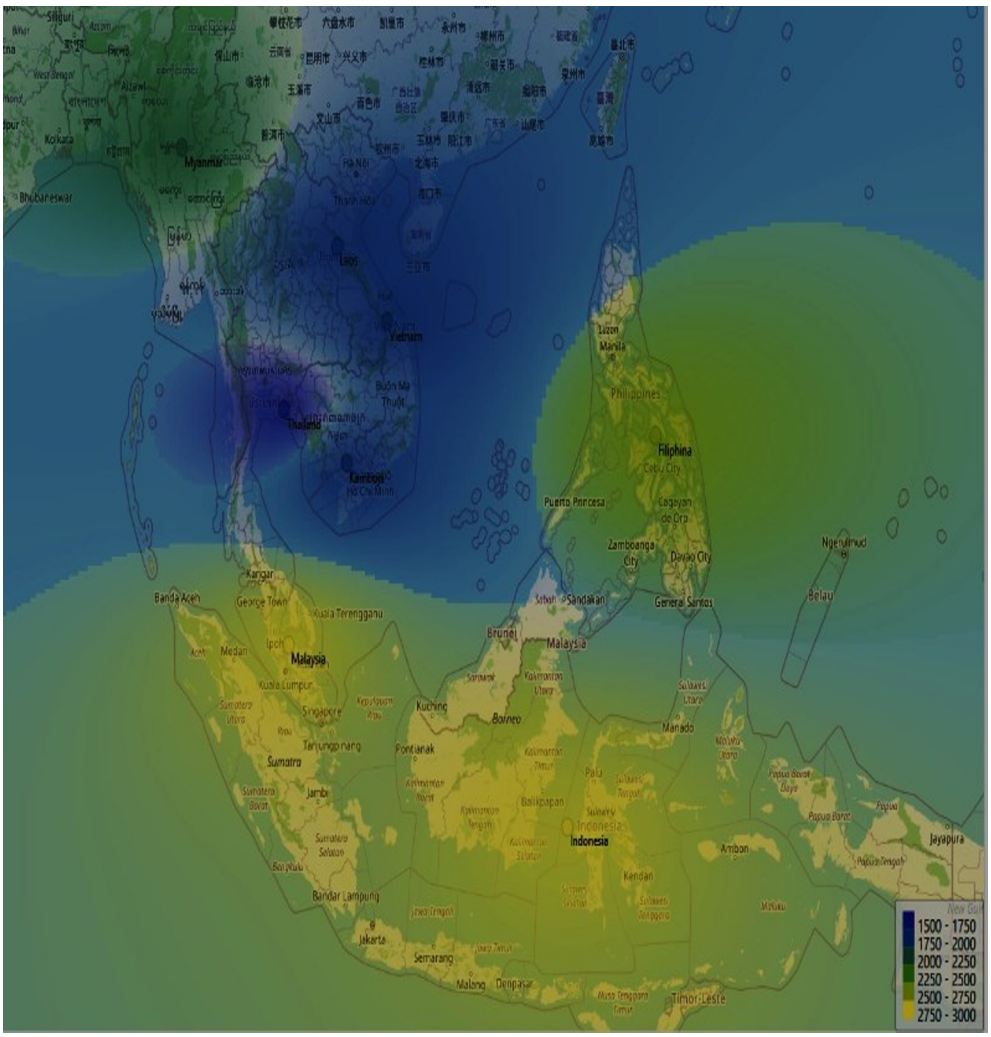

Fig. 2 Map of Average Precipitation

Fig. 2 shows the annual precipitation levels in several major rice-producing countries in Southeast Asia. The more yellow the colour, the higher the precipitation in the country, including Malaysia and Indonesia, with an average of 2750-3000 mm/year. Countries with high precipitation levels generally have a humid tropical climate, which is very supportive of rice-focused farming systems. However, the bluer the colour on the map, the lower the average precipitation in the country. Thailand has the lowest precipitation at 1500-1750 mm/year. Low precipitation conditions can be a challenge in themselves to ensure the availability of water for irrigation needed for rice farming. A lot of rain will not always bring goodness to farmers, but too much precipitation will cause crop failure. High precipitation results in flooding of crops, while low salinity has a significant impact on rice yield [11]. Precipitation variations are very important for planning agricultural strategies and efforts to adapt to climate change. Water availability can also affect rice productivity and have an impact on food security in each country. Good precipitation management in the irrigation process can support agriculture in the country.

3.2. ARIMA Analysis Results

The data provided shows large variations in rice production in Southeast Asia countries. Indonesia recorded an average rice production of 56.9 million tons, the highest figure in the region, followed by Vietnam, with an average production of around 41.6 million tons. The Philippines, with a figure of around 17.7 million tons, is in third place, while Malaysia and Thailand each have an average rice production of 282,734 tons and 32.8 million tons, respectively. Countries such as Cambodia and Myanmar also recorded quite large production figures, around 17.7 million tons and 28.5 million tons, respectively. With an average of 3.4 million tons, Laos has the lowest rice production, far below other countries. Some countries show a symmetrical distribution of data, such as Indonesia, with a median that is almost the same as the mean, while other countries, such as Thailand and Vietnam, show a distribution that is slightly skewed to the right or left, reflecting an imbalance in rice production. The significant variation in rice production can be seen from the high standard deviations in some countries, such as the Philippines and Indonesia, which indicate substantial fluctuations in production output.

Tabel 1. Statistic Analysis of Agricultural Production in Southeast Asian Countries

Country	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
Malaysia	282,734	304,055	100,795	113,700	451,981	-0.107	1.991
Philippines	17,700,000	18,100,000	1,624,696	14,600,000	20,000,000	-0.3812	1.925
Indonesia	56,900,000	56,500,000	2,527,731	54,000,000	61,000,000	0.1824	1.331
Thailand	32,800,000	32,400,000	2,871,732	27,700,000	38,100,000	0.3586	2.71
Cambodia	17,700,000	18,100,000	1,624,696	14,600,000	20,000,000	-0.3812	1.925
Myanmar	28,500,000	27,600,000	2,425,580	26,000,000	32,700,000	0.8012	2.039
Laos	3,395,424	3,492,050	492,745	2,568,000	4,148,800	-0.0761	2.027
Vietnam	41,600,000	42,800,000	3,177,283	35,800,000	45,100,000	-0.8437	2.268

Source: The data Analysis, 2025

Table 1 shows the descriptive statistical analysis, the results of rice agricultural production in Southeast Asian countries show significant variations both in terms of production volume and distribution. Indonesia is one of the countries with the highest rice production and has an average production of 56.9 million tons. The next countries are Vietnam and Thailand, each with an average rice agricultural production of 41.6 million tons and 32.8 million tons. Meanwhile, Laos has the lowest rice production, with an average of only 3.4 million tons, compared to other Southeast Asian countries. The distribution pattern of rice production data in these Southeast Asian countries also varies through the skewness value, showing a different distribution pattern. Countries such as Malaysia, Indonesia, and Thailand have a relatively symmetrical distribution, with skewness approaching zero, reflecting the stability of their rice production. Countries such as Vietnam show negative skewness, indicating a higher distribution tendency above the average but with more extreme spikes. Myanmar also shows a distribution that is skewed to the right with positive skewness, indicating greater fluctuations in production at the highest values. Several countries show a sharper or flatter distribution than the normal distribution in terms of kurtosis.

Thailand has the highest kurtosis (2.71), indicating that there are some extreme values at the top of the rice production distribution. Meanwhile, countries with lower kurtosis include Indonesia (1.331) and Laos (2.027), which show a flatter distribution, with most of the data centered around the middle value and without significant production spikes. Overall, large

countries with large populations, such as Indonesia and Thailand, show stability in rice production. Meanwhile, smaller, developing countries with smaller populations, such as Indonesia and Thailand, as well as Laos and Myanmar, tend to experience greater fluctuations in their data distributions, reflecting the amount of fluctuation in production.

The results of the analysis have significant differences caused by various factors. Indonesia has the highest rice production, but also a large population, so food needs are high. Government policies must support the rice farming sector, such as subsidies for farmers and providing facilities for using more advanced technology in agricultural production. Vietnam and Thailand are also countries with high rice production and advanced agricultural sectors with better technology and infrastructure support than other countries. Laos is the country with the lowest rice production, which can be explained by its smaller population and lack of modern agricultural infrastructure. Laos relies more on subsistence farming, which causes its production results to be disproportionate to those of other countries that are more developed in the agricultural sector. Natural factors such as precipitation, temperature, soil quality, and climate in a country also affect agricultural output.

Table 2. Parameter estimates of ARIMA for production of rice in Southeast Asia

Country		Malaysia	Philippines	Indonesia	Thailand	Cambodia	Myanmar	Laos	Vietnam
Intercept	Coefficient	13.55	1.74	0.14	0.76	1.74	0.37	2.18	1.06
	Std. Err.	8.35	0.64	0.79	2.35	0.64	1.46	2.44	0.8
	z	1.62	2.73	0.18	0.32	2.73	0.25	0.89	1.32
	P>|z|	0.11	0.01	0.86	0.75	0.01	0.8	0.37	0.19
AR(1)	Coefficient	-0.41	0.06	-0.41	0.01	0.06	0.29	0.01	0.08
	Std. Err.	0.28	0.21	0.36	0.44	0.21	0.29	0.42	0.42
	z	-1.48	0.28	-1.13	0.03	0.28	1.01	0.03	0.19
	P>|z|	0.14	0.78	0.26	0.98	0.78	0.31	0.98	0.85
AR(2)	Coefficient	-0.24	-0.51	-0.32	-0.26	-0.51	-0.08	0.2	-0.03
	Std. Err.	0.39	0.21	0.25	0.68	0.21	0.46	0.25	0.39
	z	-0.61	-2.37	-1.3	-0.38	-2.37	-0.18	0.81	-0.07
	P>|z|	0.54	0.02	0.2	0.71	0.02	0.86	0.42	0.95
	Sigma	45.29	3.45	3.77	7.69	3.45	4.94	6.31	2.92
	Std. Err.	7.77	1.17	0.61	2.02	1.17	0.77	1.11	0.54
	z	5.83	2.95	6.13	3.81	2.95	6.45	5.68	5.45
	P>|z|	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The intercept coefficient of the Philippines is 1.74, indicating a significant effect on the level of rice production with a p-value of 0.01. The AR (2) coefficient is also significant with a p-value of 0.02, indicating that rice production in the Philippines is influenced by past data, especially in the second lag. This shows that fluctuations in rice production in the Philippines have a strong relationship with output in the previous two periods. The intercept coefficient of Cambodia is also significant with a p-value of 0.01, indicating a relatively stable base level of rice production. In addition, the AR (2) coefficient is also significant (p-value 0.02), indicating a significant effect of the previous period on rice production.

Meanwhile, Vietnam shows a moderate level of variability in rice production with a significant sigma (p-value 0.00). Although the other coefficients are not significant, this

indicates that even though external factors influence Vietnam's rice production, it has more control over fluctuations. The Philippines has many insignificant coefficients but shows quite large variability in rice production with a significant sigma (p-value 0.00).

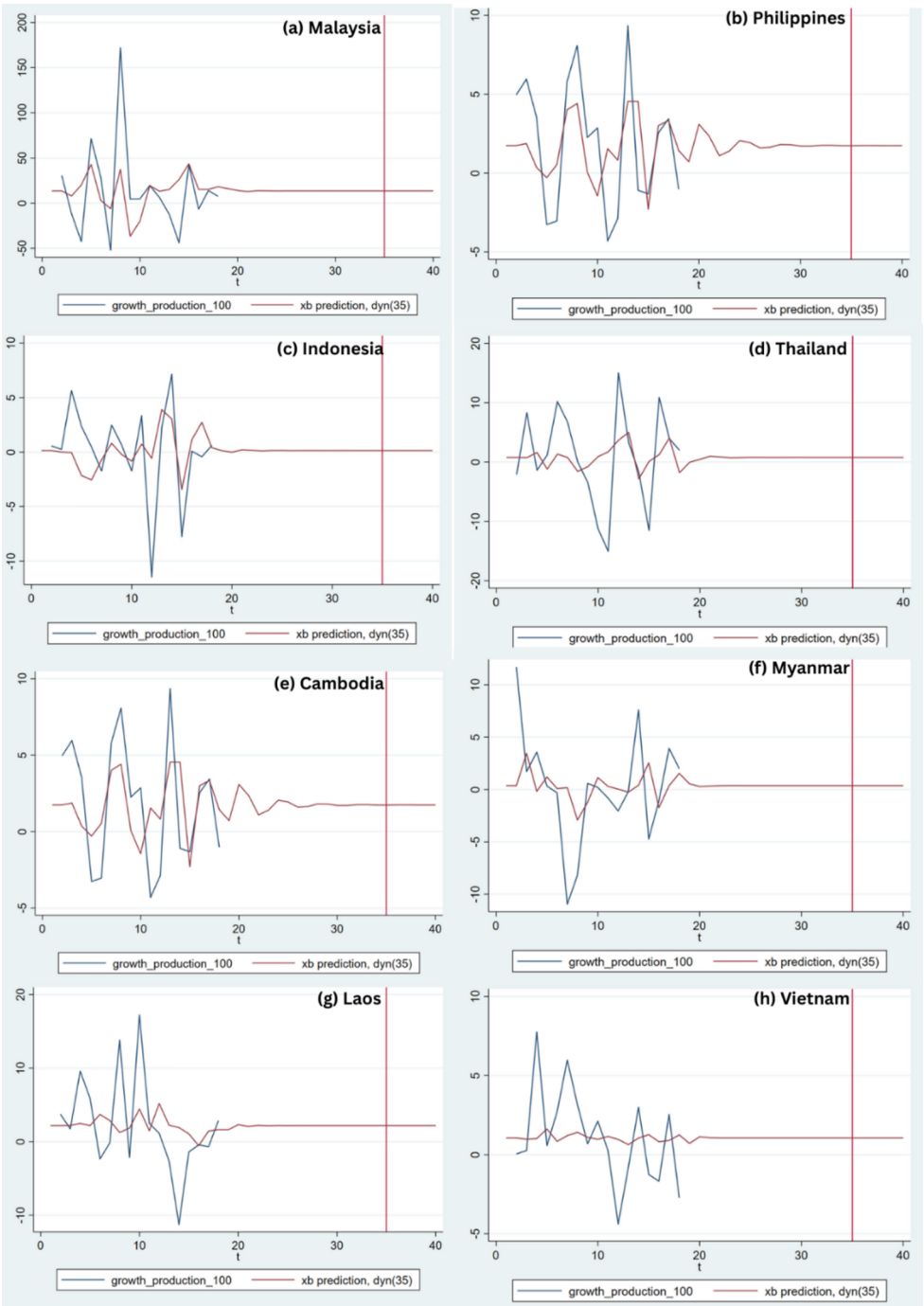

Fig. 3 Prediction of ARIMA for the production of rice in Southeast Asia

Malaysia is shown in Fig. 3a, where the actual data shows sharp fluctuations, especially at time points around 10, which the ARIMA model cannot capture. However, the model follows the general trend quite well after that period. Similarly, Cambodia (fig. 3e), where the model does not predict the extreme spikes at certain time points, indicates the model's limitations in capturing large fluctuations in rice production. The Philippines (Fig. 3b) shows minor variations in the actual data, and the ARIMA model predictions are closer to the data pattern. However, there are still differences in fluctuations at some time points. Indonesia (Fig. 3c) shows smoother variations, with the model able to follow the overall trend of the data, although there are some differences in extreme spikes. In Thailand (Fig. 3d), the ARIMA model predictions follow the data pattern better than the other countries, although there are still differences in larger fluctuations at certain time points. Myanmar (Fig. 3f) shows larger fluctuations in the actual data, but the model predictions remain flatter and fail to capture the large spikes in the data.

Meanwhile, in Laos (Fig. 3g), the actual data shows smaller variations, and the ARIMA model predictions are closer to the actual data. However, there are small fluctuations that the model cannot perfectly predict. Vietnam (Fig. 3h), with large fluctuations in the data, shows a clear difference between the actual data and the model predictions, especially at time points around 5 and 10, where the model cannot capture the extreme fluctuations that occur. Although the ARIMA model successfully describes the long-term trend in most countries, its inability to capture extreme fluctuations suggests that other factors not captured by the model may be affecting rice production in these countries.

4 Discussion

Temperature and precipitation play a crucial role in determining rice productivity in Southeast Asian countries. [12] said that several countries experienced significant average temperature increases. Temperatures have increased significantly over the past decade, such as in Myanmar and the Philippines. Increasing temperatures have the potential to disrupt rice productivity because they increase the rate of evaporation and cause heat stress. Temperature fluctuations in a country have exacerbated the occurrence of extreme hot and cold weather events that can disrupt the agricultural sector during the growing period, which has become a serious challenge for agriculture. Meanwhile, precipitation that is too high, such as in Malaysia and Indonesia, can cause water saturation, flooding, and physiological disorders in plants. The imbalance between temperature and precipitation is reflected in the results of the ARIMA model, which shows high fluctuations and instability in productivity, especially in countries with extreme climate stress.

The results of the analysis using the ARIMA model on rice production data in Southeast Asia countries show extreme fluctuations for long-term extreme fluctuations. In Malaysia, Cambodia, and Vietnam, the ARIMA model has not been able to predict sharp spikes caused by external factors such as natural disasters, climate change, sudden agricultural policies, commodity price fluctuations, or political instability. However, in Thailand and Laos, with relatively stable data, the ARIMA model shows a trend that is in line with the research of [13], which shows that ARIMA is more suitable for data with seasonal patterns or trends without major fluctuations. Large fluctuations in Malaysian and Vietnamese data indicate that high temperatures and changes in precipitation patterns characterize extreme events such as climate change. According to [14] the productivity and responsiveness of the agricultural sector to climate change can be boosted through their cognition, agrarian policies, social networks, and technologies for food security.

Problems that occur unexpectedly, such as floods and droughts, can affect rice production and cannot be predicted using historical data models. Other problems that cannot be predicted are changes in policies in the agricultural sector, such as subsidies, export policies, political

instability, changes in fertilizer prices, or supply disruptions that add uncertainty to predictions. These phenomena can affect production costs or market demand, which can affect agricultural output. Good agricultural techniques can enhance plant growth and agricultural productivity while also promoting a healthier soil ecosystem by stimulating microbial activity [15].

5 Conclusion

The ARIMA prediction results explain the imbalance between temperature and precipitation, which indicates high productivity variation in countries experiencing extreme climate stress. Meanwhile, the ARIMA model can better represent productivity trends in countries with more stable temperatures and precipitation, such as Thailand and Laos. Therefore, the ARIMA prediction results suggest that climate change, particularly in relation to temperature and precipitation, plays a significant role in the long-term dynamics of rice production and should be considered in the formulation of food security strategies in Southeast Asia. Strengthening climate adaptation programs should be a primary focus, including the development of heat- and drought-resistant rice varieties, as well as the implementation of environmentally friendly agricultural technologies and precision irrigation tailored to local conditions. Regional collaboration, particularly in Asia, should foster a strong region with adaptation technologies and shared strategies to prepare for disruptions to food security.

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