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Oil Palm Production in the 20th Century and Beyond: The Impact of Climate Change in Malaysia

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ABSTRACT

The widespread concern about the devastating impact of climate change, especially in the agricultural sector, has become severe. This paper aims to explore and predict the impact of climate change on oil palm production using future climate conditions projected by the National Water Research Institute of Malaysia (NAHRIM). An error correction model (ECM) and autoregressive distributed lags (ARDL) cointegration approach were applied to assess the short-run and long-run impact of climate change on oil palm production. The estimated short-run coefficients disclosed that the oil palm own price and fertilizer use positively affected oil palm production in the second lag period, and increased acreage benefited oil palm production in the long run. The rainfall variable negatively affected the second lag period but positively rose oil palm production in the long run. The results of forecasting analysis revealed that SN1 (minimum climate variability), SN2 (maximum climate variability), and SN3 (average climate variability) would increase oil palm production by 5%, 1%, and 2%, respectively. Meanwhile, the oil palm yield would rise from 16.73 t/ha in 2020 to 16.89 t/ha in 2030 under SN1. However, with maximum rainfall, the yield would drop to 16.41 t/ha in 2030. Overall, climate change would likely reduce oil palm yield. This research could serve as empirical guides for policymakers and oil palm stakeholders in terms of practical and policy implications to adapt to climate change-related risks and uncertainties. The practical cover investments in technologies, such as developing drought-tolerant and early-maturity crop varieties, boosting water saving, and reducing evapotranspiration.

Keywords: Oil palm; Climate change; Autoregressive distributed lags; Forecasting

INTRODUCTION

Climate change has impacted various economic sectors, primarily agriculture, since the end of the 20th century. Its impact on agriculture spans a wide range of attributes depending on the geographic location, specific climate scenarios, such as scale, frequency, and the significantly different outcomes among countries, regions and areas within a country (Global Climate Change Impacts in the United States, Karl, Melillo, & Peterson, 2009). Climate change can be caused by natural factors such as continental drift, volcanoes, ocean currents, and the earth's tilt (Alam, Chamhuri, Murad, & Toriman, 2011). Recently, the main causes of climate change are human activities in the agricultural sector, mass utilization of fossil fuels, industrial activities, transportation, and energy consumption.

In Southeast Asia, the common climate-related hazards are tropical hurricanes, floods, landslides, droughts, and sea-level rise (Malaysian Meteorological Department, 2009). In regard, Malaysia has experienced rapid climate change for decades, associated with heavy rainfall leading to flooding. It was estimated that around 9% of Malaysia was flood-prone, affecting 3.9 million people in the country (Jabatan Pengaliran dan Saliran Malaysia, 2018; Malaysian Meteorological Department, 2009; National Hydraulic Research Institute of Malaysia, 2006). The second significant hazard related to extreme climate change is drought caused by high temperatures, which was recorded in 1982, 1987, 1997 and 1997 (Khor et al., 2021). Accordingly, studies on the impact of climate change on agricultural production are essential because agriculture is closely linked to food security. Among the direct and indirect impacts associated with climate change in agriculture are physical damage, decreased productivity, an increase in the spread of pests and diseases, reduced quality of most food crops, reduced soil fertility, and threats to livestock (Raza et al., 2019).

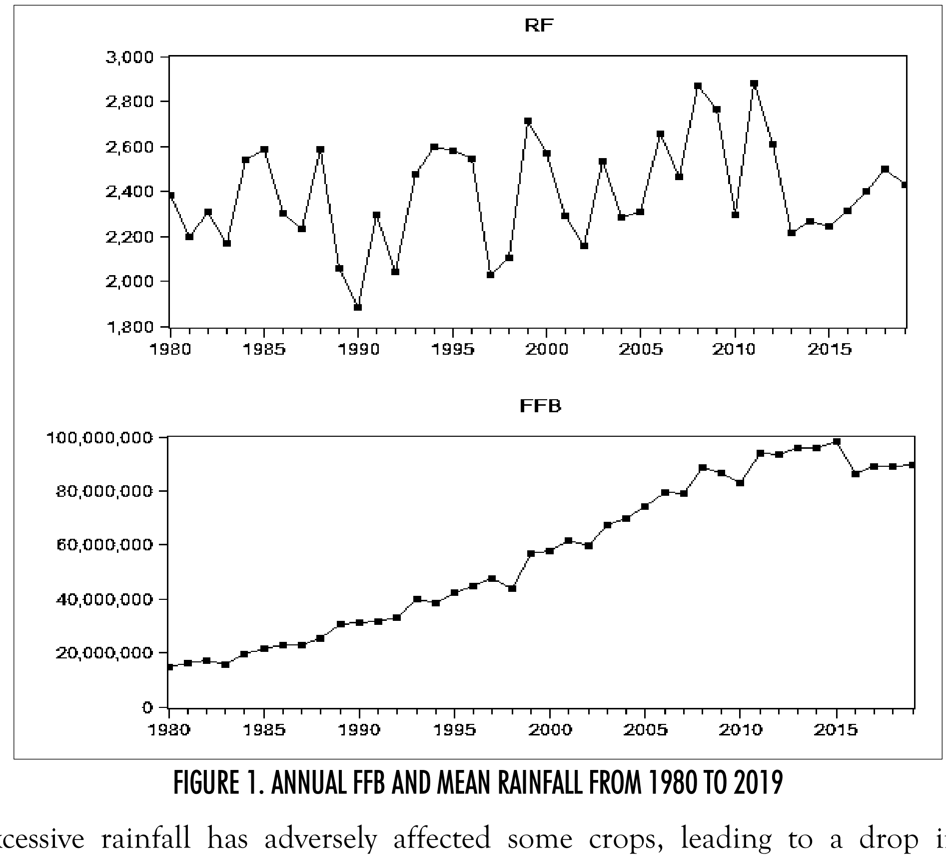

FIGURE 1. ANNUAL FFB AND MEAN RAINFALL FROM 1980 TO 2019

Excessive rainfall has adversely affected some crops, leading to a drop in rubber production due to loss of tapping days, possibly increased plant chlorosis, poor fruit set, and cherelle wilt. Diseases have infected cocoa crops (Thong, Goh, Leong, Nawi, & Yew, 1990), and it was estimated that a 1% rise in rainfall could cut current paddy yield by 0.12% (Alam, Siwar, Talib, & Toriman, 2014). Some crops, like oil palm, could endure high rainfall; however, excessive rainfall of more than 2,030 mm annually is unfavorable as yield is significantly affected (Paterson & Lima, 2018). Figure 1 displays the relationship between the annual fresh fruit bunch (FFB) yield and annual mean rainfall from 1980 until 2020.

The historical rainfall data demonstrate that the rainfall peaked at the end of 2004, 2006, 2008, and 2009, impacting the country's annual FFB yield in subsequent years (Kamil & Omar, 2017; Malaysian Meteorological Department, 2009). Prolonged water-logging could inhibit the respiration of oil palm roots, disrupt pollination, and reduce the mean of fruit bunch weight (Kamil & Omar, 2017; Khor et al., 2021). Production typically declines as heavy rainfall usually brings floods that could disrupt normal harvesting operations and damage roads, bridges, and palm oil processing equipment in low-lying oil palm areas. For instance, in December 2014, oil palm planted in Pahang, Terengganu, and Kelantan experienced rainfall exceeding 1,750 mm or 70 inches, equivalent to roughly 300–600% of the monthly average rainfall, causing significant localized flooding. Subsequently, the production of FFB drooped by approximately 500,000 tonnes from October 2014 until September 2015 compared to the previous year due to the decline in harvested crop yield (United States Department of Agriculture, 2015). A more detailed regional analysis of rainfall simulations of Providing Regional Climates for Impact Studies (PRECIS) released by the Malaysian Meteorological Department (MMD) has predicted a significant period of increased annual rainfall toward the century's end (2090-2099), with a higher rise in rainfall for product manager (PM) compared to engineering manager (EM). During 2050-2059, North-West PM recorded the highest increase in rainfall (6.4%), followed by North-East PM, while Sabah recorded a negative anomaly. The least rainfall increment was simulated in Sabah, with East Sabah recording negative anomalies during 2090-2099 compared to other regions in Malaysia, which recorded positive anomalies during the same period.

Thus, an enhanced understanding of the climate impact on crop production is necessary to cope with the expected climate variability and change. This study is crucial because the contribution of palm oil is highly significant to the Malaysian economy. Total exports of palm oil and other products derived from palm reached 24.72 million tonnes in 2022, rising 1.8% from the 24.28 million tonnes reported in 2021. As a result of higher pricing, the total export revenues grew by 27.1% to RM137.89 billion from RM108.52 billion in 2021 (Malayasian Palm Oil Board, 2023). The Department of Statistics Malaysia (DOSM) (2022) asserted that oil palm was the main contributor to the value added in agriculture, representing over 35.2.1%, followed by other agriculture, livestock, fishing, forestry and logging, and rubber, with the percentage contributions of 29.3%, 16.7%, 11.4%, 5.2%, and 2.3%, respectively in 2022. Palm oil production has surpassed other vegetable oils since 2004, a position previously held by soybeans (United Nations Development Programme China, 2020). Demand for this edible oil is related to the strength of economy and population growth, particularly in major importers, such as China and European countries. Furthermore, surging prices of crude oil along with growing concerns for global warming have led many countries to seek alternative energy from renewable resources. Among other renewable resources that are being researched, biodiesel has drawn a great deal of interest because of its similarity to conventional diesel (Ganjehkaviri, Mohd Jaafar, Hosseini, & Musthafa, 2016; Lam, Tan, Lee, & Mohamed, 2009;

Parveez et al., 2021). Biodiesel is made from renewable biological resources, such as rapeseed, soybean, and sunflower. The modification of palm oil could be utilized as palm diesel. Ganjehkaviri et al. (2016) highlight the fuel properties of palm diesel as practically identical to those of petroleum diesel and can be used directly in unmodified diesel engines. Approximately 80% of palm oil is consumed for food products and the rest for non-edible use, such as oleochemicals. The oleochemicals are believed to have thousands of uses in personal care products, detergents, lubricants, and agrochemicals (Kushairi et al., 2018; Malaysian Palm Oil Promotion Council, 2005).

Research disclosed that oil palm yielded an average of 3.5 tonnes per hectare per year, four times higher than rapeseed and about seven times more than soybeans (United Nations Development Programme China, 2020). In terms of comparative analysis, one tonne of palm oil could be produced from 2.2 hectares of soybeans, 1.5 hectares of sunflowers, 1.3 hectares of rapeseed, and only 0.3 hectares of oil palm (European Commission Report, 2019; Malaysian Palm Oil Promotion Council, 2020). Undoubtedly, oil palm cultivation can minimize the amount of land required to generate the same quantity of vegetable oils, thereby attracting the interest of other tropical nations seeking to generate profits from it.

The findings of this research hold multidimensional significance in the study area for oil palm stakeholders, government, educational institutions, and research organizations related to oil palm. It provides enormous benefits for farmers and oil palm stakeholders to adapt to these uncertain climate conditions. Farmers and oil palm stakeholders can take the initiative by planting genetically engineered superior varieties that can boost the trees' resistance to disease and withstand the effects of temperature and rainfall variability. These can be accomplished through intensive research and development conducted by educational institutions and oil palm research organizations.

Numerous specialized studies have been conducted to understand better how oil palm is affected by climate change. For instance, Ahmad, Chin, and Heng (2012), Kamil and Omar (2017), Khor et al. (2021), Paterson and Lima (2018), Shanmuganathan and Narayanan (2012) investigated the impact of climate change on oil palm growth and yield, as well as mitigation and adaptation strategies. Most scholars employed forecasting based on some simulation with a variety of assumptions. However, quantitative studies have also been performed, including (Zainal, Shamsudin, Mohamed, & Adam, 2012), unveiling the significant non-linear impact of climate change on oil palm net revenue based on the Ricardian approach. In econometrics, the Cobb-Douglas production function is among the popular approaches. It has several advantages, such as it is flexible to use the number of input variables to explore the effects of the production, the elasticity of substitution is unity, and the scale of economies can be estimated as restricted input coefficients that sum to one to reflect the type economy of scale.

The Cobb-Douglas production function was applied in this present research to examine the effects of climate change, along with other variables, on FFB production. Chizari, Mohamed, Shamsudin, and Seng (2017b, 2017a) and Sarkar, Begum, and Pereira (2020) are a few examples of earlier studies adopting a similar methodology to evaluate the effects of climate change. Sarkar et al.(2020) estimated the palm oil model using the OLS method and disclosed that raising the temperature by 1°C, 2°C, 3°C, or 4°C reduced oil palm production by 10.17%, 20.38%, 30.55%, and 40.73%, respectively. On the other hand, Chamhuri, Ahmed, and Begum (2013) projected that surface temperature would rise from 1.5°C to 2.0°C by 2050 and would cause palm oil production to drop to 30% if the temperature rises by 2°C above the optimum level and rainfall falls by 10%. Shrestha and Bhatta (2018) claimed that when all variables are stationary at the first difference, as in the case of the augmented dickey-fuller (ADF) results from the Sarkar et al.(2020), the adoption of the OLS method will result in biased and unreliable estimates. The use of the appropriate methodology for the time series data is the most critical element to avoid spurious regression.

Prior to this, Chizari et al. (2017b) investigated the economic impact of climate change on cocoa yield in Malaysia using the ARDL cointegration technique. The application of ARDL cointegration is advantageous when dealing with integrated variables with different orders, I(0) and I(1), or a combination of both, and robust when there is a single long-run relationship between the underlying variables in a small sample size (Nkoro & Uko, 2016). Chizari et al. (2017a) discovered that temperature was insignificant, while the rainfall variable had a negative effect on the first lag period of the short-run basis. Some quantitative research findings, including the production function approach, have produced inconsistent results, prompting this present study to be conducted to estimate the impact of climate change on oil palm production. This study has been enhanced by performing a stationary test prior to testing on the oil palm model and specifically to estimate the short-run and long-run impact of the variables associated with the climate variable and to predict the future impact of climate change on Malaysian oil palm production. This study also takes into consideration the non-linear relationship between the climate variable and oil palm production to address the knowledge gap.

RESEARCH METHOD

Study Area and Data

Malaysia is located between latitudes 4.2105°N and longitudes 101.9758°E, with a land area of about 131,598 km^2 across all 14 states. This study utilized annual time data spanning 39 years (from 1980 to 2018) from Peninsular Malaysia, Sabah, and Sarawak. Annual average rainfall (mm) was retrieved from the MMD website. The time series data related to forecasted rainfall were collected from NAHRIM using ECHAM 5A1B1 (Fifth Generation of the Coupled Atmospheric-Oceanic Global Climate Model of the European Center-Hamburg) scenario. Some data on oil palm yield and mature area of oil palm and fertilizer consumption were obtained from the DOSM website, the Malaysian Palm Oil Board (MPOB), and the Food and Agriculture Organization of the United Nations (FAOSTAT), respectively. The production function depicts a boundary representing the maximum amount of output that can be obtained from any possible combination of inputs. It can be expressed as Equation 1:

$$Y = f\,(PFFB, A, F, \ldots, Z) \tag{1}$$

Where *'f'* represents the functional relationship between yield, *Y*, and other factors affecting the production process, such as price variable (*PFFB*), planted area (*A*), fertilizer use (*F*), and so on. Yield variations are not only determined by economic conditions such as price variables, which are either contemporaneous or with short lags, but also by uncontrollable variables such as climate. Therefore, an essential climate variable rainfall was added to estimate the long-run and short-run models to achieve the objective of the study. An economic model was drawn from equation (1) by adding an intercept (α_0), disturbance variable (μ), and subscript (t) in each variable with the exception of intercept as follows:

$$FFB = \alpha 0 + \beta 1PFFBt + \beta 2At + \beta 3Ft + \beta 4RFt + \mu t \quad (2)$$

Equation (3) could be determined from equation (2) with the addition of natural logarithmic transformations applied to both dependent and independent variables. These transformations were applied to generate the desired linearity in parameters and to measure the elasticities of a Cobb-Douglas production function. The resulting oil palm production equation is written as follows:

$$In\ FFB = \alpha 0 + \beta 1InPFFBt + \beta 2InAt + \beta 3InFt + \beta 4InRF + \mu t \quad (3)$$

FFB denotes the FFB yield (tonne), *PFFB* signifies the FFB price (RM), A represents the mature area of oil palm (hectare), *F* indicates fertilizer use (tonne), and *RF* implies rainfall (millimeter).

Model Estimation

Several diagnostic tests were conducted during the estimation to prevent model misspecification errors in regression analysis. These diagnostic tests, crucial for measuring the reliability of the ARDL model, included the normality test (Jarque and Bera), the Breusch-Godfrey Serial Correlation LM test, the Breusch-Pagan Godfrey Heteroskedasticity test, the Regression Equation Specification Error Test (RESET), and model stability through Cumulative Sum of the Recursive Residual (CUSUM) and Cumulative Sum of Squared Recursive Residual (CUSUMSQ) tests.

It was necessary to establish a long-run equilibrium relationship among the variables, as referenced in the equations (Alam et al., 2011). In this regard, this study applied an ARDL Bounds test for cointegration. When dealing with variables with different integration orders, such as I(0) and I(1), or a combination of both, the ARDL cointegration approach, or bound cointegration testing technique, has been proven to be superior and robust for small data sets (Omoniyi & Olawale, 2015; Pesaran, Shin, & Smith, 2001; Verma, 2007). However, it should be noted that ARDL is not suitable for non-stationary variables of order two, I(2) (Haq & Larsson, 2016). This approach is particularly efficient in identifying long-term relationships with relatively small sample sizes ranging from 30 to 80 observations Narayan (2005) and Kwan, Tangang, and Juneng (2013), and it allows for the inclusion of dummy variables in integrated relationships. In this study, a maximum of two lags for yearly data was utilized to establish a cohesive model. The ARDL model was re-parameterized into an error correction term (ECM) to determine the short-run dynamics and long-run relationships of the underlying variables.

Model Validation

Model validation is essential to evaluate a model's prediction ability and improve its confidence. In model validation, the actual values are compared to the predicted values of the model. This present study employed two statistical forecasting evaluation criteria for model validation: root mean square error (RMSE) and Theil inequality coefficient (U-test). Both metrics are negatively oriented scores, meaning that the lower the values, the better. RMSE expresses an average model prediction error in units of the variable of interest, ranging from 0 to ∞ and is indifferent to the direction of errors.

Model Simulation

The simulation and forecasting techniques proposed by the Malaysian Agricultural Policy (MAgPa) were adopted in this study due to their suitability for estimating models with elasticity (Arshad et al., 2012). Three scenarios were employed to forecast the impact of climate change from 2020 to 2030, with the 2010 to 2018 data set as the base year, representing the current factors of oil palm production. The effect of climate change on oil palm production was stimulated using three types of climate variable projections of ECHAM (5A1B1) provided by NAHRIM: minimum scenario (SN1), maximum scenario (SN2), and average scenario (SN3), as displayed in Table 1.

TABLE 1. PREDICTION OF RAINFALL VARIABLE (SCENARIO)

Year	Rainfall (mm)		
	Minimum Scenario (SN1)	Maximum Scenario (SN2)	Average Scenario (SN3)
2020	1,230.8	1,508.1	1,369.4
2021	1,763.4	2,388.4	2,075.9
2022	1,644.4	2,034.3	1,839.4
2023	1,702.4	2,089.9	1,896.1
2024	1,279.2	1,836.6	1,557.9
2025	2,269.9	2,581.8	2,425.9
2026	1,643.1	2,123.6	1,883.3
2027	1,567.1	2,137.2	1,852.1
2028	1,334.5	1,955.0	1,644.8
2029	1,411.0	1,754.8	1,582.9
2030	1,425.3	1,842.2	1,633.7

Source: Estimated climate variable prediction by National Hydraulic Research Institute of Malaysia (2006)

RESULTS AND DISCUSSION

Estimated Model

The model was selected based on the basis of Schwartz's Bayesian criterion (SBC) and Akaike's information criterion (AIC). A unit root test was conducted using the Augmented

Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to determine the stationarity of the data, as exhibited in Table 2.

TABLE 2. ADF AND PP UNIT ROOT TEST

Variable	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)	
	Level	First Difference	Level	First Difference
lnFFB	-2.652	-8.271***	5.612***	-8.374***
lnPFFB	-0.506	-8.349***	-1.179	-9.008***
lnA	-5.812***	-4.727***	-7.245***	-5.147***
lnF	-2.930	-8.869***	-3.254**	-8.869***
lnRF	-3.313***	-6.932***	-3.235***	-8.635***

Notes: *** denote significance at 1%, respectively.

The results reported that mature area and rainfall were stationary at the 1% significant level, while the price of FFB was stationary after first differencing. The results of ADF and PP tests conflicted in determining the stationary status of FFB yield and fertilizer use; thus, further effort was made by plotting the correlogram function of FFB and F variables. The results confirmed that both variables were best treated as an I(I) variable. The combination of stationary and stationary and first-differenced data provided a basis for implementing the ARDL approach to cointegration. Meanwhile, Table 3 presents that F- statistics (5.474) is greater than F-tabulated at the 5% significant level based on Narayan (2005) critical values, providing a basis to proceed with the estimation of long-run basic.

TABLE 3. ARDL COINTEGRATION TEST

Bound test result	K	F-statistics	Narayan critical values	
			I(0)	I(1)
Equation 3	5	5.474**	2.86	4.01

Notes: *** denote significance at 1%, respectively.

Table 4 depicts the short-run and long-run coefficients of the oil palm model. The estimated coefficient for the residual, the error correction term with a one-period lag (ECT-1), indicates that the climate equation corrected the previous period's level of disequilibrium by 53.4%. The negative sign and statistical significance of the speed of adjustment provided evidence of the cointegrating relationship among the variables in the oil palm equation. The estimated equation was subjected to pass all diagnostic tests and appeared stable as CUSUM test statistics did not exceed the bound at a 5% level of significance.

The oil palm price was positively related, inelastic, and statistically significant at a lag of two periods, suggesting that the price variable affected oil palm production. It implies that a 1% increase in price over two periods would lead to a 0.11% increase in palm oil yield. The positive sign for the estimated price coefficient aligns with production theory, and the inelastic result unveiled that oil palm, being a perennial crop, took more than one period to respond to changes in its price positively. The fertilizer consumption at one lag and two lag periods positively impacted the production of FFB, as exhibited in Table 4. However, an inelastic coefficient of fertilizer variable appeared to highlight that most oil palm smallholders were less responsive to the use of sufficient fertilizer to acquire the desired result. It was due to the cost of fertilizer accounted for 35.09% of the total production cost of palm oil (Simeh, 2010).

TABLE 4. COEFFICIENT OF THE ESTIMATED SHORT-RUN AND LONG-RUN

Independent Variable		Coefficient	T-Statistics
Long-run model result			
InPFFB		-0134	-1.696
InA		1.176***	7.417***
InF		-0.059	-0.343
InRF		0.919***	3.778***
C		-2.122**	-2.549**
Short-run model result			
ΔInPFFB		-0.175***	-4.107
ΔInPFFB(-1)		0.112**	-2.728
ΔInA		-0.407	-1.033
ΔInF		0.194*	1.866
ΔInF(-1)		0.176*	1.757
ΔInRF		0.295***	3.494
ΔInRF(-1)		-0.199**	-2.299
ECT_{t-1}		-0.534***	-3.784
R^2	0.995	LM	1.036
Adjusted R^2	0.992	HET	17.435
DW	2.224	JB	1.407
F-Stat	434.095***	RESET	0.358

Notes: Values in parenthesis are the t-statistics;*, ** and ***denote significance at 10%, 5% and 1%, respectively.

The rainfall variable emerged as an essential climate variable, with a positively significant effect at one lag period, implying the effects of time lag between the availability of rainwater and the phonological response of the oil palm plant. Sing (1992) discovered substantial positive correlations between oil palm yield and rainfall at a lag of 10-11 months before harvest, closely related to crucial periods of inflorescence abortion. In contrast, the short-run coefficient of rainfall was negatively significant at a lag of two periods, indicating a time lag effect on the oil palm plant's phenological response to rainfall. Sing (1992) also noted that a negative correlation at a lag of 14 months may indicate adverse effects of excessive rainfall on inflorescence development.

The long-run coefficient findings revealed a positive and statistically significant correlation between the mature area of oil palm and FFB production at the 1% significance level, signifying a substantial increase in oil palm production. Specifically, for every 1% expansion in a mature area, FFB production would rise by 1.18% in the long run, all else being equal. The elasticity of the mature area variable in relation to oil palm production has been attributed to the introduction and implementation of the National Agricultural Policy (NAP) in 1984. Furthermore, the rainfall variable contributed to an increase in FFB yield in the long run. A 1% rise in average annual rainfall would result in a 0.92% increase in FFB yield. These findings align with previous research by Unjan, Nissapa, and Chiarawipa (2017), which revealed that oil palm cultivation required more rainfall, more frequent rainy days, higher relative humidity, and a wider range of air temperatures compared to natural rubber in Nakhon Si Thammarat, Southern Thailand.

Validation and Simulation Results

The closeness and deviation of the estimation results and actual values were assessed using RMSE and U-test (Table 5). The results disclosed that the value of RMSE (0.0175) and the calculated value of the U-test (0.0011) were less than one, implying the very low and significant predictive errors associated with the estimated climate equation in tracking the actual data. Therefore, the results could be applied to ex-ante projections.

TABLE 5. MODEL EX-POST PREDICTION POWER (VALIDATION) TESTS

Economic Model	RMSE	U
Equation 3	0.0175	0.0011

All the simulation results were compared with the actual data, as exhibited in Figure 2. In Figure 2, the model demonstrates higher stability, evident from the small difference between the red line (simulation results) and the blue line (actual results). For out-of-sample validation purposes, the results of the endogenous variables were projected based on the actual values of exogenous variables.

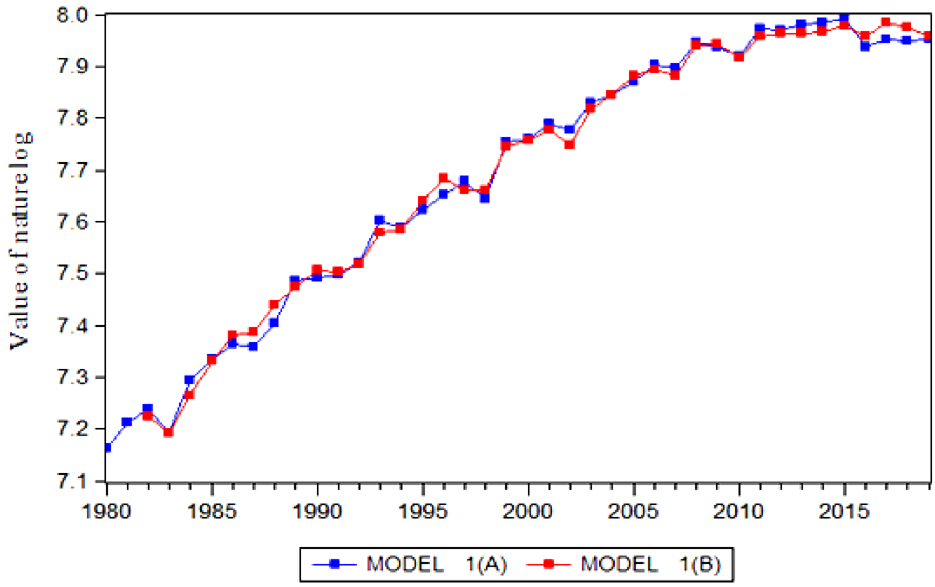

FIGURE 2. PREDICTIVE VALIDATION GRAPH
NOTE: (A) AND (B) DENOTE THE ACTUAL DATA AND SIMULATED DATA, RESPECTIVELY

Figure 3 illustrates the forecasting effect of climate change on FFB production for 2020-2030. The simulation results of SN1 unveiled that the rainfall variable positively affected FFB production under minimal rainfall conditions. The FFB yield would rise from 16.73 t/ha in 2020 to 16.89 t/ha in 2030. In contrast, under the SN2 scenario, including maximum rainfall and prolonged wet conditions, FFB yield was expected to decline from 16.73 in 2021 to 16.41 in 2030. The SN2 scenario revealed that maximum rainfall, coupled with extended wet conditions, could adversely affect pollination and fruit set, leading to a delayed impact on production.

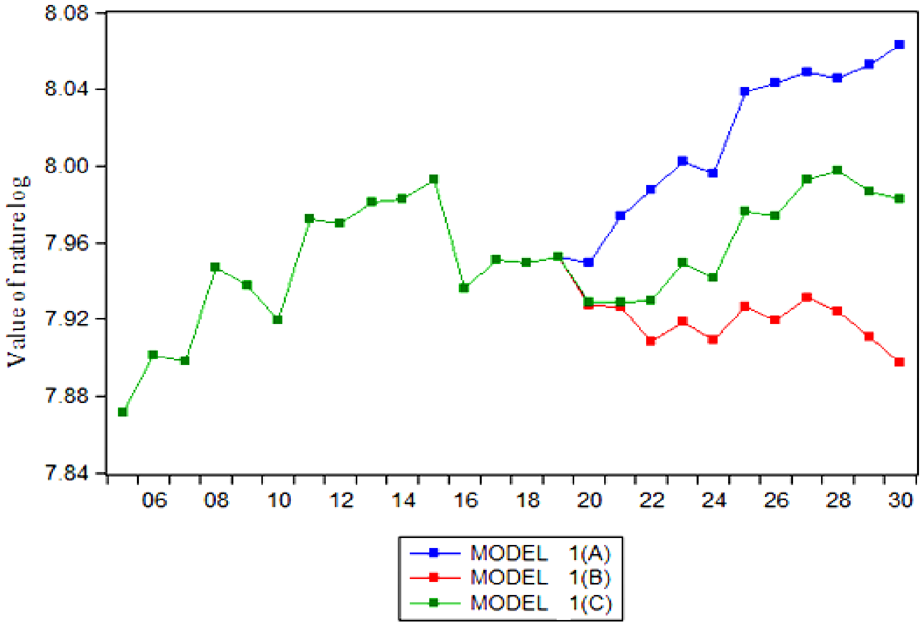

FIGURE 3. SN1, SN2 AND SNI3 EFFECTS
NOTE: (A), (B) AND (C) DENOTE THE SN1, SN2, AND SN 3, RESPECTIVELY

CONCLUSION

The estimated coefficients demonstrated that FFB production was positively influenced by the price of FFB and fertilizer use, while the rainfall variable negatively affected FFB production in the short run. The negative coefficient of rainfall indicated that an excess in maximum rainfall would lower FFB production for two lag periods. These findings align with the prediction results, indicating that SN1 (the minimum scenario) was more stable than other scenarios. It disclosed that oil palm required minimal rainfall to boost FFB production by an average of 1%. In other words, oil palm needed minimal rainfall to rise FFB yield from 16.73 t/ha in 2020 to 16.89 t/ha in 2030.

Conversely, under the SN2 scenario with maximum rainfall, FFB yield was projected to decline from 16.89 t/ha in 2020 to 16.41 t/ha in 2030, as excessive rainfall negatively impacted FFB production. In response to the outcome of this study, adaptation measures should be implemented, such as developing new varieties more tolerant to high rainfall, pests and diseases. Besides, studies on pollinator behavior, specificity and effectiveness, palm species, and other agronomic practices should be carried out in-depth for better management of pollination due to the changes in rainfall patterns altering the timings of phenological phases of oil palm insect pollinators.

The findings of this study have prompted a number of further investigations, including the application of supply response to other crops and agricultural-related activities, considering other climate indicators such as radiation, light duration, CO_2 concentration, humidity, and sea level. Moreover, the research could be extended to cover specific regions, such as Peninsular Malaysia, Sabah, and Sarawak, to produce more accurate results regarding climate change scenarios. In conclusion, this work provides valuable information that can either validate or refute past research findings. This information is useful for educational purposes and contributes to the growing body of literature, especially regarding the methodologies employed.

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Conflict of interest: The authors declare that there is no conflict of interest regarding the publication of this article.

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