Unraveling the Impact of Climate Change on Food Security in Malaysia: Insights from Vector Error Correction Modeling

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ABSTRACT

This study examines the influence of climate variables on paddy production in Malaysia, focusing on historical data from 1980 to 2016. The employed methodology incorporates Multiple Linear Regression (MLR) to identify the critical predictors, Johansen cointegration tests to explore the long-term relationships, and Vector Error Correction Models (VECMs) alongside Granger causality tests to analyze the dynamic interactions among variables. The performed analysis reveals consistent patterns in mean rainy days and rainfall amounts, indicating a relatively stable climate. In contrast, mean 24-hour temperatures show an upward trend, while mean 24-hour relative humidity exhibits a decline. The findings identify the mean rainfall amount and 24-hour relative humidity as significant predictors of the paddy production. The advanced analytical techniques confirm two long-term cointegrating relationships among the variables. Granger causality tests reveal a bidirectional relationship between the mean rainfall amount and paddy production, suggesting mutual predictability. Conversely, the mean 24-hour relative humidity exhibited a unidirectional relationship, predicting paddy production but not vice versa. These findings underscore the critical role of climate variables, particularly rainfall and humidity, in shaping the paddy cultivation outcomes in Malaysia.

Keywords-Vector Error Correction Model (VECM); Multiple Linear Regression (MLR); climate change; food security; Granger causality

I. INTRODUCTION

Urbanization is a global trend despite the lack of sufficient attention devoted to its environmental consequences. The repercussions of climate change on agriculture are profound [1]. In Malaysia, rice constitutes a staple food, underscoring the heightened concern regarding the sensitivity of plants, particularly to elevated temperatures [2-3]. In recent years, Malaysia has experienced erratic weather patterns, characterized by unexpected droughts and protracted rainy spells. This has had a significant impact on the nation's food security and agricultural sector. Notably, Malaysia, despite its abundant natural resources, expansive territory, and government initiatives, continues to grapple with the persistent challenge of food insecurity [4]. Consequently, the nation has been compelled to rely on food imports from other countries to ensure the nutritional well-being of its population. The precarious state of the agriculture sector, which is contingent upon favorable climatic conditions for fruitful crop production, renders Malaysia particularly vulnerable to the adverse effects of erratic weather patterns. Severe heat waves and sporadic downpours can cause significant damage to the agricultural industry, reducing crop productivity [5]. Consequently, the diminished productivity in the agricultural sector gives rise to a scarcity of raw materials, essential for food production. This predicament, in turn, engenders food insecurity, a condition that predominantly afflicts marginalized populations with constrained access to sustenance. This research examined the impact of climate change on food security. Mann Kendall and Sen's slope methods have been previously employed to assess the trends in temperature and precipitation in granary regions. In the Malaysian context and globally, authors in [6] examined the static interplay of food security, climate change, rice and paddy policy, and the sustainability of paddy farming. The availability of food is a critical component of sustainability, particularly in Malaysia, where approximately 33 million individuals heavily rely on rice as a staple food. The nation's rice imports, predominantly from Thailand and Myanmar, amount to millions of tons, underscoring its reliance on external sources to satisfy the domestic demand. The recent floods in Johor have exacerbated the challenges posed by the climate change, underscoring the need for an integrated research to ensure food security in variable climates. The employment of regression analysis holds considerable potential in elucidating variable relationships and facilitating the prediction of food production outcomes. For instance, authors in [7] studied the impact of climate change on agriculture in India, revealing the high sensitivity of the wheat yields to temperature increases. Authors in [8] examined the global food security from 2000 to 2014, using multivariate non-linear regression analysis of FAO data. Their findings indicated that temperature and GDP have a substantial impact on food security patterns.

The Vector Autoregressive (VAR) and VECM methods have been employed in numerous studies to examine the factors influencing food security and economic growth. Notably, authors in [9] identified population and the food production index as positive determinants of food security in Malaysia. Authors in [10] identified adverse effects of temperature, rainfall, and population growth on Nigeria's food availability. In a similar context, authors in [11] explored the relationship between the transport infrastructure and economic growth in India, discovering a mutual causality involving road transport and capital formation. Authors in [12] examined the housing market in Greece, establishing a correlation between the housing price index and macroeconomic factors, such as mortgage loans. Furthermore, authors in [13] highlighted the connections, on China's agricultural sector, between the food production, carbon emissions, and cereal yields. Conversely, authors in [6] found that the rising temperatures had a negative impact on paddy yields in Malaysia. The findings from the various studies reviewed indicate that the existing studies specifically concentrated on using static models, such as multiple linear/nonlinear regression, to predict food security based on climate variables. The majority of extant studies neglect to address the autocorrelation assumption, a crucial element in validating the applicability of static models. This methodological decision, however, imposes limitations on the dynamic implications of the relationship between food security and climate variables. Consequently, this study aims to address this knowledge gap by proposing a hybrid model that integrates static (backward selection multiple regression) and dynamic VECM models to elucidate the relationship between food security and climatic variables.

II. MATERIALS AND METHODS

A. Dataset

The present study uses data from two primary sources: the Food and Agriculture Organization (FAO) and the Institute of Climate Change at Universiti Kebangsaan Malaysia (UKM). The dataset under consideration spans a period of 37 years, from 1980 to 2016, and includes yearly time series data focused on climate variables and paddy production in Malaysia. The climate-related variables encompass the average daily rainfall, 24-hour temperature records, 24-hour relative humidity, and the mean number of wet days. These serve as independent variables in the analysis, with paddy production, a critical food security metric, designated as the dependent variable. This study builds upon prior research, including Aloui's exploration of the interplay between export, import, and economic growth from 1980 to 2013 and Alam's investigation into the effects of climate change on Malaysian paddy production [14-15]. The data's extensive temporal coverage and comprehensive variable inclusion render them particularly well-suited for the analysis of the relationships between the climatic factors and agricultural output. Employing MLR facilitates the estimation of the impact of the independent variables on annual paddy production.

B. Analysis Approach

1) Multiple Linear Regression Analysis

MLR is employed in this study to examine the relationship between the annual paddy production in Malaysia (dependent variable) and key climatic factors (independent variables) from 1980 to 2016. The independent variables encompass the mean number of wet days, mean rainfall, mean 24-hour temperature, and mean 24-hour relative humidity. The regression coefficients, denoted by β, are estimated by MLR to determine the linear relationship between the variables. The regression equation is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_p X_p \quad (1)$$

where Y is the dependent variable, β represents the regression coefficients, and X is the vector of the p independent variables. This technique has found widespread application across various disciplines for modeling and understanding variable interactions. The validity of the MLR model hinges on the assumption of normality in residuals, constant error variance, and minimal correlation among independent variables. Diagnostic tests, including residual plots, the Breusch-Pagan (BP) test, the Durbin-Watson test, and multicollinearity checks via the Variance Inflation Factor (VIF) and Tolerance (TOL), ensure model reliability. The presence of heteroscedasticity is evaluated through residuals versus fitted plots and the BP test, with a significance threshold of 0.05. Multicollinearity is identified when the VIF values exceed 10 or the TOL values are below 0.1, while autocorrelation is assessed using the Durbin-Watson statistic. These measures address potential violations of regression assumptions, ensuring robust insights into how climatic factors influence paddy production [16-21]. This comprehensive approach facilitates the accurate modeling of complex interactions and informs strategies for mitigating climate impacts on agriculture.

2) Vector Autoregressive Analysis

The VAR model is a statistical method that has been demonstrated to be powerful for the analysis of multivariate time series data. In contrast to univariate models, such as Autoregressive Integrated Moving Average (ARIMA), which are limited to a single variable, the VAR model is capable of capturing multiple interrelated time series, thereby facilitating the exploration of the relationships between the variables over time. The general VAR(p) model, which is employed in this study, involves n variables and p lags. The coefficients, lagged variables, and error terms are represented by matrices. Prior to implementing the VAR model, it is imperative to ascertain the stationarity of the time series. This is achieved by conducting rigorous tests, such as the Augmented Dickey-Fuller (ADF) test, which serves to identify the presence of a unit root. If the p-value from the ADF test is less than 0.05, the time series is deemed stationary. The model's lag order is determined using criteria, such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which identify the optimal lag by minimizing these metrics. In instances where the data are non-stationary, the Johansen cointegration test can be employed to assess the long-term relationships between the variables [22–26]. In instances where cointegration is established, a VECM, a constrained version of a VAR model, is employed to analyze both the short-term and long-term dynamics. The VECM equation incorporates the first difference operator and coefficients for time trends, lags, and errors, thereby capturing both the immediate and persistent influences among variables. The validity of the VECM model is validated through the implementation of diagnostic tests, including the Jarque-Bera normality test, the Breusch-Godfrey serial correlation LM test, and White's heteroscedasticity test. Specifically, the Jarque-Bera test assesses residual normality, the Breusch-Godfrey test detects autocorrelation in errors, and White's test identifies heteroscedasticity. In each instance, a p-value below 0.05 leads to the rejection of the null hypothesis, therefore indicating violations of the respective assumptions [27, 28]. These diagnostics ensure the robustness of the VAR or VECM models. The Granger causality test is a statistical tool that is used to determine whether one variable exerts a statistically significant influence on another. The test utilizes a comparison of the error sums of squares from restricted and unrestricted regressions to ascertain the presence of causality between variables. In the event that the test's F-statistic yields a p-value below 0.05, the null hypothesis of no causality is hence rejected, thus indicating a predictive relationship [29].

III. RESULTS AND DISCUSSION

Malaysia is a tropical country with a humid climate. The country's seasonal climate is characterized by distinct rainy and summer seasons. The observed climate patterns in Malaysia are of interest in the context of their potential impact on food security. Figure 1 presents the climate patterns observed in Malaysia from 1980 to 2016. Malaysia has exhibited a consistent mean number of rainy days from 1980 to 2016. The annual precipitation range is from 170 to 200 days. Conversely, the mean rainfall amount in Malaysia exhibits a slight upward trend. The least precipitation was documented in 1989 and 1990, with amounts of 2161 mm and 2150 mm, respectively. Conversely, the highest recorded rainfall was observed in 2008, with a total of approximately 3,200 mm. A similar trend was observed between 1999 and 2000, with higher levels of rainfall having been recorded during that period. This high record was believed to be related to a larger scale of the La Niña phenomenon [30]. The La Niña phenomenon is characterized by a significant climate pattern, distinguished by cooler than average sea surface temperatures in the central and eastern equatorial Pacific Ocean. This phenomenon is known to induce shifts in the atmospheric circulation patterns, consequently leading to alterations in the weather patterns, including an augmentation in rainfall [30].

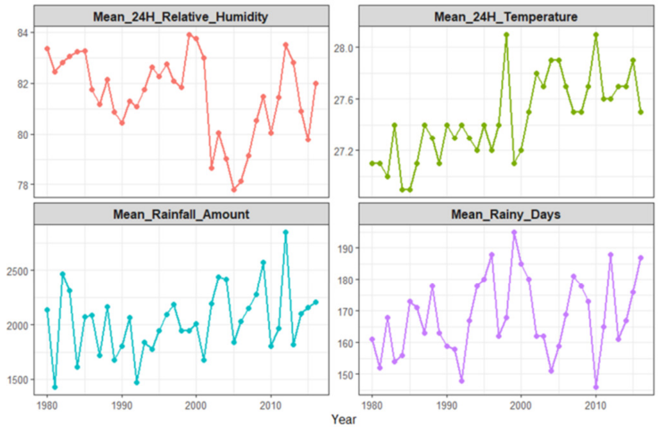

Fig. 1. Pattern of climate variables in Malaysia from 1980 to 2016.

There is an increasing trend in the mean temperature in Malaysia on an annual basis. The highest recorded temperature was 27.75 °C in 1998. A modest yet statistically significant increase of approximately 0.03 °C has been observed in the mean temperature from 1980 to 2016. This increase is believed to be attributable to the strong El Niño phenomenon that impacted Malaysia in 1998 [31]. Concurrently, Malaysia has experienced a decline in the humidity levels. This decline is attributed to deforestation activities [32]. Malaysia has allocated approximately 2.3 million hectares of forest for deforestation, which is a substantial area, as it encompasses more than 50% of the Malaysia's total forest cover [33].

A. Multiple Linear Regression Results

This study uses MLR to ascertain the critical factors influencing Malaysia's food security. The methodology employed encompasses a series of rigorous analytical procedures, including a thorough normality test, a meticulous model selection process, and a comprehensive diagnostic test. These rigorous procedures are employed to identify the critical factors underpinning Malaysia's food security. The optimal model created is summarized in Table I. The adjusted R-squared value of 0.6949 indicates that the variation in the dependent variable is explained by independent factors to the extent of 69.49%. The F-test, which is used to determine the linear association between the climate factors and paddy production, revealed a p-value of 0.0001, indicating a highly significant relationship. The statistical significance of each variable in the model is substantiated, and the model successfully attains the t-test criteria. The intercept value of the model signifies the predicted value of the independent variables, $X(s)$, when the values of such variables are set to zero. Consequently, when all independent variables in this study are set to zero, the high intercept value indicates the prediction value for the paddy production. The mean quantity of rainfall and the mean 24-hour relative humidity emerged as the significant variables affecting the paddy output, as indicated in Table I. Conversely, the mean 24-hour temperature and the mean number of wet days exhibited minimal influence on the paddy production, and were consequently excluded from the model. The variables were then subjected to a backward elimination procedure, a statistical method that involves the removal of variables one by one until the model's fit is optimized. The model underwent a diagnostic checking process to ensure its validity. As shown in Figure 2, the dependent variable was found to be normally distributed, as evidenced by its bell-shaped curve. Subsequently, the variables were integrated into a regression model. The q-q plot in Figure 3 suggests that the residuals closely follow a straight line, indicating a normal distribution. This finding is consistent with the underlying assumptions of normality. The residual versus the fitted plot demonstrates scattered points around zero without a discernible pattern, confirming equal variance and supporting homoscedasticity. The scale-location plot corroborates this, reinforcing the conclusion that the residuals satisfy the assumption of equal variance and do not violate heteroscedasticity. The BP test is a statistical procedure employed to assess the heteroscedasticity of residuals.

TABLE I. MULTIPLE LINEAR REGRESSION MODEL RESULTS

Coefficients	Estimate	*t*-value	*p*-value
Intercept	13517265.1	7.431	<0.0001
Mean rainfall amount	596.1	4.800	<0.0001
Mean 24 h relative humidity	-156115.2	-7.341	<0.0001
R-squared	0.7118		
Adjusted *R*-squared	0.6949		
Overall model significance *p*-value - *F*	<.0001		

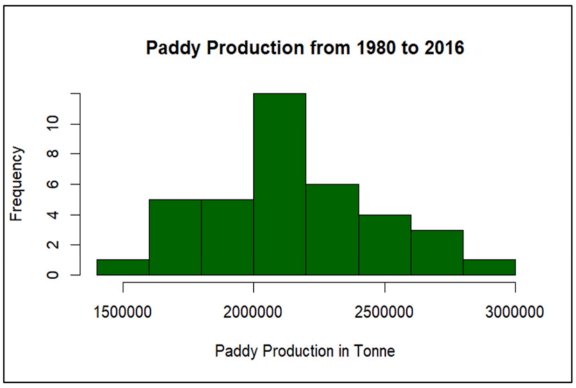

Fig. 2. Histogram of paddy production from 1980 to 2016.

As presented in Table II, given that the p-value exceeds 0.05, the BP test confirms that the residual errors are distributed with constant variance. Consequently, the null hypothesis, which posits that the errors possess a constant variance, cannot be rejected. Thus, the variability of error is presumed to be constant. The presence of a correlation between the independent variables in a statistical model is referred to as multicollinearity. The VIF and TOL measurements are used to identify multicollinearity.

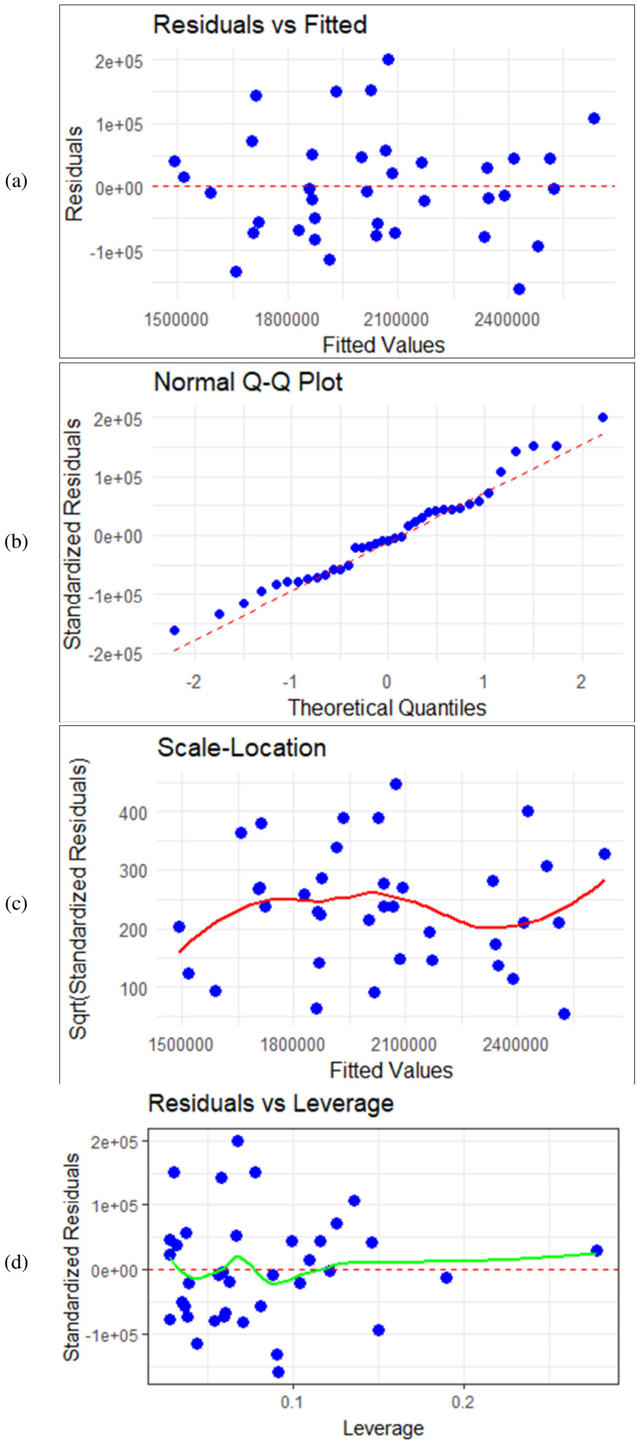

Fig. 3. Residual plots of best regression model: (a) residuals vs fitted values, (b) normal q-q plot, (c) scale-location, (d) residuals vs leverage.

As displayed in Table III the TOL values for both independent variables are approximately 1.0. Additionally, the VIF values for both variables are less than 10. These findings indicate the absence of multicollinearity among the independent variables. Consequently, the assumption of no multicollinearity is substantiated. Autocorrelation is defined as a condition in which there is a correlation between two errors. The Durbin-Watson test is a statistical method employed for the detection of autocorrelation. A model is deemed to possess autocorrelation if its p-value is less than 0.05.

TABLE II. BREUSCH-PAGAN TEST FOR TESTING THE RESIDUAL HOMOSCEDASTICITY OF THE CLIMATE AND PADDY OUTPUT MODEL

Test statistics	***p*-value**
3.8187	0.1482

TABLE III. TOL AND VIF VALUES FOR ASSESSING THE PRESENCE OF MULTICOLLINEARITY IN THE CLIMATE AND PADDY OUTPUT MODEL

Independent variables	**TOL**	**VIF**
Mean rainfall amount	0.99	1.01
Mean 24H relative humidity	0.99	1.01

As demonstrated in Table IV, the model exhibits autocorrelation, indicated by a p-value less than 0.05. This finding reveals the presence of a correlation between the errors. The presence of this phenomenon is attributed to the utilization of time series data in this study. The diagnostic test results suggest that the model fulfills the assumptions of normality, correlation among independent variables, and homoscedasticity. However, the assumption of autocorrelation is not met. When the dataset is small, MLR is a more suitable method for addressing autocorrelation compared to Feasible Generalized Least Squares (FGLS) and Heteroscedasticity and Autocorrelation Consistent (HAC) methods. While FGLS and HAC are conventionally employed to address autocorrelation issues, the limited size of the dataset in this study renders MLR a viable alternative, even in the presence of autocorrelation. Consequently, the finalized regression model is:

$$Paddy\ Production = 13517265.1 + 596.1 \times Mean\ Rainfall\ Amount - 156115.2 \times Mean\ 24H\ Relative\ Humidity \quad (2)$$

According to (2) a 1-mm increase in the mean rainfall is associated with an estimated increase of 596.1 tons in the paddy production. Conversely, a 1% rise in the mean 24-hour relative humidity is predicted to result in a 156,115.2-ton decrease in the paddy yield. Consequently, it can be deduced that an augmentation in the mean 24-hour relative humidity exerts a deleterious effect on the paddy production.

TABLE IV. DURBIN-WATSON TEST FOR AUTOCORRELATION

Test statistics	***p*-value**
0.685	< .0001

B. Vector Error Correction Model

After obtaining the significant variables from the MLR analysis, they are used to explore the relationship between the paddy production and climate data using the VECM method. The significant variables obtained from MLR are the mean rainfall and 24-hour relative humidity. The first step in the VECM method is to plot a time series of the variables. As presented in Figure 4, the paddy production in Malaysia shows an increasing trend from 1980 to 2016. For the climate variables, the mean rainfall in Malaysia displays a slightly increasing pattern. However, the humidity in Malaysia exhibits a decreasing pattern. From the graph, there are no seasonal patterns in the variables. The ADF test is used to test the stationarity of the paddy production in Malaysia and the climate variables. Table V shows the results of the unit root test on the variables.

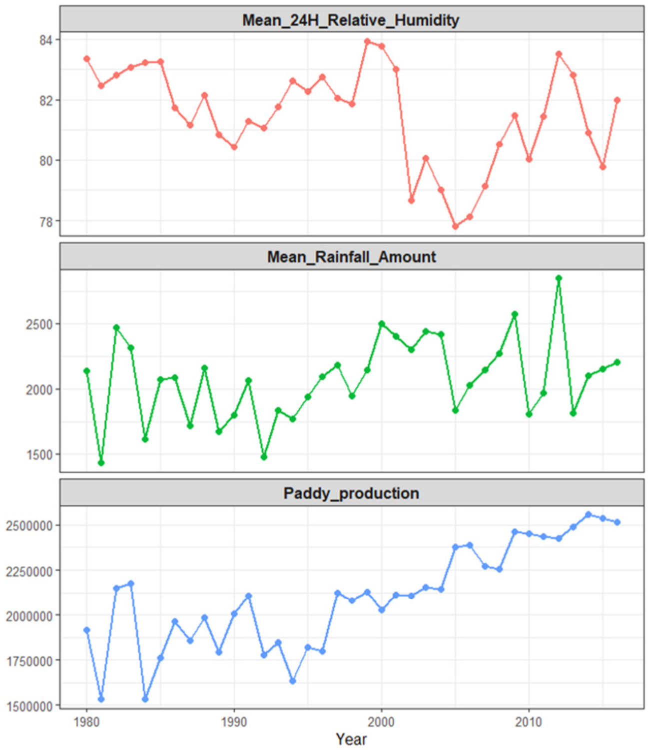

Fig. 4. Time series plot of paddy production and best climate variables.

The outcomes of the ADF unit root test for the variables at both levels, and the first difference forms are depicted in Table V. The mean 24-hour relative humidity and paddy production exhibit p-values above 0.05 in the level form, indicating non-stationarity and the presence of a unit root. However, the average amount of rainfall is stable, with a p-value less than 0.05. The application of the first difference form is predicated on the necessity of stationarity in all series prior to the execution of the Johansen cointegration test. The p-values of all variables in the first difference form are less than 0.05, thereby rejecting the null hypothesis of unit roots and indicating stationarity. The probability of a long-run relationship between the variables is high. The implementation of a cointegration test is necessary to investigate potential long-term correlations among the variables. Estimating the order of the VAR model allows for the selection of the ideal lag duration, which is determined using the AIC and BIC criteria. According to the optimal lag length criteria, a lag order of 7 is proposed. Consequently, this model will use a VAR order of 7. Following the establishment of the optimal lag length for the VAR model, the Johansen cointegration test will be conducted. The study employs a trace test to ascertain the cointegration relationship among the variables. The results presented in Table VI suggest the presence of two long-run cointegration relationships, hence indicating long-term relationships between the paddy production and climate variables. A long-run relationship is defined as a stable connection between two or more variables, under the condition that the variables fluctuate individually in the short run. However, if the variables exhibit stability in the short run, it is plausible to hypothesize a long-term relationship between them.

TABLE V. ADF TEST RESULT AT LEVEL AND FIRST DIFFERENCE

Variables	ADF test			
	At level		At first difference	
Paddy production	-0.0053 (0.9581)	Non-stationary	-6.8087 (0.000)	Stationary
Mean rainfall amount	-4.1448 (0.0008)	Stationary	-5.1013 (0.000)	Stationary
Mean 24H relative humidity	-2.2902 (0.1751)	Non-stationary	-7.0795 (0.000)	Stationary

number in paratheses indicates p-value at 5% significance level

TABLE VI. TRACE TEST RESULTS OF JOHANSEN COINTEGRATION

Hypothesis	Test statistics	5% critical value
$r = 0$	183.9	29.80
$r \leq 1$	28.23	15.49
$r \leq 2$	9.110	3.841

The presence of cointegration between the variables signifies the existence of at least one causal relationship between them. The VECM model is a suitable technique for estimation if the variables have one or more cointegrating relationships [34]. The number of lags employed in the VECM is equivalent to minus one of the numbers obtained in the VAR model. Consequently, in this study, the VECM lag is designated as 6. Equation (3) provides the coefficient of the long-run cointegrating equation between the paddy production, mean rainfall amount, and mean 24-hour relative humidity.

$$Paddy\ production = -0.0063 Mean\ Rainfall\ Amount - 0.00002035 Mean\ 24H\ Relative\ Humidity \quad (3)$$

Equation (3) demonstrates the long-term relationship between the climate variables and paddy yield. The findings indicate that both the average rainfall levels and 24-hour relative humidity exert a negative influence on the paddy production. Specifically, an increase of one unit in the average rainfall results in a decrease of 0.0063 tons in the paddy output, while a one-unit rise in the mean 24-hour relative humidity leads to a paddy output decline of 0.00002035 tons. The impact of rainfall on the paddy production is subject to variation, exhibiting both advantageous and harmful effects, contingent on the specific characteristics of the growing season and the crop's geographical location [34]. Conversely, an elevated rainfall accompanied by high rice production suggests that the water requirements for rice cultivation are being met. However, excess rainfall can precipitate natural disasters, such as floods, which can lead to crop failure. The deleterious impact of such natural disasters on the paddy production is well-documented. Paddy requires sufficient humidity to ensure an optimal rice yield. Insufficient or excessive humidity can result in waterlogged conditions, which can adversely impact the rice yield and quality. The optimal relative humidity for paddy cultivation is typically within the range of 60% to 80%. In contrast, humidity levels exceeding 85% have been observed to exert a deleterious effect on the paddy yield [35]. As indicated by the findings presented in Table VII, EC1 corresponds to the error correction term within the VECM model. The error correction term's coefficient is negative, and the p-value is less than the significance level of 0.05 at 0.001. This finding suggests the presence of a substantial long-term relationship between the climate variables and paddy productivity.

TABLE VII. LONG-RUN RELATIONSHIP OF CLIMATE VARIABLES ON PADDY PRODUCTION

ECT	Variable	Coefficient	Std. error	p-value
EC1	Paddy production	-3.3845	1.017	0.001

As shown in Table VIII, the climate variables exhibit a short-run relationship with the paddy production. Subsequent to the implementation of the VECM model, a diagnostic test is conducted to ascertain its reliability. The diagnostic test encompasses a series of critical evaluations, including tests of normality, heteroscedasticity, and correlation. As demonstrated in Table IX, the null hypothesis that the residuals are normally distributed can be rejected based on the p-value of 0.739 obtained from the Jarque-Bera normality test. This finding indicates that the residuals are most likely normally distributed, thus confirming the applicability of the VECM (6) to this investigation. The study employs a White test for heteroskedasticity. However, it is noteworthy that the p-value for the White test is more significant than 0.05, indicating that the errors are consistent. Consequently, the Breusch-Godfrey test is employed to identify potential correlations in the residuals. According to Table IX, the Breusch-Godfrey test has a p-value greater than 0.05, suggesting that the residuals are not correlated.

TABLE VIII. SHORT-RUN RELATIONSHIP BETWEEN PADDY PRODUCTION AND CLIMATE VARIABLES

Dependent variable	Independent variable	p-value
Paddy production	Mean rainfall amount	0.000
	Mean 24H relative humidity	0.011

TABLE IX. DIAGNOSTIC TESTS FOR VECM

Diagnostic Tests	Test Statistics	p-value
Jarque-Bera normality test	0.606	0.739
White test for heteroscedasticity	5.766	0.330
Breusch-Godfrey correlation test	3.169	0.787

C. Granger Causality Test

The Granger causality test is employed to discern the direction of the relationship between the variables. As illustrated in Table X, a bidirectional relationship is observed between the mean quantity of rainfall and paddy production in the near term. Furthermore, a bidirectional association is observed between the mean rainfall amount and the mean 24-hour relative humidity, while a unidirectional relationship is evident between the paddy productivity and the mean 24-hour relative humidity. The bidirectional relationship signifies that the past value of one variable can serve as useful information in predicting the future value of another variable. The bidirectional relationship between the mean rainfall amount and paddy production indicates that the past value of the mean rainfall amount can serve as a useful predictor of the paddy production, and conversely, the past value of the paddy production can be a valuable predictor of the mean rainfall amount. Conversely, the unidirectional relationship between the mean 24-hour relative humidity and paddy production signifies that only the mean 24-hour relative humidity is useful in predicting the paddy production, and not vice versa.

TABLE X. GRANGER CAUSALITY TEST RESULTS

	Paddy production	**Mean rainfall amount**	**Mean 24H relative humidity**
Paddy production	1.000	0.0223	0.0000
Mean rainfall amount	0.0003	1.000	0.0372
Mean 24H relative humidity	0.2157	0.0155	1.000

IV. CONCLUSIONS

This study investigates the interrelationships between the climate change variables and food security in Malaysia over the period from 1980 to 2016. To this end, it deploys hybrid static and dynamic modeling approaches. The analysis reveals consistent patterns in the rainfall metrics, signifying climate stability, while the mean 24-hour temperatures display an upward trend and the relative humidity shows a decline. The Multiple Linear Regression (MLR) analysis indicates that the mean rainfall amount and 24-hour relative humidity are pivotal factors affecting the paddy production. Furthermore, the Johansen cointegration tests substantiate two long-term associations between the variables. A further analysis using the Vector Error Correction Models (VECMs) and Granger causality tests highlights a bidirectional relationship between the paddy production and rainfall, suggesting mutual predictability, while the humidity demonstrates a unidirectional influence, solely predicting production. These findings are consistent with the conclusions drawn in [14] on the importance of causality and cointegration in understanding the economic relationships, and in [15] on the impacts of climatic changes on the paddy production in Malaysia. Collectively, these findings underscore the vital role of meticulous monitoring and management of the climatic variables, particularly rainfall and humidity, in fostering sustainable agricultural practices and bolstering food security in the region. The present study has several limitations. Firstly, it focuses solely on the climate variables and their effects on the paddy yield, overlooking other important factors, such as the land area and fertilizer usage. To achieve a more comprehensive understanding of the determinants of the paddy output, future research should incorporate these additional elements. An inclusive approach, one that incorporates a wider range of factors, would enhance the accuracy and value of the research. The analysis in this study is constrained by the use of data only up to 2016, which limits the study's ability to provide insights into recent trends. It is recommended that subsequent studies integrate the most recent data to comprehensively grasp the contemporary trends in climate change and paddy production, which is a necessity for ongoing research and decision-making. The findings of this study are expected to provide an in-depth understanding of the impact of the climate change on paddy production. The findings underscore the critical influences of the humidity and rainfall volume on the paddy yields. By leveraging this knowledge, pertinent authorities can assess and address specific climatic factors affecting yield, thereby enhancing the agricultural outcomes in Malaysia.

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