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The Effect of Energy Consumption in the Agricultural Sector on CO_2 Emissions in Malaysia

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ABSTRACT

The agriculture sector is one of the most important sectors and drivers of Malaysia's economic growth. It has become the backbone of the agro-based industry and provided many job opportunities to the community. The use of technology in agriculture affects CO_2 emissions through the use of energy sources. Therefore, this study is conducted to explore the effect of energy consumption in the agricultural sector on CO_2 emissions in Malaysia. Using annual data from 1981 to 2018 and the Autoregressive Distributed Lag (ARDL) method, results show that there is a negative relationship between energy consumption in the agricultural sector and CO_2 emissions in the long run. However, there is no relationship between energy consumption in the agricultural sector and CO_2 emissions in short run. Other than that, population growth and economic growth can affect CO_2 emissions in the short and long run. Therefore, the findings indicate that an increase in energy consumption in the agricultural sector can reduce CO_2 emissions. This situation is considered to be good for the environment. Therefore, the improvement of the agricultural sector can indirectly improve the environment as CO_2 emissions can be reduced.

1. INTRODUCTION

The agricultural sector plays an important role in determining economic growth [1] as it can increase income in rural areas, ensure food security, generate job opportunities, and increase society's well-being [2]. In 2019, the agricultural sector contributed 7.3% of Malaysia's total gross domestic product (GDP). In addition, palm oil contributed the largest share of total GDP from agriculture at 36.5%, followed by livestock and fisheries at 15.9% and 12.5%, respectively. Rubber, rice, fruits and vegetables are essential agricultural products. Large businesses cultivate commercial crops, including palm oil, rubber, and cocoa, while small businesses cultivate most food crops [3]. The government's plans and initiatives aim to increase yields and productivity while tackling several challenges such as price volatility, plant pests and disease, long-run fertilizer and pesticide usage, and aging farmers [4]. One of the most crucial inputs of agricultural production that must be addressed other than capital and labor is energy [5]–[7]. It is used in various ways, including manufacturing and transportation of fertilizers and pesticides [8]–[11].

The agricultural sector, especially agro-food, tends to face shortages of land, labor, input, and capital to supply more agricultural products. Therefore, without innovation and advanced technology, this sector will remain uncompetitive. Hence, the main goal of national agricultural policy is to progress technologically and sustainably increase productivity [12]. For the agricultural sector to cater to the needs of the growing population and fulfill other social and economic goals, energy supplies in the sector must be sufficient [13] because energy is vitally consumed to produce agricultural output. This implies that Malaysia's agricultural sector is extensively reliant on energy. This is supported by Islam *et al.* (2009), Bari *et al.* (2012), and Lean and Smyth (2014). They stated that the demand for energy in Malaysia had risen significantly over the past 30 years [14]–[16]. Furthermore, in 2018, energy consumption in the agricultural sector (including fishery) recorded the highest growth of 51.5% [17].

Energy consumption has rapidly increased in Malaysia's agricultural sector. However, it becomes more complexed when higher energy consumption can result in greater CO_2 emissions, thus affecting air quality and exposing people to several hazards, such as mental diseases and cancers [18]. CO_2 emissions account for the greatest share of total greenhouse gas and thus lead to global warming [43]. Therefore, the environment should be conserved by reducing energy consumption. However, reducing energy consumption may affect the agricultural sector. Therefore, it is imperative to investigate whether energy consumption significantly

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CO_2 emissions. If it does, this suggests that policies on energy should be formulated. Numerous previous studies have examined the relationship between energy consumption and CO_2 emissions [18]–[24]. However, studies investigating this relationship in the context of the agricultural sector in Malaysia are still limited. Hence, this study attempts to delve into the effect of energy consumption in the agricultural sector on CO_2 emissions in Malaysia. Figure 1 shows an upward trend in total CO_2 emissions in Malaysia over 27 years. CO_2 emissions dropped by 9.8% in 2009 due to an economic recession. CO_2 emissions increased again in the following year by 8.94%.

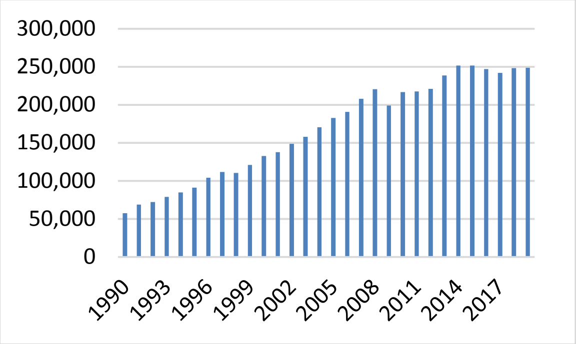

Fig. 1. Total CO_2 emissions (ktons).
Source: World Bank, 2021.

This paper is organized into five sections. The next section discusses previous literature related to the variables, while the following section outlines research methodology. The next section presents empirical analysis, and finally, the last section concludes the present study.

2. LITERATURE REVIEW

Many studies have previously investigated the impacts of energy consumption, economic growth, and population on CO_2 emissions in various countries. For example, Song *et al.* (2014) explored the impacts of GDP per capita and energy consumption on CO_2 emissions in Shadong Province, China. Data from 1995 to 2012 were collected and analyzed using the Logarithmic Mean Divisia Index (LMDI) method. Their model was based on the STRIPAT model, and the findings revealed that GDP per capita has the largest impact on CO_2 emissions compared to energy consumption intensity and structure. Population growth in the province was also found to affect CO_2 emissions [25] significantly. Sulaiman and Abdul-Rahim (2018) supported that population growth, economic growth and energy consumption can influence CO_2 emissions. However, their focus is on the impact of population growth on CO_2 emissions in Nigeria. They employed the autoregressive distributed lag (ARDL) approach and analyzed data from 1971-2000, 1971-2005, and 1971-2010 recursively [26]. However, Begum *et al.* (2015) found no association between population growth and CO_2 emissions in Malaysia. They also used the same method. Other variables (GDP per capita and energy consumption per capita) can significantly impact CO_2 emissions. [22].

Ameyaw and Yao (2018) proposed a new approach in their study to investigate the impact of economic growth on CO_2 emissions in West African countries. The results showed a unidirectional relationship running from economic growth and labor force to CO_2 emissions [27]. Tong *et al.* (2020) used a different method which was the bootstrap ARDL bound approach with structural breaks to achieve the same objective as other studies, but they focused on the E7 countries using data ranging from 1971 to 2014 except for Russia (1992–2014). Their findings suggested that energy consumption does Granger cause CO_2 emissions in the E7 countries except for Indonesia. Economic growth does Granger cause CO_2 emissions in Brazil, India, Mexico, and China [28]. Due to mixed findings by previous studies, Osobajo *et al.* (2020) examined whether energy consumption and economic growth can significantly affect CO_2 emissions. They employed the POLS method to analyze data from 1994 and 2013. Their findings supported that energy consumption and economic growth can be harmful to the environment [29].

Munir *et al.* (2020) reinvestigated the relationships between energy consumption, economic growth and CO_2 emissions in the ASEAN-5 countries. Data from 1980 to 2016 were analyzed by considering cross-sectional dependence (CD). Their model was derived from the environmental Kuznets curve (EKC). They found that economic growth can Granger cause CO_2 emissions in the ASEAN-5 countries except for Vietnam. Energy consumption can Granger cause economic growth in Singapore. A bidirectional relationship between economic growth and energy consumption was found only in the Philippines. The results also lent credence to the EKC hypothesis in the ASEAN-5 countries [30].

In comparison with those studies in question, Nain *et al.* (2020) investigated the impacts of electricity consumption as a proxy for energy consumption, rather than total energy use, on CO_2 emissions in India. The Toda–Yamamoto causality approach was adopted to analyze data from 1971 to 2011. Their results indicated that electricity consumption influences the economy and CO_2 emissions in India [31]. Valadkhani *et al.* (2019) extended into more energy types, such as oil, coal, gas, hydroelectric, *etc*. They employed a panel-breaking regression with four endogenously determined breakpoints to analyze data from 1965 to 2016 from 60 main polluting countries in the world. The results revealed that replacing oil and coal with gas can reduce CO_2 emissions in the highest-income countries. Besides, using more hydroelectricity instead of non-renewable energy in low-income countries is good to alleviate environmental degradation [32].

Islam *et al.* (2017) extended the aforementioned studies by adding poverty and forest area to their model. However, they focused on Malaysia, Indonesia, and Thailand by using panel co-integration and panel Granger causality. 20-year data were collected from 1991 to 2010 and analyzed. The results showed that there is a unidirectional relationship running from poverty to CO_2 emissions. The results also indicated no causal relationship between energy consumption and

CO_2 emissions and no causal relationship between GDP and CO_2 emissions. No significant linkage between forest areas and CO_2 emission was also found [33]. From a different perspective, Alsarayreh *et al.* (2020) investigated factors other than energy consumption and GDP, namely population growth, agriculture area, education level and urbanization. Their analysis of 25 EU countries was based on data from 2000 to 2019. The findings disclosed that population growth and urbanization can be detrimental to the environment. However, the average year of schooling does not have any impact on CO_2 emissions [34].

Shahzad *et al.* (2017) focused on open economies rather than closed economies, and thus trade openness and financial development were treated as potential factors in CO_2 emissions. The ARDL bounds testing approach was employed, and data from 1971–2011 were analyzed to see the impacts of trade openness and financial development on CO_2 emissions in Pakistan. Their findings revealed that increases in both variables can increase CO_2 emissions [35]. Hasanov *et al.* (2018) focused on oil-exporting countries and treated exports and imports separately as potential determinants of CO_2 emissions. Long-run estimations were made using Panel Dynamic Ordinary Least Squares (PDOLS), Panel Fully Modified Ordinary Least Square (PFMOLS), and Pooled Mean Group (PMG.). The results showed that exports and imports play an important role in determining CO_2 emissions [36]. Dogan and Aslan (2017) investigated economic growth and energy consumption as factors in CO_2 emissions and tourism. The study was conducted on the EU and candidate countries, employing heterogeneous panel estimation techniques with cross-sectional dependence. Based on data ranging from 1995 to 2011, their findings disclosed that energy consumption, economic growth, and tourism can affect CO_2 emissions [37].

So far, the effect of energy consumption in the agriculture on CO_2 emissions has not been previously investigated. Although the sector consumes a small share of total energy, an investigation into energy in the sector is still needed to reduce environmental degradation.

3. METHODOLOGY

This study uses time-series data for Malaysia from 1981 to 2018. The IPAT model is used in this study due to its advantages. From the model, we can understand the factors that affect the environment [18,38]. The factors consist of environmental impact (I), population growth (P), affluence (A) and technology (T). Therefore, the IPAT equation is as follows:

$$I = f(P, A, T) \tag{1}$$

To apply the IPAT model, some appropriate variables are used to achieve the objective of this study. The variables include carbon emission (CO_2), gross domestic product (GDP), energy consumption in the agriculture sector (E), and population growth (P). From the IPAT model, the STRIPAT model was developed. The equation is as follows:

$$I = \delta . P^{\alpha} . A^{\beta} . T^{\gamma} \tag{2}$$

Each variable has its own measurement, justification and definition. Table 1 describes the variables used in this study.

Table 1. Variable description.

Variable	IPAT Model	Definition/Proxy and Data Source	Unit Measurement
CO_2	Impact (I)	Total CO_2 emission	ktons
P	Population (P)	Population growth	%
GDP	Affluence (A)	Real gross domestic product per capita	Malaysian ringgits
E	Technology (T)	Total energy demand in the agriculture sector	ktoe

CO_2 emissions have been widely used by previous studies as a proxy for environmental degradation. This is because CO_2 are the primary driver of climate change. In comparison with other gasses, CO_2 emissions contribute the greatest share of the total greenhouse gasses. To examine the impact of energy consumption in the agricultural sector on CO_2 emissions, the Autoregressive Distributed Lag (ARDL) method will be used. The model specification is as follows:

$$\begin{aligned} \ln CO2_t = \beta_0 + \beta_1 \ln P_t + \beta_2 \ln GDP_t \\ + \beta_3 \ln E_t + \varepsilon_t \end{aligned} \tag{3}$$

where t is time, β0 to β3 are the coefficients, and ε is the error term. Prior to the ARDL test, statistical descriptive and unit root tests are performed. A root unit test is used to see the stationarity for all the variables [39]. The method used in the unit root test is Augmented Dickey-Fuller (ADF), involving level and first difference with and without trends.

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{a} \varphi_1 Y_{t-1} + \sum_{j=1}^{b} \theta_j \Delta Y_{t-1} + \varepsilon_t \tag{4}$$

whereas Δ represents the first difference, α, φ, θ are the coefficients, Y represents the variable. Based on the root unit test hypothesis, if the result shows no significance at level, then the null hypothesis is accepted, and vice versa. If the t-statistic value is less than the critical t-value, then the null hypothesis is accepted. This indicates that the variable is not stationary, and there is a unit root. In contrast, the alternative hypothesis is accepted if the t-statistic value is greater than the t-critical value. This indicates that the variable is stationary, and there is no unit root. If the variable is significant at the first difference, then the alternative hypothesis is accepted. The hypothesis for the root unit test is as follows:

H_0: $\beta = 0$, has a unit root (not stationary)
H_1: $\beta \neq 0$, no unit root (stationary)

In applying the ARDL approach, several tests are conducted: bound, long-run estimation, short-run estimation, diagnostic test and cumulative sum of recursive residuals (CUSUM) tests. The advantage of this method is that it can address the distributed lag problem in the model more efficiently [40]. Firstly, a bound test is conducted to examine the existence of a long-run relationship for Equation (3). If the F-statistic value obtained is significant at a certain level, then the model has a long-run relationship, and the following tests can be conducted [41]. If the F-statistic value is not significant, then the following tests cannot be performed. The F-statistic value should not fall between I(0) and I(1). The best result for the bound test is when the F-statistic value is higher than I (1). Then, we can infer that there is co-integration. The equation for the long-run relationship is as follows:

$$\Delta Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 X_{1t-1} + \beta_3 X_{2t-1} + \beta_4 X_{3t-1} + \beta_{5,i} \sum_{i=j}^{p} Y_{t-1} + \beta_{6,i} \sum_{i=1}^{q1} \Delta X_{1t-1} + \beta_{7,i} \sum_{i=1}^{q2} \Delta X_{2t-1} + \beta_{8,i} \sum_{i=1}^{q3} \Delta X_{3t-1} + \mu_t \tag{5}$$

where p, q1, q2, and q3 refer to parameters. The long-run hypothesis for this model is as follows:

H_0: $\beta_1 = \beta_2 = \beta_3 = 0$ (no long-run relationship)
H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq 0$ (long-run relationship exists)

Based on the long-run hypothesis, if the variable is not significant at a certain level, then the null hypothesis is accepted and vice versa. If the t-statistic value is less than the critical value, then the null hypothesis is accepted. This indicates that the long-run relationship between dependent and independent variables does not exist. If the t-statistic value is greater than the t-critical value, then the alternative hypothesis is accepted. This indicates that there is a long-run relationship. Next, the short-run estimation can be made, and the equation is as follows:

$$\Delta Y_t = \mu + \sum_{i-1}^{p} \sigma_1 \Delta Y_{t-i} + \sum_{j-1}^{q1} \vartheta_1 \Delta X_{1t-j} + \sum_{k-1}^{q2} \pi_1 \Delta X_{2t-k} + \sum_{m-1}^{q3} \tau_1 \Delta X_{3t-m} + \theta_1 ECT_{t-1} + \varepsilon_t \tag{6}$$

where σ, ϑ, π and τ are the coefficients in the short-run while θ is the speed of adjustment in the long-run. If the model has a long-run relationship, it takes a certain time to correct the long-run error. Therefore, the long-run error correction (ECT) is included in Equation (6). Next, diagnostic tests and CUSUM tests are conducted. The diagnostic tests are used to see the model's goodness in Equation 1. The CUSUM test is used to check the stability of the model. For diagnostic tests, if the probability values of heteroscedasticity, correlation of LM, Jarque-Bera and Ramsey RESET tests are insignificant, then the study model is good [42]. Besides, the model is stable if the CUSUM lines are within the 5% significant lines.

4. FINDINGS

This study aims to examine the effect of energy consumption in the agricultural sector on CO_2 emissions in Malaysia. Descriptive statistics summarize the data on the logs of CO_2 emissions, GDP, population growth, and energy consumption in the agricultural sector, in Table 2. Based on the table, lnCO_2 has the highest mean and median at 11.9575 and 12.0815, respectively. lnP has the lowest mean and median at 0.6727 and 0.6886, respectively. lnE has the largest difference between the maximum and minimum with a total of 2.852. lnP has the lowest difference between the maximum and minimum with a total of 0.7003.

Table 2. Descriptive statistic.

Items	lnCO_2	lnGDP	lnE	lnP
Mean	11.9575	10.2431	5.73126	0.67265
Median	12.0815	10.2384	5.84778	0.68857
Maximum	12.4362	10.6742	6.97915	1.00002
Minimum	11.1400	9.75497	4.12713	0.29975
Srd. Dev.	0.42275	0.25071	0.94064	0.24933
Skewness	-0.54339	-0.05899	-0.13090	-0.32201
Kurtosis	1.95768	2.16803	1.65562	1.66864
Jarque-Bera	2.64543	0.82378	2.18856	2.55183
Probability	0.26641	0.66240	0.33478	0.27918
Sum	334.810	286.806	160.475	18.8343
Sum Sq. Dev.	4.82531	1.69707	23.8899	1.67845
Observations	28	28	28	28

In time-series analyses, checking the stationarity of data is of utmost importance. Therefore, this study conducts a unit root test based on Augmented Dickey-Fuller, and the results are reported in Table 3. From the table, it can be learned that all the variables (lnCO_2, lnGDP, lnE and lnP) are not stationary at level but stationary at the first difference for intercept. This implies that they are integrated of order one, I(I). As for the intercept and trend, the results show that only lnP is stationary at both level and the first difference. The other variables, particularly $\ln CO_2$, lnGDP and lnE, are not stationary at level but stationary at the first difference. These findings suggest that the variables are mixed order of integration. According to the rule of thumb, if the variables are integrated of mixed order or order one, the ARDL approach can be employed.

Another modeling issue that must be dealt with is to examine co-integrated relationships. Hence, a bound test is performed, and the results are reported in Table 4. The F-statistic value is higher than the upper bound value at 1%. Therefore, the null hypothesis that there are no co-integrated relationships can be rejected. This means that the long-run and short-run relationships can be estimated.

Table 5 shows the results of the estimated long-run relationship using the restricted Error Correction Models (ECM). The findings reveal that lnE has a significant and negative effect on $\ln CO_2$ at a significant level of 5% in the long run. The coefficient value is 0.1453. This suggests that a 1% increase in energy consumption in the agricultural sector can result in a 0.15% decrease in CO_2 emissions in the long run. The Third National Agricultural Policy has helped Malaysia to boost the agriculture sector and conserve the environment. This policy focuses on sustainable development. Various rules, regulations and incentives have been introduced to ensure the development of environmentally friendly agriculture. lnGDP has a significant and positive effect on CO_2 emissions in the long run, with a significance level of 1%. The coefficient value is 3.6220, and this implies that a 1% increase in economic growth can cause CO_2 emissions to rise by 3.62% in the long run. lnP can also contribute to CO_2 emissions significantly and positively in the long run. The coefficient value is 2.3967. This means that a rise of 1% in population growth can contribute to a 2.40% increase in CO_2 emissions in the long run.

Table 3. Unit root test results.

Variable	Intercept		Intercept & Trend	
	Level	First Difference	Level	First Difference
$\ln CO_2$	-2.550 (0.112)	-4.312*** (0.002)	0.349 (0.998)	-5.092*** (0.001)
lnGDP	-0.409 (0.897)	-5.065*** (0.000)	-1.790 (0.689)	-4.993*** (0.001)
lnE	-1.489 (0.528)	-6.067*** (0.000)	-2.035 (0.563)	-6.024*** (0.000)
lnP	-1.359 (0.591)	-8.393*** (0.000)	-6.398*** (0.000)	-11.725*** (0.000)

*Note: Numbers in parentheses denote the probability, *** and ** denote the significance levels of 1% and 5%.*

Table 4. Bound test results.

F-statistic	7.6099***	
Maximum Lag	2	
Lag Order	(2, 1, 1, 2)	
Significance	Lower Bound	Upper Bound
10%	2.72	3.77
5%	3.23	4.35
1%	4.29	5.61

*Note: *** denotes the significance level of 1%.*

Table 5. Long-run estimation results.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
lnE	-0.145**	0.063**	-2.318**	0.029**
lnGDP	3.622***	0.739***	4.899***	0.000***
lnP	2.397**	0.920**	2.635**	0.014**
C	-25.857***	7.782***	-3.323***	0.003***

*Note: *** and ** denote the significance levels of 1% and 5%.*

The short-run results are shown in Table 6. From the table, it can be learnt that lnE does not have any significant effect on $\ln CO_2$ in the short run in Malaysia. This suggests that any change in energy consumption does not affect environmental degradation in the short run. According to Malaysia Energy Information Hub (2020), energy consumption in the agriculture sector accounted for the smallest share of the total energy consumed in 2018 at 2% only [17]. Hence, it does not have any impact on CO_2 emissions in the short run. Energy consumption in the industrial sector contributed the largest share of the total energy consumed in the same year at 29%. The results also show that lnGDP can have a significant and positive effect on $\ln CO_2$ in the short run. The coefficient value stands at 0.8846. This indicates that a 1% rise in economic growth can increase CO_2 emissions by 0.88% in the short run. The significant impact of economic growth on environmental degradation is attributed to the fact that Malaysia is extensively dependent on non-renewable energy consumption in generating its economic activity. According to the World Bank (2020), renewable energy consumption captured about 5.2% of the total energy consumption in 2015 [44]. This means that the country consumes more than 90% of non-renewable energy. lnP has a positive and significant relationship with $\ln CO_2$ with a coefficient value of 1.0150. This suggests that a 1% increase in population growth can contribute to a 1.01% increase in CO_2 emissions in the short run.

Table 7 shows the results of several diagnostic tests, including Serial Correlation, Heteroscedasticity, Jarque-Bera and Ramsey RESET. The findings indicate that the model does not suffer any diagnostic problems. Therefore, the findings of this study are reliable. The stability test using Cumulative Sum (CUSUM) was also performed, and the results are depicted in Figure 1. The CUSUM and CUSUM of Square graphs are plotted within the 5% significance lines. This suggests that the model is stable.

Table 6. Short-run estimation results.

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable
lnE	-0.0029	0.007	-0.423	0.676	lnE
lnGDP	0.885***	0.173***	5.110***	0.000***	lnGDP
lnP	1.015**	0.492**	2.065**	0.049**	lnP
ECT	-0.160**	0.066**	-2.430**	0.022**	ECT

*Note: *** and ** denote the significance levels of 1% and 5%.*

Table 7. Diagnostic test result.

Diagnostic Test	F-statistic	Prob.
Serial Correlation	0.5453	0.5867
Heteroscedasticity	0.2960	0.9694
Jarque-Bera	0.4386	0.8031
Ramsey RESET	1.2852	0.2677

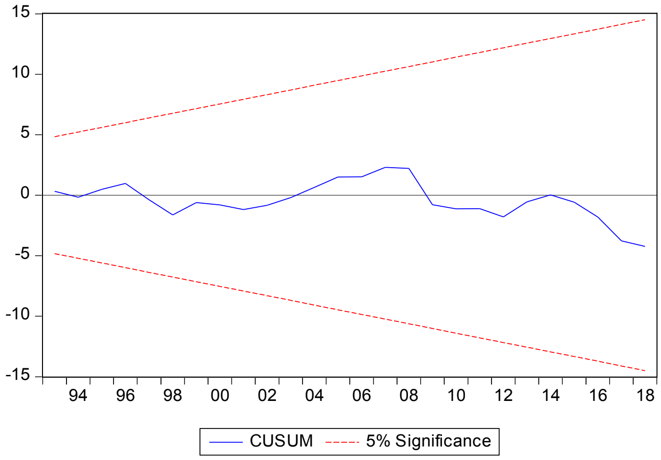

Fig. 2. Cumulative Sum (CUSUM) Results.

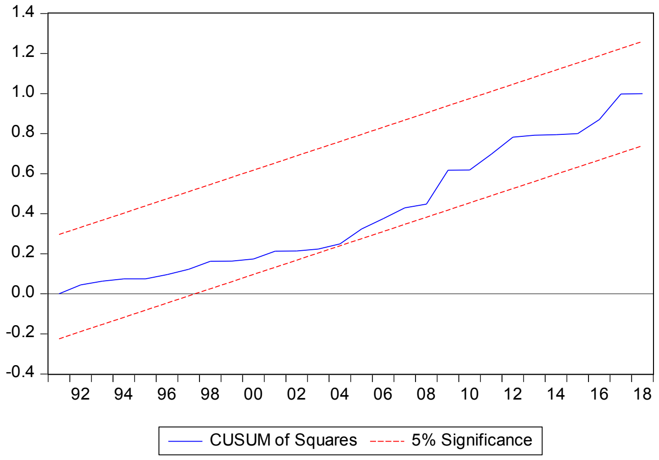

Fig. 3. Cumulative Sum (CUSUM) of Squares.

5. CONCLUSION AND POLICY IMPLICATIONS

This empirical study aims to investigate how energy consumption in the agricultural sector affects CO_2 emissions. The study carried out a unit root test (non-stationary at level and stationary at the first difference) and further applied the ARDL method. Based on the results, energy consumption in the agricultural sector has no significant effect on CO_2 emissions in the short run. Thus, higher energy consumption does not influence CO_2 emissions in the short run. However, the results show that energy consumption can significantly and negatively affect CO_2 emissions in the long run. Hence, increased energy consumption in the agricultural sector is likely to decrease CO_2 emissions. The results also show that GDP and population growth can have significant and positive effects on CO_2 emissions both in the long run and short run. This implies that higher economic growth and population can influence CO_2 emissions in the long and short run. These findings have some important implications on how the government can effectively manage energy consumption in the future. Hence, this will boost production in the agricultural sector and conserve the environment simultaneously. Apart from that, since GDP and population growth are positively related to CO_2 emissions, the government should increase the use of renewable energy, such as biomass (agricultural waste and animal waste like dung) and solar to reduce CO_2 emissions in the agricultural sector. Presently, the use of renewable energy in Malaysia is still low. Hence, the country aims to achieve 31% of renewable energy in its installed capacity by 2025. This target is good for Malaysia to reduce CO_2 emissions. Besides, the country has also introduced several environmental policies in the 12th Malaysia plan, particularly carbon pricing and carbon taxes. These policies aim to reduce environmental regulations. However, despite the fact that this study has achieved the research aim, it still has several limitations. One of them is data unavailability, and hence the data used in this study are limited to 37 years only from 1981 to 2018. In addition, future studies should focus on other economic regions of the world to investigate how energy consumption in the agricultural sector affects CO_2 emissions

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