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The effects of environmental pollution on food security in Malaysia

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ABSTRACT

Environmental pollution has emerged as a critical global challenge, significantly affecting various aspects of human life, including food security. This research paper investigates the effects of environmental pollution on agricultural output (a proxy for food security) in Malaysia from 1990 to 2020, utilising the Autoregressive Distributed Lag (ARDL) method. The results obtained from the bounds cointegration testing approach provided strong evidence supporting the existence of a long-term relationship among Methane emissions in the energy sector (thousand metric tons of CO_2 equivalent) (CH_4), Carbon dioxide emissions (metric tons per capita) (CO_2), Nitrous oxide emissions in the energy sector (thousand metric tons of CO_2 equivalent) (N_2O), GDP, population, index of agricultural total factor productivity, and agricultural output. Estimation of long-run and short-run ARDL with diagnostic and model stability reveals that there is a positive correlation between the index of agricultural total factor productivity (TFP) and agricultural output in Malaysia in all four of the models analysed. The discoveries illuminate the possible mechanisms by which environmental pollution affects food security in Malaysia, offering valuable insights to policymakers and stakeholders for crafting effective strategies toward sustainable development. By uncovering the implications of environmental degradation on food availability, access, and nutritional quality, the study highlights the urgency of addressing environmental challenges to ensure long-term food security for the Malaysian population. Moreover, the study can serve as a basis for formulating sustainable policies that promote resource conservation, waste management, and eco-friendly practices in the agricultural and industrial sectors, fostering a harmonious coexistence between economic development and environmental preservation.

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INTRODUCTION

According to the International Strategy for Disaster Reduction (2004), environmental pollution is defined as "the reduction of the environment's capacity to meet social and ecological objectives and needs". Environmental pollution emerged as a critical global challenge in recent decades, having profound effects on various aspects of human life. Among the sectors most vulnerable to environmental pollution, agriculture stands at the forefront due to its heavy reliance on natural resources (Çetin et al., 2020; Harizanova-Bartos & Stoyanova, 2018; Kwakwa et al., 2022; Naghavi et al., 2022). This research article aims to explore the effects of environmental pollution on agricultural production as a proxy for food security, shedding light on the consequences and underlying mechanisms that drive this interaction.

In Malaysia, there is very little study on the effects of environmental pollution on food security compared to the effects of food security on environmental pollution. According to Ashraf and Javed (2023) due to the quick depletion of the earth's resources, food security can result in considerable environmental deterioration. As a result, it may be to blame for a sizable portion of Green House Gases emissions, a decline in biodiversity and soil fertility, and a water shortage. One study by Subramaniam and Masron (2021), also shows that the level of environmental degradation tends to be higher with a higher level of food security. Moreover, according to the Generalized Method of Moments GMM system's findings, increased carbon emissions due to food security will lower environmental quality (Ashraf & Javed, 2023). This showed that in Malaysia, many past studies only focused on the effects of food security on environmental pollution rather than the effects of environmental pollution on agricultural output as a proxy for food security. Hence, this study intends to investigate the effects of environmental pollution on food security in Malaysia, not vice versa.

Environmental pollution, all of which is aggravated by human activity such as industrialisation, urbanization and unsustainable farming practices, involves a wide range of processes, including deforestation, soil degradation, water pollution or climate change. These activities lead to the gradual deterioration of natural ecosystems and the depletion of vital resources, thereby jeopardizing the productive capacity of agricultural systems worldwide. Climate change causes crop damage, low productivity, and high production costs that lead to losses in farmers' income, a high poverty level, high inequality, and finally a reduction in farmers' active involvement (Alalade et al., 2021; Alam et al., 2018; Maja & Ayano, 2021; Pilo et al., 2021; Sallawu et al., 2022).

The impact of environmental pollution on agricultural production is comprehensive and demonstrated in several ways. Firstly, soil pollution resulting from erosion, nutrient depletion, and chemical pollution reduces the fertility and structural integrity of soils, diminishing their ability to support crop growth. Consequently, agricultural yields decrease, posing significant challenges to global food production. Moreover, climate change has changed the temperature and precipitation patterns, resulting in increased extreme weather events such as droughts, floods or heat waves due to greenhouse gas emissions and deforestation. These climate-induced disturbances disrupt agricultural activities, affecting crop cycles, livestock health, and overall farm productivity. Climate scientists have predicted that, by 2030, about a quarter of Malaysia's population will be displaced because of climate change (Sahani et al. (2022).

The impact of the decline in agricultural production because of Environmental Pollution is much wider than farm boundaries, and there are serious implications for food security. According to the United Nations Committee on World Food Security, food security is defined as everyone, at all times, having physical, social, and economic access to enough, safe, and nourishing food that satisfies their food choices and dietary needs for an active and healthy life. Food security has four components namely availability, accessibility, utilization, and stability (Food and Agriculture Organization Statistics, 2018). As the global population continues to rise, maintaining a sufficient and stable food supply becomes a vital concern. Projections from United Nations (2022) suggest that by 2030, the world's population could reach approximately 8.5 billion individuals, a figure expected to surge to 9.7 billion by 2050. Moreover, these projections indicate a peak

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population of 10.4 billion people during the 2080s, which is projected to remain relatively stable until the year 2100.

Environmental pollution undermines the ability of agricultural systems to meet this demand, heightening the risk of food shortages, price volatility, and malnutrition. Particularly in vulnerable regions with limited alternative livelihood options, such as rural areas in developing countries, the consequences of reduced agricultural production can be devastating, leading to increased poverty, social unrest, and migration.

This study will utilise Autoregressive Distributed Lag (ARDL) method to analyse the effects of environmental pollution on agricultural production as a proxy for food security. Through an examination of empirical data, valuable insights into the interactions between environmental factors, agricultural practices, and food production dynamics will be addressed. Ultimately, the findings of this study will contribute to informed decision-making processes and pave the way for the development of resilient and sustainable agricultural systems in the face of environmental challenges. The paper is organized as follows: Section 2 on literature review, Section 3 on methodology, Section 4 on results and discussion, and Section 5 on conclusions and policy implications.

LITERATURE REVIEW

Environmental pollution has emerged as a critical factor that significantly impacts global food security. Numerous studies have highlighted the complicated effects of pollution on various dimensions of food production, distribution, and access. The ability of an economy's agriculture sector to feed the world's rapidly expanding population currently ranks among its greatest difficulties. However, ongoing environmental deterioration poses a significant threat to agricultural production (Sun et al., 2017). Environmental pollution, particularly the emission of greenhouse gases (GHG), contributes to climate change, leading to shifts in temperature and precipitation patterns. Studies by the Intergovernmental Panel on Climate Change (2018) and Rosenzweig et al. (2020) have shown that climate change-induced extreme weather events, such as droughts and floods, adversely impact agricultural production. Changing climatic conditions disrupt planting schedules, alter crop suitability zones, and increase the incidence of pests and diseases, further challenging agricultural production.

Keeping up with agricultural production to feed the world's constantly expanding population is one of the biggest difficulties (Tan et al., 2022). Everyone on Earth is witnessing unprecedented heat waves, severe droughts, and rising greenhouse gas levels (Ramzan et al., 2022). The unrelenting increase in greenhouse gases, including methane (CH_4), nitrous oxide (N_2O), and carbon dioxide (CO_2), is having a severe impact on water and land resources as well as the pattern of rainfall and temperature (Alexandratos & Bruinsma, 2012). Additionally, the environment, human health, and agricultural output are all clearly negatively impacted by CO_2 emissions. Industrialisation is fuelled by economic growth, which in turn accelerates the extraction of natural resources. According to de Haas and Andrews (2022), environmental sustainability may be negatively impacted by most of the natural resource use associated with industrialisation, agriculture, mining, and deforestation.

Combating a large amount of released GHG emissions is a critical issue on the battlefield of the environment. Fossil fuels like coal, natural gas, and oil are burned in industrial, commercial, and other operations, which contaminate the air and water. These fires contribute to the growing season's increased warmth, which has an impact on agricultural output and food security (Ramzan et al., 2022). Finding a way to reduce pollution levels without sacrificing agricultural yield is the biggest problem facing the global ecosystem. Environmental change is expected to have a significant ripple impact; however, it will vary by region and crop (Ramzan et al., 2022). Several studies have found that environmental pollution harms agricultural production as well as development. According to Kwakwa et al. (2022), emissions from the transportation, industrial, and other sectors have a negative impact on the development of Ghana's agriculture. Together with other explanatory factors, carbon emissions often contribute more to changes in agricultural development over time. Based on the research done by (Dong & Wang, 2023), in many nations with varying levels of development, pollution levels, and industrial systems, air pollution has a negative influence. The link between fine particulate matter and agricultural total factor productivity (TFP) is moderated by temperature, according to their study's findings.

Tan et al. (2022) used a sample of 350 observations for the European Union countries during 2009–2018 and found environmental deterioration as one of the most pressing issues facing modern society and its connection to agriculture production. To increase the effectiveness of pro-environmental policies, the causes of environmental issues that affect agriculture as well as the economic and social drivers must be examined simultaneously. An increase in the forms and types of environmental degradation is brought on by the rise in consumer goods demand in a setting of high interdependence between nations.

Additionally, the random forest analysis supports the notion that one of the most significant drivers of agricultural output is air pollution. A major threat to the development of worldwide agricultural production is air pollution. For agricultural sustainability and world food security, global efforts should be made to improve air quality.

According to projections, the ongoing rise in carbon dioxide (CO_2) emissions will have a significant impact on the climate system, with disastrous results that would affect all aspects of society (Rehman et al., 2022). However, a decrease in global temperature has been linked to a reduction in carbon dioxide emissions, which will benefit agricultural production whereas the growing seasons, soil moisture levels, and yield quality will all benefit from an ideal temperature regime (Subramaniam et al., 2020). Additionally, the price of food will reduce to the extent that greater food production is caused by improved environmental quality.

In order to ensure sustainable development and to reduce the negative effects of climate change, it has become a global issue to reduce CO_2 emissions and improve environmental quality. According to this paradigm, figuring out what influences CO_2 emissions is crucial for choosing the best solutions to improve environmental quality (Churchill et al., 2020). Environmental degradation is inevitable if the functional relationship between natural resources and modern development processes cannot be prevented.

METHODOLOGY

For a successful empirical study, it is crucial to ascertain the stationarity properties of the variables under consideration. To achieve this, unit root tests developed by Dickey and Fuller (1979) and Phillips and Perron (1988) can be employed to assess the stationarity status of the variables. If these tests confirm that the variables are stationary at either level I(0) or first difference I(1), the investigation can proceed accordingly. As suggested by Pesaran and Smith (2001), it is crucial to underline that none of the variables should be in the second difference.

The long-term association between variables was investigated in this work using the Autoregressive Distributed Lag (ARDL) bound testing approach suggested by Pesaran et al. (2001). If Fcal > Ftab is true, then there is a long-run association between the variables. If Fcal < Ftab, then there is no long-run association between the variables, but the cointegration between the variables is inconclusive. Only if the requirement of Fcal > Ftab is met may the study continue.

In this study, we utilised the ARDL bound testing method, which offers various advantages compared to traditional techniques. One of the benefits is that the ARDL estimation can address problems related to serial correlation and determine the right lag order by considering both the short and long-term connections between the selected variables via auto-regressive lags and error correction (Xiong et al., 2022). Moreover, the ARDL method is known to be more efficient when dealing with a small sample size (Villanthenkodath et al., 2021) and suitable for variables that are nonstationary or have mixed integration order (Ullah et al., 2022). The bound test method assumes that there is long-term cointegration among the variables of interest. Additionally, an ECM can be established through linear transformation, which incorporates both short and long-term dynamics in the model without omitting any data (Xiong et al., 2022). The ARDL bounds test equation is as follows:

$$\Delta QA_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i}\Delta QA_{ti-1} + \sum_{i=1}^{n} \beta_{2i}\Delta CH4_{1\,ti-1} + \sum_{i=1}^{n} \beta_{3i}\Delta CO2_{2\,ti-1} + \sum_{i=1}^{n} \beta_{4i}\Delta N2O_{3\,ti-1} + \sum_{i=1}^{n} \beta_{5i}\Delta POP_{4\,ti-1} + \sum_{i=1}^{n} \beta_{6i}\Delta GDP_{5\,ti-1} + \sum_{i=1}^{n} \beta_{7i}\Delta TFP_{6\,ti-1} + \beta_{8i}Y_{ti-1} + \beta_{9i}CH4_{1\,ti-1} + \beta_{10i}CO2_{2i\,t-1} + \beta_{11i}N2O_{3i\,t-1} + \beta_{12i}POP_{4i\,t-1} + \beta_{13i}GDP_{5i\,t-1} + \beta_{14i}TFP_{6i\,t-1} + E_t \tag{1}$$

Equation (1) includes the dependent variable denoted by QA_t, explanatory variables represented by X, and the first difference indicated by Δ. A long-run cointegration among variables exists in a specified model only if the null hypothesis of $\beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = 0$ is rejected by the Wald test.

As depicted in equation (1), after confirmation of cointegration association among variables through the bound testing approach, the short and long-run coefficients of equation (3) are estimated by employing $\rho1, q1, q2, \ldots \ldots qn$ ARDL models.

$$QA_t = \sigma_0 + \sum_{i}^{p1} \sigma_{1i}QA_{ti-1} + \sum_{i=0}^{q1} \sigma_{2i}CH4_{1\,ti-1} + \sum_{i=0}^{q2} \sigma_{3i}CO2_{2\,ti-1} + \sum_{i=0}^{q3} \sigma_{4i}N2O_{3\,ti-1} + \sum_{i=0}^{q4} \sigma_{5i}POP_{4\,ti-1} + \sum_{i=0}^{q5} \sigma_{6i}GDP_{5\,ti-1} + \sum_{i=0}^{q5} \sigma_{7i}TFP_{6\,ti-1} + E_t \tag{2}$$

The long-run dynamics of equation (3) are estimated by using the ARDL technique in equation (2), where long-run relationships in equation (1) are calculated using subsequent formulas, where j = 1, 2, ….., 4 and m = 2, 3, … ….,6.

The short-run dynamics of equation (3) are estimated using equation (2).

$$\Delta QA_t = \gamma_0 + \sum_{i=1}^{n} \sigma_{1i}QA_{ti-1} + \sum_{i=1}^{n} \sigma_{2i}CH4_1 + \sum_{i=1}^{n} \sigma_{3i}\Delta CO2_{2\,ti-1} + \sum_{i=1}^{n} \sigma_{4i}\Delta N2O_{3\,ti-1} + \sum_{i=1}^{n} \sigma_{5i}\Delta POP_{4\,ti-1} + \sum_{i=1}^{n} \sigma_{6i}\Delta GDP_{5\,ti-1} + \sum_{i=1}^{n} \sigma_{7i}\Delta TFP_{6\,ti-1} + \sum_{i=1}^{n} \sigma_{ni}ECT_{ti-1} + e_t \tag{3}$$

In order to detect any possible problems with the model, various diagnostic tests are employed. These tests include the Jarque-Bera (JB) test for normality, the Breusch-Pagan-Godfrey test for heteroskedasticity, and the Breusch-Godfrey LM test for serial correlation. Additionally, a Granger causality test based on VAR is performed to investigate the causal direction among variables (Lee & Brahmasrene, 2013).

DATA

Annual data is collected from 1990 to 2020. The duration is based on data availability. The data on total agricultural output, environmental pollution consisting of carbon dioxide emissions (metric tons per capita) (CO_2), Methane emissions in the energy sector (thousand metric tons of CO_2 equivalent) (CH_4), and Nitrous oxide emissions in the energy sector (thousand metric tons of CO_2 equivalent) (N_2O), population growth, the index of agricultural total factor productivity (TFP), and economic growth (GDP growth) are collected from World Development Indicators (WDI). Represents the detailed description and source of each variable used in this study as follows:

Table 1. Variable description and sources

Acronym of variable	Description of Variables	Data Source	Year
QA	Quantity of total agricultural output (proxy of food security)	Food and Agricultural Organization (FAO) statistic	1961 - 2020
CH_4	Methane emissions in the energy sector (thousand metric tons of CO2 equivalent) (CH4)	World Development Indicator (WDI) 2023	2019 - 2021
CO_2	Carbon dioxide emissions (metric tons per capita) (CO2)	World Development Indicator (WDI) 2023	2019 - 2021
N_2O	Nitrous oxide emissions in the energy sector (thousand metric tons of CO2 equivalent) (N2O)	World Development Indicator (WDI) 2023	2019 - 2021
POP	Population growth (annual %) – Annual population growth	World Development Indicator (WDI) 2023	2019 - 2021
GDP	GDP growth (annual %) – Annual percentage change in GDP	World Development Indicator (WDI) 2023	2019 - 2021
TFP	Index of agricultural total factor productivity (TFP)	Food and Agricultural Organization (FAO) statistics	1961 - 2020

Source: Authors' compilation

RESULTS

Descriptive Statistic

Table 2. Descriptive Statistic

Variables	Mean	Max	Min	St.Dev.
QA	7.145665	7.282140	63949807	0.113207
CH_4	4.037070	4.138066	3.818892	0.090310
POP	2.091346	2.877740	1.079364	0.599865
TFP	89.52522	104.9348	69.71543	11.98685
GDPG	0.759463	1.00017	-0.285943	0.228397
CO_2	6.056943	7.719436	3.117819	1.408996
N_2O	3.886019	4.01587	3.666071	0.116721

Source: Authors' compilation

Unit Root Test

Table 3. Unit root test of stationary

Variables	ADF		Philip Perron		Order of indifference
	Level	1st Different	Level	1st Different	
QA	-2.2981	-7.4077***	-1.6529	-7.1396***	I(1)
CO_2	-2.1594	-6.6295***	-3.261**	-6.6295***	I(1)/ I(0)
N_2O	-1.7797	-6.2204***	-1.8976	-6.2107***	I(1)
CH_4	-3.2841**	-4.1939**	-3.1848**	-4.2114**	I(0)
POP	0.4236	-3.2276**	1.1376	-3.1073**	I(1)
TFP	-1.3613	-8.4776***	-1.4637	-8.0410***	I(1)
GDP	-4.7300**	-6.4200***	-4.7380**	-25.1245***	I(0)

Note: *** and ** denote 1% and 5% significant levels.

Source: Authors' compilation

Before analysing the long- and short-term dynamics of the model, we conducted unit root tests to check the stationarity level of each series. Our study primarily used the widely-used "Phillips–Perron" (PP) and "Augmented Dickey–Fuller" (ADF) tests, though there have been various tests proposed for stationarity in previous studies. We examined the stationarity of all variables in the log form at both the "level" [I(0)] and the "first difference" [I(1)], as shown in Table 3. According to the results from both the PP and ADF tests, all variables were found to be stationary at I(1).

Bound Test

Table 4. Bound testing cointegration results

ARDL Model	F-stats	Lag order	Critical bound values			Cointegration
			L-U (1%)	L-U (5%)	L-U (10%)	
QA (CH_4, POP, TFP, GDP)	8.9487***	4,4,4,3, 4	4.28 – 5.84	3.06 – 4.22	2.53 – 3.56	Yes
QA (CO_2, GDP, POP, TFP)	7.6743***	1,0,2,0,3	4.28 - 5.84	3.06 – 4.22	2.53 – 3.56	Yes
QA (N_2O, GDP, POP, TFP)	6.9005***	1,2,2,0,3	4.28 - 5.84	3.06 – 4.22	2.53 – 3.56	Yes
QA (N_2O, POP, TFP)	5.5277**	1,2,4,3	4.16 – 5.97	3.27 – 4.31	2.68 – 3.59	Yes

Note: The unrestricted assumption is used in all models. Terms 'L' and 'U' denote lower and upper critical bound values. Likewise, *** and ** respectively represent the presence of a cointegration at 1% and 5% significance levels.

Source: Authors' compilation

Before delving into the analysis of both long- and short-term relationships, we employed the bounds cointegration testing approach, coupled with a joint-F significance test, to determine if the variables in the study exhibit cointegration over the long run. The results, which are displayed in Table 4, include the computed F-values and their corresponding significance levels (10%, 5%, and 1%), as well as the lower critical values for I(0) and I(1). Notably, the fixed (tabulated) values of the upper bound I(1) were found to be smaller than the calculated F-values, and even at the 1% level, Narayan's (2005) test (with intercept and without trend) showed high significance. As a result of these procedures, it was effectively confirmed that there exists a long-term relationship among CH_4, CO_2, N_2O, GDP, population, the index of agricultural total factor productivity (TFP), and agricultural output.

In this section, we presented the empirical results of both long-run and short-run dynamics by employing the ARDL approach to examine the relationship between environmental pollution (CH_4, CO_2, N2O), GDP, population, the index of agricultural total factor productivity (TFP), and agricultural output in the context of Malaysia. To facilitate our analysis, most of the variables used in the model have been converted into logarithmic form. Consequently, the probabilities of the resulting coefficients can be interpreted as elasticities in the long term.

Estimation of the ARDL Model

Table 5. Estimation of long-run and short-run ARDL with diagnostic and model stability

Variables	Model 1	Model 2	Model 3	Model 4
Long run				
CH_4	0.2770***	-	-	-
	(0.0774)			
CO_2	-	0.0240	-	-
		(0.0157)		
N_2O	-	-	0.3696**	0.3104***
			(0.1360)	(0.1114)
GDP	0.0521	0.0889	0.0735	-
	(0.0281)	(0.0637)	(0.0423)	
POP	-0.0714***	-0.0474*	-0.0677***	-0.0644***
	(0.0122)	(0.0254)	(0.0186)	(0.0165)
TFP	0.0047***	0.0048**	0.0030**	0.0033**
	(0.0008)	(0.0018)	(0.0014)	(0.0012)
Constant	5.7299***	6.6216***	5.5399***	5.7923***
Short run				
	0.2023***	-	-	-
CH_4	(0.0595)			
CO_2	-	0.0167**	-	-
		(0.0064)		
N_2O	-	-	0.1495**	0.1490**
			(0.0607)	(0.0601)
GDP	0.0132	0.0115	0.0058	-
	(0.0081)	(0.0087)	(0.0084)	
POP	-0.0520***	-0.0329***	-0.0395***	-0.0390***
	(0.0132)	(0.0116)	(0.0128)	(0.0127)
TFP	0.0031***	0.0026***	0.0024***	0.0024***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)
ECT_{t-1}	-0.7203***	-0.6493***	-0.6031***	-0.6009***
	(0.0655)	(0.0643)	(0.0606)	(0.0611)
RAMSEY Test	0.0714	1.7478	1.3525	0.5456
	(0.7915)	(0.1981)	(0.2558)	(0.4668)
CUSUM test	Yes	Yes	Yes	Yes
CUSUMSQ	Yes	Yes	Yes	Yes
Diagnostic tests				
JB-Norm	0.1548	0.8098	0.1008	1.8650
	(0.9255)	(0.6670)	(0.9508)	(0.3936)
LM – BG	0.5281	0.2854	0.0282	0.0516
	(0.5964)	(0.7542)	(0.9722)	(0.9498)
Hetro – BPG	0.6400	0.9736	0.6419	0.6422
	(0.6713)	(0.4522)	(0.6699)	(0.6371)

For coefficient, standard errors are in parenthesis. *, **, and *** represent the level of significance at 10, 5, and 1%, respectively. Probabilities for diagnostic tests are in parenthesis.

Source: Authors' compilation

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Table 5 presents the long and short-term effects of CH_4, CO_2, and N_2O on agricultural output, (proxy of food security) and other explanatory factors. The results from Model 1 show that a 1% increase in CH_4 leads to a 0.28% increase in agricultural output in the long run and a 0.20% increase in the short run. Based on the models tested, it appears that there is no significant impact on the short-run or long-run relationship between GDP growth and other factors.

Similarly, in Models 2 and 3, a 1% increase in CO_2 and N_2O leads to a 0.02% and 0.37% increase in agricultural output in the long run, respectively. In the short run, a 1% increase in CO_2 and N_2O results in a 0.02% and 0.15% increase in agricultural output, respectively. According to Model 4, a 1% increase in N_2O results in a 0.31% increase in agricultural output in the long run and a 0.15% increase in the short run.

The research findings indicate that population growth has a negative and statistically significant impact on agricultural output in all models. Specifically, a 1% increase in population leads to a 0.07% decrease in agricultural output in the long run and a 0.05% decrease in the short run in Model 1. In addition, a 1% increase in population growth causes a reduction in agricultural output in Model 2, Model 3, and Model 4 by 0.05%, 0.07%, and 0.06% respectively in the long run. Similarly, in the short run, a 1% upsurge in population growth results in a decrease in agricultural output of Model 2, Model 3, and Model 4 by 0.03%, 0.04%, and 0.04% respectively.

It has been found that there is a positive correlation between the index of agricultural total factor productivity (TFP) and agricultural output in Malaysia in all four of the models analysed. Specifically, a 1% increase in TFP leads to a corresponding increase in agricultural output of 0.005% in Models 1 and 2, and 0.003% in Models 3 and 4 in the long run. On the other hand, in the short run, a 1% increase in TFP only results in a 0.003% increase in agricultural output in Models 1 and 2, and a 0.002% increase in Models 3 and 4.

Several diagnostic tests have been conducted to ensure accurate and dependable results. The Jarque-Bera test was used to assess data normality, with a critical value lower than 5 and a probability value greater than 5% indicating statistical insignificance, meaning that all models contain normally distributed data. The serial correlation LM test revealed insignificant results, with F-stats greater than 1% of the critical value, indicating that none of the models have serial correlation problems.

To examine heteroscedasticity, we conducted the Breusch-Pagan (BP) test, resulting in a statistically insignificant Chi-square test probability value. This indicates that the null hypothesis of homoscedasticity cannot be rejected, suggesting that the variance of residuals is constant across all observations. To ensure the robustness of the models' results, we also assessed their stability using the cumulative sum of recursive residual (CUSUM) and cumulative sum of recursive residual square (CUSUMSQ) tests (Brown et al., 1975). An appendix contains the graphical results for CUSUM and CUSUMSQ, which indicate dynamic stability.

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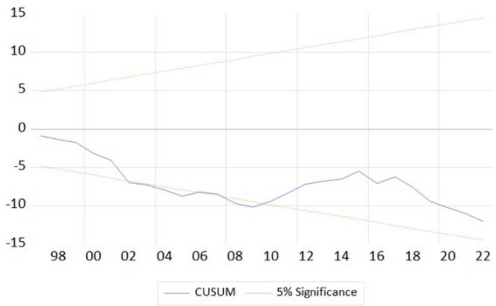
Model 1

CUSUM	CUSUMSQ



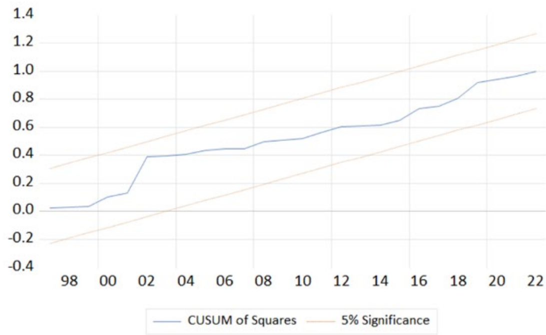


Fig. 1. CUSUM and CUSUMSQ Model 1

Source: Authors' compilation

Model 2

CUSUM	CUSUMSQ

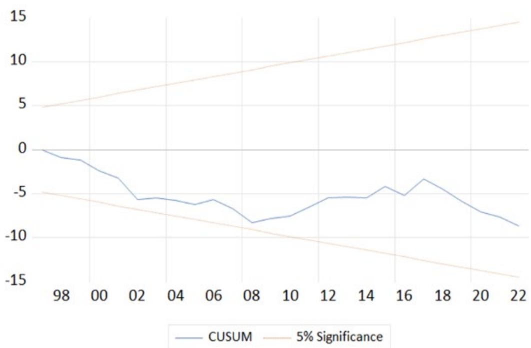


Fig. 2. CUSUM and CUSUMSQ Model 2

Source: Authors' compilation

Model 3

CUSUM CUSUMSQ

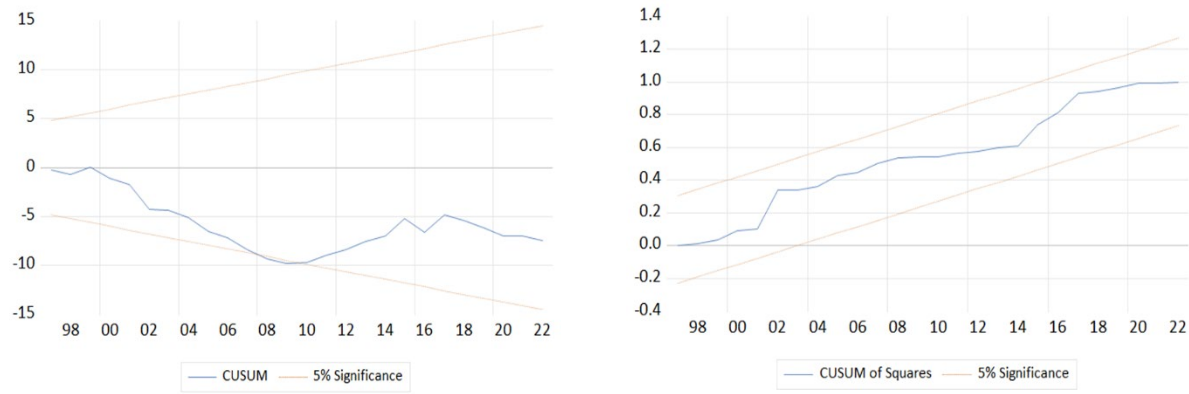


Fig. 3. CUSUM and CUSUMSQ Model 3

Source: Authors' compilation

Model 4

CUSUM CUSUMSQ

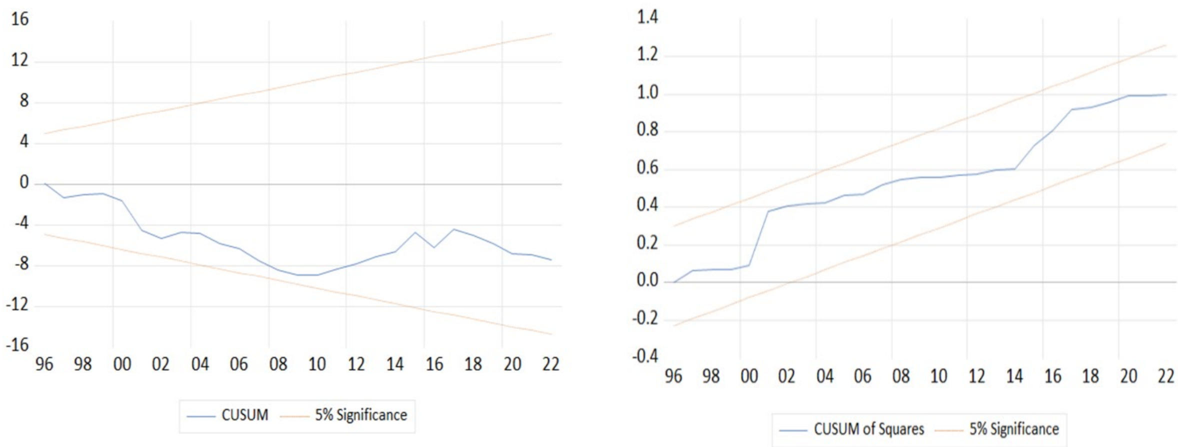


Fig. 4. CUSUM and CUSUMSQ Model 4

Source: Authors' compilation

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CONCLUSIONS AND POLICY RECOMMENDATIONS

Reducing environmental pollution becomes a key concern for both rising and advanced economies. As China now ranks first in the world for greenhouse gas emissions, significant increases in greenhouse gas emissions and air pollution have become a serious concern (Irfan et al., 2023). A preliminary analysis indicates that there is a significant relationship between agricultural output and environmental pollution, especially, CH_4, CO_2, and N_2O. This relationship shows that environmental pollution and food security are related based on the bounds cointegration testing approach that has been done using the ARDL method. The correlation is positive, indicating a link between increased environmental contamination and increased agricultural production.

Environmental pollution, such as air pollution, water contamination, soil degradation, and chemical residues, can harm agricultural ecosystems, reduce crop yields, and compromise the quality and safety of food (Boregowda et al., 2022). It can also negatively affect the health of livestock and aquatic resources, leading to food scarcity, reduced food security, and potential risks to human health. However, several practices can be considered such as implementing eco-friendly agricultural techniques, conservation efforts, and sustainable practices, which can have positive effects on food production, foster environmental health and enhance long-term food security.

Particularly, as environmental regulations become more stringent, agricultural producers are forced to consider their issues with low factor utilisation and high pollution emissions during production. As a result, they are compelled to adopt new production technologies to optimize factor allocation, lower pollution emissions, and raise the value added to their products. Increased competitiveness brought on by higher-valued products can also help agricultural producers generate excess profits in the short term, offsetting the negative effects of higher environmental management costs. The optimisation of factor allocation efficiency can increase agricultural production efficiency (Chen et al., 2022).

A study on the contribution of agricultural output and energy consumption to environmental pollution in Portugal explores the correlation between carbon dioxide emissions and agricultural activities, including crop production, livestock production, and agricultural land use. The findings also reveal that, over the long term, agricultural activities and energy consumption have a positive association with environmental pollution. Consequently, there is a need for Portuguese agriculture to adopt more sustainable practices, while also mitigating the adverse effects of intensive crop cultivation and animal husbandry (Leitão & Balogh, 2020).

From the findings, it has been found that there is a positive correlation between the index of agricultural total factor productivity (TFP) and agricultural output in Malaysia in all four of the models analysed. Specifically, a 1% increase in TFP leads to a corresponding increase in agricultural output of 0.005% in Models 1 and 2, and 0.003% in Models 3 and 4 in the long run. On the other hand, in the short run, a 1% increase in TFP only results in a 0.003% increase in agricultural output in Models 1 and 2, and a 0.002% increase in Models 3 and 4. Hence, the TFP index allows the government to assess the performance of the agricultural sector over time. By comparing TFP trends across different periods, policymakers can identify whether productivity improvements are keeping pace with input growth. This assessment helps gauge the sector's overall efficiency and informs decision-making. Besides that, governments can use the TFP index to identify areas of inefficiency within the agricultural production process. Sectors with declining or stagnant TFP growth indicate the need for interventions to address underlying inefficiencies. Policymakers can pinpoint where resources are being underutilised and implement measures to optimize their allocation. Additionally, the TFP index can guide policies that promote sustainable practices, including soil conservation, water management, and agroecological approaches. By encouraging environmentally friendly practices, governments ensure long-term agricultural productivity.

Other than that, governments should give priority to community participation and educational initiatives that spread awareness of the negative consequences of pollution on food security. Policymakers

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may build a groundswell of support for sustainable food production by involving local populations in efforts to reduce pollution and by promoting environmentally friendly behaviours. In conclusion, authorities can pave the path for a more resilient and secure food future by implementing a multi-pronged strategy that encompasses sustainable agriculture, research, and community participation.

Environmental pollution poses substantial challenges to food production in multiple ways. To ensure a sustainable and secure food supply, it is imperative to implement comprehensive measures to mitigate pollution, promote eco-friendly agricultural practices, conserve natural resources, and reduce greenhouse gas emissions. By addressing environmental pollution, we can safeguard agricultural ecosystems, enhance food production, and work towards achieving a resilient and sustainable food system for future generations.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

AUTHORS' CONTRIBUTIONS

Irlisuhayu carried out the research, methodology, wrote and revised the article. Nor Azira anchored data curation, methodology, and writing. Noor Zahirah designed the research, supervised research progress, review & editing, methodology, revision, and validation.

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