



PLANNING MALAYSIA:

Journal of the Malaysian Institute of Planners

VOLUME 23 ISSUE 6 (2025), Page 317 – 331

THE INTERACTION OF AGRICULTURE AND ECONOMIC FACTORS IN SHAPING EMISSIONS: INSIGHTS FROM SOUTHEAST ASIA USING PANEL QUANTILE REGRESSION

**Sayed Kushairi Sayed Nordin¹, Mohd Fariduddin Mukhtar², Nurul Amira Zainal³,
Bushra Abdul Halim⁴, Muhammad Aziz⁵**

*^{1,3}Fakulti Teknologi dan Kejuruteraan Mekanikal,
UNIVERSITI TEKNIKAL MALAYSIA MELAKA*

*^{1,5}Institute of Industrial Science,
THE UNIVERSITY OF TOKYO*

*²Fakulti Pengurusan Teknologi dan Teknousahawan,
UNIVERSITI TEKNIKAL MALAYSIA MELAKA*

*⁴Fakulti Sains Komputer dan Matematik,
UNIVERSITI TEKNOLOGI MARA CAWANGAN MELAKA*

Abstract

Environmental degradation remains a critical concern in Southeast Asia, driven by rapid economic expansion, agricultural activity, population growth and trade liberalization. This study examines the heterogeneous impact of key agricultural and economic factors, namely, trade openness, Gross Domestic Product (GDP), population growth, technology, and agricultural land use, on CO₂ emissions across Southeast Asia countries from 1996 to 2021. We employ panel quantile regression (PQR) to capture variations in emissions across different quantiles. All variables are transformed into natural logarithmic form to address skewness, ensure consistency and interpret elasticities effectively. We address cross-sectional dependence and non-stationarity using Pesaran's CD test, CADF unit root test, and Westerlund cointegration analysis. The findings reveal that trade openness significantly increases emissions across all quantiles, while GDP shows a negative association with emissions, in line with the Environmental Kuznets Curve (EKC) hypothesis. In addition, population growth, technology and agricultural land use are found to be statistically insignificant across the emission distribution. These insights offer important implications for policy formulation aimed at balancing economic growth with environmental protection in Southeast Asia.

Keywords: Agriculture, Panel Quantile Regression, Pollution, Environmental

¹ Corresponding author. Email: sayedkushairi@utem.edu.my

INTRODUCTION

Environmental pollution is a growing concern worldwide and Southeast Asia (SA) faces acute challenges from rapid economic growth, industrialization and population expansion. As prosperity increases, the environmental toll becomes visible through higher greenhouse-gas emissions, air and water pollution, and ecosystem degradation (He et al., 2024; Song et al., 2024). Agriculture, trade and technology have each contributed to these pressures, making it crucial to understand how economic activity and farming practices affect pollution. With countries at different stages of development and environmental readiness, SA requires a region-specific strategy to manage and reduce emissions effectively.

Economic growth, central to development, poses a dual challenge for environmental sustainability. The Environmental Kuznets Curve (EKC) hypothesis posits that growth first increases environmental degradation but eventually fosters sustainability through technological progress and stricter regulation (Özcan & Öztürk, 2019; Liu & Lai, 2021; Pesaran & Takashi, 2008, Potipituk, 2019). In SA, Malaysia and Thailand show signs of the inverted U relationship between GDP and emissions (Nordin et al., 2024), while lower-income economies such as Cambodia and Myanmar still experience rising emissions as resource-intensive industries expand (Madni, 2023). Balancing economic growth with sustainability policies is therefore essential for the region's long-term ecological health.

Trade liberalization, another major growth driver, has diversified SA's economies and deepened global integration, yet its environmental effects are mixed. The pollution-haven hypothesis suggests that trade openness can relocate polluting industries to countries with weaker environmental standards (Chaudhry et al., 2022; Liu et al., 2021; Weixian, 2024). At the same time, trade enables technology transfer and cleaner production in economies with stronger institutions such as Singapore. Understanding this duality is vital for crafting balanced trade and environmental policies across ASEAN.

Technological innovation also shapes emission trajectories. The adoption of automation, artificial intelligence and the Internet of Things, key elements of Industry 4.0, offers pathways to greater efficiency and circular-economy practices (Muhammad et al., 2022; Matarneh et al., 2024; Shabur, 2024). However, uneven technological readiness across ASEAN creates disparities in environmental performance. Advanced economies such as Singapore and Malaysia are integrating digital solutions for cleaner growth, whereas others face infrastructure and capacity constraints.

This study investigates how economic and agricultural factors interact to influence emissions across SA using panel quantile regression (PQR). By capturing heterogeneity across pollution levels, the analysis provides a nuanced understanding of how different drivers affect emissions in low-, medium-, and

high-polluting contexts. The findings aim to inform policymakers on designing targeted strategies that align economic development with environmental sustainability in SA.

The remainder of the paper is structured as follows: Section 2 reviews relevant literature, Section 3 describes the research methodology, Section 4 presents the empirical results and Section 5 concludes with policy implications.

LITERATURE REVIEW

Environmental sustainability has become a major concern in rapidly developing regions such as Southeast Asia (SA), where economic growth, technological progress and agricultural expansion have intensified greenhouse-gas emissions and resource depletion. Studies show that agricultural production strongly influences economic output and environmental emissions in Cambodia, Thailand, and Vietnam (Sonthaya & Witsanu, 2021). The use of fertilizers, pesticides and irrigation systems contributes to agricultural emissions, while economic factors such as GDP growth and exchange rates shape agricultural productivity (SHE et al., 2024). Promoting sustainable farming practices is crucial for reducing emissions and ensuring food security under climate change (Mishra et al., 2021). Economic indicators like GDP and foreign direct investment also affect renewable energy use and emissions (Tran, 2023), emphasizing the need for policies balancing growth and sustainability (Sangco, 2024). Although studies have explored emission drivers in SA (Shiraishi et al., 2023; Mohd et al., 2022), many overlook the varying effects of trade, agriculture and GDP across pollution levels. This study addresses that gap by using panel quantile regression (PQR) to capture these differences and provide targeted policy insights.

Evidence shows that reducing pesticide use does not necessarily lower productivity, suggesting sustainable farming can preserve yields while cutting emissions (Roberto, 2014). Government support mechanisms such as subsidies, regulations and financing are essential for advancing sustainable agriculture (Barbosa, 2014). Advanced technologies further enhance productivity and environmental efficiency, though financial and infrastructural barriers persist (Ismail et al., 2024). These findings highlight the need to integrate environmental considerations into agricultural systems to mitigate pollution and secure long-term sustainability.

Trade liberalization has driven SA's economic growth but also accelerated industrialization and environmental degradation. The pollution-haven hypothesis proposes that open trade can attract emission-intensive industries to countries with weak regulations (Chaudhry et al., 2022), as seen in Vietnam and Indonesia (Muhammad et al., 2022; Liu et al., 2021). Conversely, trade can also foster technology transfer and cleaner production, especially in advanced

economies like Singapore (Weixian, 2024). This duality underscores the need for region-specific trade–environment strategies balancing growth and sustainability.

Agricultural expansion remains a leading cause of deforestation, biodiversity loss and carbon emissions in SA. Indonesia and Malaysia, as major palm oil producers, have experienced deforestation and peatland degradation contributing to transboundary haze pollution (Yin et al., 2024; Yujie et al., 2025). Precision agriculture and sustainable farming practices can mitigate these effects, yet policy and economic barriers limit their widespread adoption.

Technological innovation plays a key role in reducing emissions while supporting growth. The rise of Industry Revolution (IR) 4.0, automation, AI, big data analytics and IoT, offers pathways toward cleaner industrial production and circular economy adoption. Studies show that these technologies enhance sustainability by improving supply-chain efficiency and resource use (Matarneh et al., 2024), while smart manufacturing and digital monitoring further advance industrial environmental goals (Shabur, 2024). However, unequal digital capacity across ASEAN countries leads to disparities in environmental performance, with Singapore and Malaysia progressing faster than less-developed members.

Population growth and urbanization intensify environmental pressure through increased emissions, deforestation and waste generation. Rapid population growth and urbanization in SA have placed immense pressure on natural resources, contributing to increased emissions, deforestation and waste generation. Urban sprawl and the expansion of informal settlements exacerbate pollution levels, highlighting the need for sustainable urban planning and investment in eco-friendly infrastructure (Yujie et al., 2025; Leh et al., 2020). Population-driven resource demand also amplifies agricultural land use, worsening environmental degradation.

Quantile regression methods have proven valuable in examining the relationship between economic and environmental factors at different pollution levels. Traditional mean-based analyses often mask heterogeneity across SA countries with differing levels of industrialization, technology and agriculture (Ikram et al., 2023; Adnan et al., 2024). The PQR, by contrast, captures variations among low-, medium-, and high-polluting countries, accounting for outliers and country-specific effects. This makes PQR particularly suitable for identifying tailored policies across ASEAN. Despite extensive research on the economy–emissions nexus, few studies in SA have examined combined effects of trade, agriculture, technology and population growth or employed advanced approaches such as the method of moments quantile regression (MMQR) (Smarnika et al., 2023).

Overall, SA faces significant environmental challenges shaped by economic and agricultural drivers. While technological progress and economic growth offer opportunities for emission reduction, trade liberalization and

agricultural expansion continue to threaten sustainability. Existing PQR studies in OECD and BRICS contexts (Ikram et al., 2023; Işık et al., 2024; Smarnika et al., 2023) may not capture SA's unique structural diversity and policy constraints. This study therefore extends the literature by applying PQR to assess heterogeneous emission drivers across quantiles, advancing both methodological robustness and policy relevance for developing economies in the region.

RESEARCH METHODOLOGY

This study employs panel data for Southeast Asia (SA) countries from 1990 to 2021, including Brunei, Cambodia, Indonesia, Laos, Malaysia, Philippines, Thailand and Vietnam, collected from the World Development Indicators (WDI) and FAOSTAT. The dataset includes the pollution (CO₂ emissions) (metric tons per capita), representing environmental impact, trade as a percentage of GDP, indicating economic openness, GDP in constant 2015 US dollars, representing economic growth, annual population growth rate (%), the share of medium and high-tech manufacturing in total manufacturing value added to describe technological advancements and percentage of land area used for agriculture.

Panel quantile regression (PQR) was selected as it allows for the exploration of heterogeneous effects of key variables, such as trade openness and GDP, across varying emissions levels. Unlike mean-based models, PQR captures variations across quantiles, offering more profound insights into the dynamics of low, medium, and high pollution regions. This method is particularly suited to the socio-economic diversity of SA.

Before conducting further analysis, diagnostic tests, namely cross-sectional dependence (CSD), were conducted to determine whether the variables exhibit interdependencies across countries. Ignoring cross-sectional reliance can lead to biased results and invalid inferences. Pesaran's CSD test detects cross-sectional dependence in the panel data; the null hypothesis, H_0 is that there is no cross-sectional dependence in the panel data. The tests are:

$$\text{Pesaran (2004) CD Test, } CD = \sqrt{\frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}} \quad (1)$$

$$\text{Breush-Pagan LM Test, } LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \quad (2)$$

$$\text{Pesaran Scaled LM Test, } LM_{scaled} = \frac{1}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N (\hat{\rho}_{ij}^2 - 1) \quad (3)$$

where $\hat{\rho}_{ij}$ represents the pairwise correlation of residuals between cross-section units i and j . These diagnostic tests utilize $\hat{\rho}_{ij}$ to evaluate the linear association of residuals, ensuring cross-sectional dependence is thoroughly

examined. The Breusch-Pagan LM test evaluates cross-sectional dependence using the defined $\hat{\rho}_{ij}$ metric, computed across all panel units.

To check the stationarity of the panel data, the study employs a second-generation panel unit root test, which accounts for the CSD, CADF (Cross-sectionally Augmented Dickey-Fuller) Test. This test helps determine whether the variables are stationary at levels or first differences, guiding the choice of appropriate econometric models. For a given y_{it} , the CADF test is based on the following regression:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \gamma_i \bar{y}_{t-1} + \delta_i \Delta \bar{y}_t \sum_{j=1}^p \phi_{ij} \Delta y_{it-j} + \varepsilon_{it} \quad (4)$$

where $\Delta y_{it} = y_{it} - y_{it-1}$, $\bar{y}_t$ is the cross-sectional mean of y_t , α_i is an individual-specific intercept, β_i is the coefficient for the lagged level of y_{it} , γ_i and δ_i are coefficients for the cross-sectional mean terms and ε_{it} is the error term. The H_0 is the panel contain a unit root (non-stationary) against H_a at least some cross-sectional units are stationary.

In analysing panel data, it is essential to determine whether a long-run equilibrium relationship exists among the variables. The Westerlund Error-Correction Model (ECM) Panel Cointegration Test, introduced by Westerlund (2007), is employed to assess the presence of cointegration among the variables in the panel data. Unlike traditional residual-based tests such as the Pedroni or Kao test, Westerlund's approach is based on an error correction model (ECM). It is advantageous because it accounts for CSD and provides robust results in heterogeneous panels. For a dependent variable y_{it} and explanatory variables x_{it} the ECM representation is:

$$\Delta y_{it} = \alpha_i + \delta_i (y_{it-1} - \beta_i x_{it-1}) + \sum_{j=1}^p \phi_{ij} \Delta y_{it-j} + \sum_{k=1}^q \phi_{ik} \Delta x_{it-k} + \varepsilon_{it} \quad (5)$$

where δ_i is the speed of adjustment to the long-run equilibrium, $y_{it-1} - \beta_i x_{it-1}$ is the long-run equilibrium relationship and ε_{it} is the error term. This test examines the H_0 : There is no cointegration exists among the variables, and it provides four test statistics, Gt statistic, Ga statistic, Pt statistic and Pa statistic, to test the presence of cointegration in individual units, to test whether most units have cointegration, to test for cointegration across the whole panel and to evaluate cointegration across all units in the panel collectively.

Given the heterogeneous relationship between emissions and their determinants, PQR captures varying effects across different pollution levels. Unlike traditional regression methods focusing on mean effects, quantile regression provides a more detailed analysis of how explanatory variables

influence the conditional distribution of emissions. The empirical quantile regression model for this study is specified as follows:

$$Q_{\tau}(\ln CO2_{it} | X_{it}) = \alpha_{\tau} + \beta_{\tau,1} \ln agr_{it} + \beta_{\tau,2} \ln pop_{it} + \beta_{\tau,3} \ln tech_{it} + \beta_{\tau,4} \ln trd_{it} + \beta_{\tau,5} \ln gdp_{it} + \varepsilon_{it} \quad (6)$$

where $Q_{\tau}(CO2_{it} | X_{it})$ denotes the conditional quantile of emissions for the country i at time t , X_{it} represents the vector of independent variables, α_{τ} and β_{τ} are the quantile-specific intercept and coefficients, respectively. τ represents the quantile level, where $\tau \in (0,1)$. The CO₂, agr, pop, tech, trd and gdp indicate the variables: carbon dioxide, agricultural, population, technology trade and GDP, respectively. The data are transformed into logarithmic forms to reduce skewness, facilitate elasticity interpretation and improve the comparability of variables. Quantile levels analyzed include the 25th, 50th, 75th and 95th percentiles, enabling the analysis of varying effects across low, medium and high pollution levels. The three main advantages of PQR are its ability to capture heterogeneity, robustness to outliers and policy-related insights. Last, similar to (Sultana et al., 2023; Işık et al., 2024), the Wald test is employed to assess the joint significance of the explanatory variables in the quantile regression model across different quantiles. This provides a robust means to determine whether the variables included in the model have a statistically significant impact on CO₂ emissions. The Wald test evaluates the joint significance of the coefficients in a linear model. In a quantile regression framework, the H_0 states that all coefficients for a set of explanatory variables are jointly equal to zero, $H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$. The test statistic W follows a chi-square distribution with degrees of freedom equal to the number of restrictions (number of coefficients tested jointly), $W \sim \chi^2(k)$ where k is the number of explanatory variables being checked for joint significance in the test.

The data analysis and econometric testing, including PQR, diagnostic checks and cointegration tests, were conducted using STATA.

ANALYSIS AND DISCUSSION

Throughout the analysis, *** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level, applicable to all statistical tests conducted in this study. To begin, the CSD tests were conducted to examine whether the residuals of the panel data are correlated across cross-sectional units. As shown in Table 1, the Pesaran's CD test (statistic=11.08, $p < 0.01$), indicates significant cross-sectional dependence. Similarly, the Breusch-Pagan LM test (statistic=163.284, $p < 0.01$) confirms the presence of strong dependence among the cross-sectional units. The Pesaran Scaled LM test result (statistic = 11.076, p

< 0.01) further supports this conclusion. These consistent findings suggest that ignoring cross-sectional dependence could lead to biased and inefficient estimates. The CADF test explicitly accounts for cross-sectional dependence by incorporating cross-sectional averages of the series and lagged differences in the model. This test is instrumental in panels with heterogeneous panels and cross-sectional correlations, common in macroeconomic and environmental studies. The results in Table 2 indicate that, at the level, most variables fail to reject the H_0 , indicating they are non-stationary at the level (i.e., they contain a unit root). After taking the first difference, the test statistics show that the H_0 of a unit root is rejected for most variables at a 1% significance level. This implies that the variables become stationary at the first difference, $I(1)$.

The Westerlund ECM panel cointegration test examines the presence of a long-run relationship among the variables, with the H_0 stating that there is no cointegration. The results in Table 3 exhibit that the Gt statistic is significant at the 5% level ($Z = -2.067$, $p < 0.05$), indicating the rejection of the H_0 for some cross-sections, suggesting evidence of cointegration for specific units. However, the Ga , Pt , and Pa statistics are insignificant, implying that there is no firm evidence of cointegration for the panel as a whole. The results suggest that while a long-run relationship may exist for a subset of the cross-sectional units, it is not prevalent across the entire panel.

Table 1: Cross-Sectional Dependence Test Results

Test	Statistic
Pesaran (2004) CD	11.08***
Pesaran Scaled LM	11.076***
Breush-Pagan LM	163.284***

Table 2: Pesaran CADF Panel Unit Root Test Results

Variable	Lags	Level (t-bar)	First Difference (t-bar)
ln CO2	0	-1.889	-4.017***
	1	-1.726	-3.333 ***
	2	-1.296	-2.054
ln agr	0	-1.155	-3.089 ***
	1	-2.096	-1.859
	2	-2.124	-1.476
ln pop	0	-1.282	-2.525 **
	1	-2.074	-3.142 ***
	2	-1.137	-2.009
ln tech	0	-1.76	-5.347 ***
	1	-1.835	-4.087 ***
	2	-1.763	-2.741 ***

Variable	Lags	Level (t-bar)	First Difference (t-bar)
ln trd	0	2.121	-6.076 ***
	1	1.774	-4.662 ***
	2	1.598	-1.170
ln gdp	0	-2.458 **	-3.103 ***
	1	-2.824 ***	-2.805 ***
	2	-1.708	-1.641

Table 3: Westerlund ECM Cointegration Test

Statistic	Z-value
Gt	-2.067**
Ga	3.403
Pt	1.163
Pa	2.169

The empirical analysis begins with the quantile regression results in Table 4, which reveal the heterogeneous effects of the explanatory variables on pollution levels across different quantiles (0.25, 0.50, 0.75, 0.95). The variable ln pop (population) shows a consistently positive but statistically insignificant impact on pollution across all quantiles, indicating that population growth does not significantly contribute to variations in pollution levels within this context. Similarly, ln agr (agricultural land) exhibits positive coefficients across all quantiles, with an increasing trend from the lower to the upper quantiles. However, the variable remains statistically insignificant at all quantiles, suggesting that agricultural land use does not play a decisive role in pollution levels in this sample. On the other hand, ln tech (technology) presents mixed effects with generally small coefficients that are statistically insignificant across all quantiles. This implies that the level of technology adoption in the observed countries may not directly impact pollution significantly, potentially due to variations in technology quality or inconsistent implementation across regions. The insignificant effects of population growth, agricultural land use, and technology may reflect several contextual and methodological factors. First, the population variable, measured as total growth rate, may not adequately capture urban concentration or consumption intensity, both of which are more directly linked to emissions. In SA, large portions of the population remain in rural or semi-urban areas with lower per capita energy use, diluting the overall statistical effect of population on emissions. Second, agricultural land use, while extensive, varies greatly in its environmental impact depending on crop type, intensity, and land management practices. Aggregate agricultural land data may therefore mask variations between high-emission (e.g., palm oil, rice) and low-emission (e.g., mixed cropping) systems across countries. Third, the technological indicator,

measured by the share of medium and high-tech manufacturing, primarily reflects industrial advancement rather than green innovation or renewable adoption. As such, it may not fully capture the environmental dimension of technology, leading to its weak statistical association with emissions. Finally, the influence of these variables may exhibit lagged effects, where technological diffusion or demographic transitions impact environmental outcomes only after several years. Future studies could incorporate disaggregated or time-lagged data to better capture these delayed and sector-specific dynamics.

In contrast, $\ln \text{trd}$ (trade openness) consistently shows a positive and highly significant effect across all quantiles, indicating that trade openness is a key driver of pollution. This result supports the notion that increased trade activities are associated with higher emissions, likely due to expanded industrial activities and the transportation of goods.

The variable $\ln \text{gdp}$ (GDP per capita) has a significant negative coefficient across all quantiles, confirming its inverse relationship with pollution. The results align with the EKC hypothesis, suggesting that higher income levels are associated with pollution reduction as countries shift toward cleaner technologies and more stringent environmental regulations. The negative relationship between GDP and emissions in higher quantiles confirms that wealthier ASEAN economies are progressing along the EKC's descending path, reflecting the benefits of industrial upgrading and environmental policy maturity. However, the persistence of rising emissions in lower-income countries underscores the need for regionally differentiated strategies that support sustainable industrialization without compromising growth.

To validate the robustness of the quantile regression results, the Wald test is performed across all quantiles. The results indicate the joint significance of the explanatory variables at each quantile (Chi-squared statistics = 373.25, 711.33, 475.63, and 156.47, $p < 0.01$) for the 0.25, 0.50, 0.75, and 0.95 quantiles. While only two out of the five variables are statistically significant, the results suggest that the set of variables collectively contributes to understanding pollution levels. The statistically significant factors demonstrate substantial individual impacts, while the remaining variables provide context for the broader relationships within the model.

SA's rapid growth has brought environmental challenges, mainly as trade openness drives up CO₂ emissions in countries like Malaysia and Indonesia. The study suggests that to keep growing without harming the environment, the region needs more innovative trade policies and targeted efforts to cut emissions, particularly from high-emitting industries. Promoting energy-efficient practices and tackling deforestation from activities like palm oil farming are also key. While technology and population growth play more minor roles for now, the path

forward lies in balancing economic progress with sustainability through greener practices and stronger environmental policies.

Table 4: Quantile Regression Estimation Results

Quantile	Q25	Q50	Q75	Q95
ln agr	0.1264	0.1506	0.1677	0.1896
ln pop	0.0232	0.0170	0.0126	0.0069
ln tech	-0.0253	-0.0112	-0.0013	0.0114
ln trd	0.2259***	0.2222***	0.2196***	0.2162***
ln gdp	-0.3634***	-0.3494***	-0.3395***	-0.3268***

Table 5: Wald Test Summary by Quantile

Quantile	Chi-square
0.25	373.25***
0.5	711.33***
0.75	475.63***
0.95	156.47***

CONCLUSION

This study examines the relationship between CO₂ emissions and their key drivers, including population growth, agricultural activities, technological progress, trade openness, and economic growth, using panel quantile regression (PQR). By capturing the heterogeneity of these relationships at different levels of pollution intensity, the analysis offers valuable insights into the varying impacts of these factors across quantiles. The findings emphasize the need for targeted, quantile-specific policy interventions that address diverse pollution levels effectively. Trade openness consistently shows a positive and significant impact on emissions, underscoring the role of trade-driven economic activities in contributing to pollution. Meanwhile, economic growth demonstrates a significant negative relationship with emissions at higher quantiles, supporting the Environmental Kuznets Curve (EKC) hypothesis. These results suggest that policies promoting green technologies and energy-efficient practices can mitigate emissions as economies grow. Agricultural activities reveal potential environmental risks, particularly in highly polluted areas, necessitating sustainable farming practices and reforestation efforts. Population growth and technological progress show limited immediate effects on emissions but may interact with other factors over time. The findings can inform policies that balance economic growth with environmental protection. Governments in SA could regulate trade-related emissions, prioritize sustainable agricultural practices and invest in renewable energy to address pollution challenges effectively. The policy implications of this study highlight the importance of

adopting targeted, sector-specific, and regionally coordinated measures to reduce emissions without compromising economic growth.

In the transportation sector, countries such as Indonesia, Thailand, and the Philippines could reduce emissions by accelerating the transition to electric public transport systems, promoting cleaner fuels and improving urban mobility planning. Given that transport contributes significantly to urban air pollution, especially in megacities like Jakarta and Bangkok, investments in green infrastructure and incentives for low-emission vehicles can yield immediate benefits.

In the agricultural sector, particularly in the context of palm oil production in Malaysia and Indonesia, stricter land-use management and reforestation initiatives are vital. Policies could emphasize enforcing “no-deforestation” supply chains, supporting smallholders through sustainable certification programs and promoting precision agriculture technologies to reduce fertilizer and pesticide overuse. These measures directly address the study’s findings that agricultural land use, though statistically insignificant in the short term, carries potential long-term risks for emissions and biodiversity loss.

The manufacturing sector also offers critical opportunities for emission reduction through technology upgrading and energy efficiency. Governments can support industries in adopting low-carbon technologies, renewable energy sources, and digital monitoring tools under Industry 4.0 frameworks. These transitions are especially relevant for upper-quantile countries (e.g., Malaysia, Thailand, Singapore), where GDP’s inverse relationship with emissions reflects growing environmental awareness and technological advancement.

At the regional level, the ASEAN Green Recovery Plan provides an important platform for collective action. By coordinating policies on clean energy investment, carbon pricing mechanisms and sustainable trade practices, ASEAN can harmonize environmental standards and promote knowledge transfer among member states. Regional initiatives can also mobilize funding for climate adaptation projects and support low-income countries such as Laos, Cambodia, and Myanmar in accelerating their transition toward sustainable industrialization. Overall, operationalizing these sectoral and regional strategies can help SA achieve a balanced path of economic growth and environmental protection. The quantile-specific insights from this study provide policymakers with evidence to tailor interventions according to pollution intensity and development level, ensuring that mitigation policies are both equitable and effective across the region.

ACKNOWLEDGEMENT

We gratefully acknowledge Universiti Teknikal Malaysia Melaka (UTeM) for supporting this study through the research grant MTUN/2023/UTEM-FTKM/CRG/MS0002.

DISCLOSURE

There is no conflict of interest in this research.

REFERENCES

- Adnan, S. A., Muhammad, A. A., Noman, A., & Yuriy, B. (2024). Nexus between economic growth, renewable energy and climate vulnerability: A global perspective using the EKC framework. *Renewable Energy*, 237, 121716. <https://doi.org/10.1016/j.renene.2024.121716>
- Barbosa, M. W. (2024). Government support mechanisms for sustainable agriculture: A systematic literature review and future research agenda. *Sustainability*, 16(5), 2185. <https://doi.org/10.3390/su16052185>
- Chaudhry, S., Yin, W., Ali, S. A., et al. (2022). Moderating role of institutional quality in validation of pollution haven hypothesis in BRICS: A new evidence by using DCCE approach. *Environmental Science and Pollution Research*, 29, 9193–9202. <https://doi.org/10.1007/s11356-021-16087-4>
- He, Z., Jing, L., & Bakhtawer, A. (2024). How do income inequality, poverty and industry 4.0 affect environmental pollution in South Asia: New insights from quantile regression. *Heliyon*, 10(13), e33397. <https://doi.org/10.1016/j.heliyon.2024.e33397>
- Ikram, J., Amine, L., & Mefteh-Wali, S. (2023). Quantile connectedness between CO2 emissions and economic growth in G7 countries. *Resources Policy*, 81, 103348. <https://doi.org/10.1016/j.resourpol.2023.103348>
- Işık, C., Bulut, U., Ongan, S., Islam, H., & Irfan, M. (2024). Exploring how economic growth, renewable energy, internet usage, and mineral rents influence CO₂ emissions: A panel quantile regression analysis for 27 OECD countries. *Resources Policy*, 92, 105025. <https://doi.org/10.1016/j.resourpol.2024.105025>
- Ismail, I., et al. (2024). Green economic development: A systematic literature review. *International Journal on Economics, Finance and Sustainable Development*, 6(8). <https://doi.org/10.31149/ijefsd.v6i8.5315>
- Leh, O. H. H., Marzukhi, M. A., Kwong, Q. J., & Mabahwi, N. A. (2020). Impact of urban land uses and activities on the ambient air quality in Klang Valley, Malaysia from 2014 to 2020. *Planning Malaysia*, 18(4), 239–258.
- Liu, L. Y., Boqiang, L., & Bin, X. (2021). Modeling the impact of energy abundance on economic growth and CO₂ emissions by quantile regression: Evidence from China. *Energy*, 227, 120416. <https://doi.org/10.1016/j.energy.2021.120416>
- Liu, Y., & Lai, X. (2021). EKC and carbon footprint of cross-border waste transfer: Evidence from 134 countries. *Ecological Indicators*, 129, 107961.

- Madni, G. R. (2023). Meditation for role of productive capacities and green investment on ecological footprint in BRI countries. *Environmental Science and Pollution Research*, 30(28), 72308–72318. <https://doi.org/10.1007/s11356-023-28176-1>
- Matarneh, S., Piprani, A. Z., Ellahi, R. M., Nguyen, D. N., Le, T. M., & Nazir, S. (2024). Industry 4.0 technologies and circular economy synergies: Enhancing corporate sustainability through sustainable supply chain integration and flexibility. *Environmental Technology & Innovation*, 35, 103723. <https://doi.org/10.1016/j.eti.2024.103723>
- Mishra, A., Willem, W. K. J., Norman, U., & Max, W. (2021). Food security and climate-smart agriculture in the Lower Mekong Basin of Southeast Asia: Evaluating impacts of system of rice intensification with special reference to rainfed agriculture. *International Journal of Agricultural Sustainability*, 19(2), 152–174. <https://doi.org/10.1080/14735903.2020.1866852>
- Mohd, H. K., Mutalib, A. A. H., Miard, P., Goh, C. S., Mohd, S. S. A., & Ruppert, N. (2022). Impact of Malaysian palm oil on sustainable development goals: Co-benefits and trade-offs across mitigation strategies. *Sustainability Science*, 17(4), 1639–1661. <https://doi.org/10.1007/s11625-021-01052-4>
- Muhammad, U., Syed, A. R. K., Mohd, Y. Y., Shahzad, A., & Zhang, Y. (2022). Industry 4.0 and green supply chain practices: An empirical study. *International Journal of Productivity and Performance Management*, 71(3), 814–832.
- Nordin, S. K. S., Hamzah, K., Khashi'ie, N. S., Zainal, N. A., & Abdul Halim, B. (2024). Testing Environmental Kuznets Curve (EKC) hypothesis in ASEAN countries: Evidence based on STIRPAT framework with cross-sectional dependency. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 46(2), 227–238. <https://doi.org/10.37934/araset.46.2.227238>
- Özcan, B., & Öztürk, I. (Eds.). (2019). *Environmental Kuznets curve (EKC): A manual*. Academic Press.
- Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, 142(1), 50–93.
- Potipituk, C. (2019). Global Environmental Kuznets Curve facts and corresponding possible consequences on Bangkok Metropolitan emission. *Planning Malaysia*, 17(2), 101–112.
- Roberto, F., Azzurra, A., & Gennaro, P. (2024). Promoting the transition towards Agriculture 4.0: A systematic literature review on drivers and barriers. *Sustainability*, 16(6), 1–29. <https://doi.org/10.3390/su16062185>
- Sangco, R. M. R. (2024). Impact of greenhouse gas emission, renewable energy, and economic growth on health expenditure in Southeast Asia: A comparative analysis of econometric models. *Economic Journal of Emerging Markets*, 16(2), 191–202. <https://doi.org/10.20885/ejem.vol16.iss2.art8>
- Shabur, M. A. (2024). A comprehensive review on the impact of Industry 4.0 on the development of a sustainable environment. *Discover Sustainability*, 5(1), 97. <https://doi.org/10.1007/s43621-024-00290-7>
- She, H., Benjamin, E. O., & Johannes, S. (2024). Factors influencing the adoption of sustainable agricultural practices for rice cultivation in Southeast Asia: A review.

- Agronomy for Sustainable Development*, 44, 27. <https://doi.org/10.1007/s13593-024-00960-w>
- Shiraishi, T., Hirata, R., Hayashi, M., & Hirano, T. (2023). Carbon dioxide emissions through land use change, fire, and oxidative peat decomposition in Borneo. *Scientific Reports*, 13(1), 11816.
- Smarnika, G., et al. (2023). Unveiling the spillover effects of democracy and renewable energy consumption on the environmental quality of BRICS countries: A new insight from different quantile regression approaches. *Renewable Energy Focus*, 46, 222–235. <https://doi.org/10.1016/j.ref.2023.06.004>
- Song, Y., Li, L., Shahbaz, M., & Bukhari, A. A. A. (2024). Does an environmental stringent policy really matter to achieve environmental sustainability in BRICS-T region? Evidence from novel method of moments quantile regression approach. *Journal of Environmental Management*, 368, 121898. <https://doi.org/10.1016/j.jenvman.2024.121898>
- Sonthaya, S., & Witsanu, A. (2021). Agricultural production factors and their effect on agricultural production and carbon emissions: Evidence from the Greater Mekong Subregion. *The Open Agriculture Journal*, 15, 75–81. <https://doi.org/10.2174/1874331502115010075>
- Sultana, T., Hossain, M. S., Voumik, L. C., & Raihan, A. (2023). Democracy, green energy, trade, and environmental progress in South Asia: Advanced quantile regression perspective. *Heliyon*, 9(10), e20488. <https://doi.org/10.1016/j.heliyon.2023.e20488>
- Tran, N. M. (2023). Renewable energy, GDP (gross domestic product), FDI (foreign direct investment) and CO2 emissions in Southeast Asia countries. *International Journal of Energy Economics and Policy*, 13(2), 284–289.
- Weixian, W., et al. (2024). Balancing river water pollution and agricultural development: A tradeoff threshold approach. *Journal of Environmental Management*, 367, 121985. <https://doi.org/10.1016/j.jenvman.2024.121985>
- Yin, F., Jinhua, C., & Yin, D. (2024). Study on agricultural water resource utilization efficiency under the constraint of carbon emission and water pollution. *Environmental Research*, 253, 119142. <https://doi.org/10.1016/j.envres.2024.119142>
- Yujie, P., et al. (2025). Identifying spatial drivers of soil heavy metal pollution risk integrating positive matrix factorization, machine learning, and multi-scale geographically weighted regression. *Journal of Hazardous Materials*, 485, 136841. <https://doi.org/10.1016/j.jhazmat.2024.136841>

Received: 2nd September 2025. Accepted: 14th September 2025