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Quantifying Drivers of GHG Emissions in ASEAN: Modeling CO_2 Emissions Using LMDI and ARIMAX Approaches

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ABSTRACT

This work aims to create a robust causal regression model that can accurately measure the influence of many variables on greenhouse gas (GHG) emissions in ASEAN nations from 1971 to 2017. The study aims to identify the main factors contributing to emissions and provide valuable information for implementing effective reduction methods. This is important because balancing economic growth and environmental sustainability in the fast-changing ASEAN area is crucial. The research used the Logarithmic Mean Divisia Index (LMDI) decomposition method to examine the individual contributions of various causes to changes in CO_2 emissions over time. In addition, a model called ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variables) is created to anticipate CO_2 emissions and determine essential factors that influence them. The dependent variable is total GHG emissions measured in metric tons of CO_2 equivalent, while independent variables include GDP, energy intensity, carbon intensity, and population growth. The study discovered that GDP, with varied degrees of impact, is the primary catalyst for CO_2 emissions in ASEAN nations. The energy intensity is projected to decline, indicating increases in efficiency, while the influence of population growth is forecast to be positive but less substantial compared to economic reasons. The research is anticipated to uncover disparities in the decrease of carbon intensity and the efficacy of policies across ASEAN nations, with more advanced economies demonstrating more resilient systems. These results provide significant knowledge for governments and companies, aiding in creating focused efforts to reduce emissions and improve carbon accounting standards across the ASEAN region.

Keywords: Autoregressive Integrated Moving Average with Exogenous Variables, Carbon Accounting, Greenhouse Gas Emissions, Logarithmic Mean Divisia Index, Emission Drivers
JEL Classifications: P18, P28, Q47

1. INTRODUCTION

During the early 1970s, several ASEAN countries' economies were mainly based on agriculture, with little progress in industrialization. Nevertheless, the evidence indicates a significant and noticeable change, especially from the 1980s. Examining the GDP growth, we see significant favourable growth rates in most nations, which indicate a fast development of the economy generally linked to industrialization and the rise of the service sector. Singapore's remarkable GDP growth rates regularly highlight its position as a prominent worldwide centre for finance and industry. Likewise, Malaysia, Thailand, and Indonesia had robust economic expansion, especially throughout the 1990s and 2000s, as they focused on developing export-driven manufacturing sectors. This transition is additionally reinforced by the energy intensity, which shows varying but predominantly declining energy intensity for numerous countries over time. This indicates enhancements in energy efficiency commonly linked to the modernization of industrial practices and a shift towards less energy-intensive service sectors.

The shift towards economies centred on manufacturing and services is also seen in the shifting carbon intensity trends and population impacts. Different patterns in carbon intensity may be seen, with nations such as Singapore and Malaysia seeing notable periods of decline. This suggests a transition towards more valuable economic activity with lower carbon emissions. The population data indicates significant and favourable growth for most nations, especially in metropolitan regions, which is usually associated with industrialization and the development of service industries. Acknowledging that this economic transition has resulted in substantial economic expansion and progress is essential. However, it has also given rise to environmental difficulties, as seen by the general rise in CO_2 emissions. ASEAN nations must prioritize the equilibrium between economic growth and sustainable practices as they advance their industrial and service sectors.

Meanwhile, the discipline of carbon accounting has been seeing consistent growth. However, more study is required to comprehensively comprehend the environmental effect of firms in each nation and the associated economic and behavioural theories (Nielsen et al., 2017). Carbon accounting is an essential component of sustainability management and is now undergoing substantial expansion. Nevertheless, it also entails distinct benefits and difficulties (Schaltegger et al., 2017). Precision is essential when dealing with sustainability data (Tóth et al., 2018), particularly in disclosing business CO_2 emissions. The ISO 14064 standard is relevant in this context. It is an essential instrument that aids firms in controlling and overseeing their greenhouse gas emissions, guaranteeing enduring sustainability and profitability (Aristizábal-Alzate and González-Manosalva, 2021). However, integrating environmental considerations into accounting calculations, such as carbon accounting, is challenging. Implementing standards and robust mechanisms is necessary (Burr et al., 2013).

The main objective of this study is to create a strong causal regression model that measures the influence of several variables on greenhouse gas (GHG) emissions in ASEAN nations. This would allow for better prioritization of initiatives aimed at reducing emissions. This objective aims to meet an urgent need in the area, which has seen substantial economic changes since the 1970s, shifting from mostly agricultural economies to ones focused on industry and services. Although this transition has resulted in rapid economic expansion, it has also amplified environmental difficulties, specifically with the release of CO_2 emissions (Anbumozhi and Kalirajan, 2017). The study seeks to thoroughly comprehend the correlation between economic advancement and environmental sustainability in ASEAN nations. The scope of the study includes the time frame from the 1970s till now, with a specific emphasis on essential factors such as GDP growth, energy intensity, carbon intensity, and demographic impacts. This research objective aligns with the expanding field of carbon accounting, which has made substantial progress. However, further detailed research specific to each country is needed to overcome the difficulties in implementing precise systems (Tóth et al., 2018), and to effectively utilize tools such as the ISO 14064 standard for managing and regulating greenhouse gas emissions (Aristizábal-Alzate and González-Manosalva, 2021).

In order to accomplish the study objective, we propose the hypothesis that the primary factor influencing CO_2 emissions in ASEAN nations is economic expansion, as shown by GDP. However, this effect is influenced by enhancements in energy efficiency and a transition towards economic activities that are less carbon-intensive. Furthermore, we propose that the increase in population, specifically in urban regions, is positively associated with the release of CO_2 into the atmosphere (Murni et al., 2022; Sudarmaji et al., 2022; Sudarmaji et al., 2022). However, the impact of this relationship differs among countries due to variations in their economic development and environmental policies. The research will use quantitative techniques to construct the causal regression model. This encompasses extensive data gathering on the economic development rate, energy efficiency, carbon emissions, population growth, and carbon dioxide emissions for the nations in the Association of Southeast Asian Nations (ASEAN).

The analysis will employ LMDI (Logarithmic Mean Divisia Index) decomposition to examine the individual contributions of various factors to the changes in CO_2 emissions over time (Ang, 2015). ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variables) modelling will also predict CO_2 emissions and identify the main predictors (George et al., 2015). Examining the quality of environmental regulations and carbon accounting processes in ASEAN nations will help give background information for the numerical results. Utilizing cross-validation procedures and out-of-sample forecasting will guarantee the reliability and predictive capability of the constructed model, thus contributing to the study objective.

Aligned to construct a causal regression model, we expect to get many significant outcomes that will enhance our comprehension of greenhouse gas (GHG) emissions in ASEAN nations. According to (Anbumozhi and Kalirajan, 2017), we anticipate that GDP growth will be the main factor influencing CO_2 emissions, but the extent of this impact would differ across nations. The energy intensity trend is expected to decrease over time, indicating advancements in efficiency usually. However, there are notable variances across different countries (Shahbaz et al., 2020). Population expansion, particularly in metropolitan regions, is expected to have a positive association with CO_2 emissions, but its influence may be less substantial compared to economic considerations (Sudarmaji et al., 2021).

Countries with more developed service sectors and industrial industries that produce higher-value goods, like Singapore and Malaysia, are anticipated to exhibit periods of decreased carbon intensity. This suggests a possible separation between economic expansion and the rise of emissions (Pui and Othman, 2019). The efficacy of carbon accounting procedures and environmental regulations is expected to differ considerably across ASEAN nations, with more advanced economies demonstrating more resilient systems (Qian et al., 2018). The anticipated outcomes from the causal regression model will provide valuable insights for policymakers and enterprises in ASEAN nations. The model will assess the influence of different variables on GHG emissions, aiding in formulating policies that balance economic growth and environmental sustainability. This will directly address the primary study objective and enhance the effectiveness of emission reduction initiatives.

2. LITERATURE REVIEW

Environmental sustainability primarily concerns the interplay between human activities and natural systems. The Ecological Modernization Theory (EMT) is well-recognized and influential. The concept of Environmental Management Technology (EMT) suggests that economic growth and environmental conservation may be mutually beneficial by incorporating environmental improvements into industrial processes. Research has shown that nations that embrace cleaner technology not only see a decline in environmental deterioration but also achieve economic development (Mol and Spaargaren, 2000). Recent empirical research substantiates this notion, demonstrating that investments in renewable energy substantially contribute to reducing carbon emissions without impeding economic performance (IRENA, 2020). Moreover, the theory supports the idea that governmental rules and regulations are crucial in fostering sustainable behaviours. Governments can provide incentives for adopting green technology and ensure compliance with environmental legislation. These measures, in turn, promote corporate environmental responsibility (Oduro, 2024). EMT offers a pragmatic framework for attaining sustainability in the contemporary period by harmonizing economic incentives with ecological objectives.

Climate change is often based on the framework of the Anthropogenic Global Warming (AGW) hypothesis. The idea of anthropogenic global warming (AGW) principally connects current global warming trends to human activities, including burning fossil fuels and deforestation. According to the Intergovernmental Panel on Climate Change (IPCC, 2021), these activities result in higher concentrations of greenhouse gases in the atmosphere. Recent empirical studies highlight the rapid rate at which climate change occurs, as shown by record-breaking temperatures and frequent severe weather events. Research by Hansen et al. (2022) emphasized that the previous 10 years have been the hottest ever recorded, leading to notable consequences such as rising sea levels and biodiversity loss. Furthermore, empirical models indicate that if the present emission patterns persist, global temperatures may increase by as much as 4°C by the end of the century. This would worsen climate-related calamities, as the World Meteorological Organization stated in 2023. These results highlight the need to promptly adopt comprehensive measures to reduce the harmful impacts of climate change. This includes shifting to renewable energy sources and improving efforts to capture and store carbon dioxide.

Empirical ideas about emission reduction tactics highlight the need to incorporate economic incentives, technical innovation, and governmental initiatives. The Decarbonization Theory suggests that a combination of regulatory actions and technological improvements may lead to systematic reductions in carbon emissions. Empirical research provides evidence that carbon pricing mechanisms, such as carbon taxes and cap-and-trade systems, effectively encourage emissions reduction by accounting for the external costs associated with carbon emissions (Gerarden et al., 2015). Recent research emphasizes the significance of renewable energy technologies, namely solar and wind, in substantially decreasing emissions in the power industry (International Energy Agency, 2005). Furthermore, it has been shown that enhancements in energy efficiency within sectors such as industry and transportation significantly contribute to decreasing emissions. Nasip and Sudarmaji (2023) revealed that implementing energy-efficient technology can decrease worldwide industrial emissions. These empirical data highlight the significance of combining economic, technical, and regulatory strategies to reduce emissions across different industries substantially.

3. METHODS

Regression modelling is crucial in studying environmental data, enabling researchers to discover connections between environmental factors and predict future trends. A frequently used method is Multiple Linear Regression (MLR), which establishes a mathematical model to describe the connection between a dependent variable and many independent variables. Using this approach in air quality research has shown to be very efficient in predicting pollutant concentrations using meteorological data and emission sources (Lumley et al., 2022). Empirical studies provide evidence that MLR models can precisely predict levels of pollutants, which in turn assists in creating solutions to reduce their impact. To do a regression analysis to determine causal relationships in carbon accounting, one often gathers data on several factors that might impact greenhouse gas (GHG) emissions (independent variables), as well as the actual GHG emissions data (dependent variable). The GHG emissions data would serve as the dependent variable in this scenario. The measurement might vary based on the analysis's scope and boundaries and can be expressed in various quantities, such as metric tons of carbon dioxide equivalent (CO_2e). Independent Variables: The independent variables include a range of characteristics that may have a causal connection with GHG emissions. These variables include energy consumption statistics, operational procedures (energy intensity), and demographic and economic indicators (GDP). It is crucial to acknowledge that carbon accounting and regression analysis can be intricate, and it may be advantageous to seek advice from specialists or consult established methodologies and guidelines, such as the Greenhouse Gas Protocol or industry-specific standards, to guarantee precise and comprehensive accounting. Carbon accounting aims to measure the amount of carbon emissions produced and find potential options for reducing these emissions.

This paper investigates the use of the LMDI technique in decarbonization. Decarbonization requires a thorough understanding of the factors affecting carbon emissions, precisely where the LMDI method shines. The LMDI methodology is a comprehensive and transparent way of analyzing the factors contributing to fluctuations in carbon emissions. The LMDI method allows analysts to precisely identify the specific elements that contribute to changes in emissions over time (Ambarwati et al., 2023; Damayanti et al., 2024; Murni et al., 2022; Sudarmaji et al., 2022). This is achieved by breaking down the total emissions into several components: Population, GDP, energy intensity, and carbon intensity. Hence, the investigation must ascertain the primary factors contributing to the increase in emissions. The

LMDI method can simulate several scenarios by modifying the assumptions about population increase, economic development, and technology adoption. These scenarios help stakeholders visualize the possible consequences of various policy options and contribute to making informed decisions.

The addictive LMDI decomposition technique was used in this experiment. The LMDI method allows for dividing a single factor into several components, and it can accurately measure the impact of each of these components on the original factor. The author of this research may integrate CO_2 into components such as POP-effect, GDP-effect, EI-effect, and CO_2-effect for Indonesia and ASEAN countries between 1971 and 2017. The IEA presented carbon dioxide (CO_2) gas emissions, gross domestic product (GDP), population, and primary energy consumption statistics. The deconstructed addictive LMDI model was used to get four dimensions, population effect, GDP impact, energy intensity, and CO_2 intensity, to accurately represent the many outcomes resulting from the rise in energy consumption. Below are the equations that describe the decomposition effect:

$$\Delta CO_{2Total} = \left(\Sigma L\left(POP^T, POP^0\right) Ln\left(\frac{POP_{effect^T}}{POP_{effect^0}}\right)\right) + \left(\Sigma L\left(GDP^t, GDP^0\right) Ln\left(\frac{GDP_{effect^T}}{GDP_{effecr^0}}\right)\right) \left(\Sigma L\left(EI^T, EI^0\right) Ln\left(\frac{PEC_{effect^T}}{PEC_{effect^0}}\right)\right) + \left(\Sigma L\left(PEC^T, EC^0\right) Ln\left(\frac{PEC_{effect^T}}{PEC_{effect^0}}\right)\right) \quad (1)$$

Where:

ΔCO_{2Total} = Carbon emission

ΔCO_{2Total} = Carbon emission

$\Delta POP\text{-}effect = \left(\Sigma L\left(GDP^t, GDP^0\right) Ln\left(\frac{GDP_{effect^T}}{GDP_{effecr^0}}\right)\right)$ was Population effect

$\Delta GDP\text{-}effect = \left(\Sigma L\left(GDP^t, GDP^0\right) Ln\left(\frac{GDP_{effect^T}}{GDP_{effecr^0}}\right)\right)$ was GDP effect

$\Delta EI\text{-}effect = \left(\Sigma L\left(EI^T, EI^0\right) Ln\left(\frac{PEC_{effect^T}}{PEC_{effect^0}}\right)\right)$ was Energy Intensity

$\Delta PEC\text{-}effect = \left(\Sigma L\left(PEC^T, PEC^0\right) Ln\left(\frac{PEC_{effect^T}}{PEC_{effect^0}}\right)\right)$ was Primary Energy Consumption

In the subsequent phase, the research used the ARIMAX model to construct a framework for predicting CO_2 gas emissions. The initial step in the ARIMAX model involves identifying the optimal ARIMA model. Once the best ARIMA model is determined, independent variables are incorporated into the previously obtained ARIMA model to estimate the ARIMAX model. Subsequently, a diagnostic test is conducted to assess the model's suitability. The ARIMA model is used as a forecasting model for CO_2 gas emissions. The ARIMA model, denoted as (p, d, q), is commonly used in statistics.

$$\varphi\, p(B)(1 - B)d\ Zt = \theta q(B)et \quad (2)$$

The ARIMAX model is widely used for long-term forecasting due to its ability to include two variables, namely the dependent variable and the primary indicator, to predict its future value. The ARIMAX model (p, d, q) may be expressed in the following manner:

$$(1 - B)d\ \varphi\ p\ (B)Zt = \Delta + \theta q\ (B)et + a1X1,t + a2\ X\,2,t +. + ak\ Xk,t \quad (3)$$

Where μ, a_1, a_2.,*ak are* constants. The ARIMAX model that has been acquired is continued with diagnostic tests, namely *the white noise test* and the normality test.

4. RESULTS AND DISCUSSION

Table 1 presents the descriptive statistics for each variable, including the mean, standard deviation, minimum, and maximum values. The paper provides the regression model values utilizing a data panel consisting of 368 data items for each member of the ASEAN Country. The descriptive analysis shows considerable variation in the levels of carbon dioxide emissions among the nations in the ASEAN area. Indonesia has the most significant average CO_2 emissions, valued at 20.476 units. Additionally, it has the most significant effects on population (5.991 units), GDP (14.126 units), and energy intensity (−5.647 units). Indonesia has the highest level of variation in these components, with a standard deviation of 22.530 units for CO_2 emissions and equally elevated values for population, GDP, and energy intensity impacts. In contrast, Brunei and Myanmar have far lower average levels and less fluctuation, suggesting a less substantial influence and more consistent patterns in their carbon dioxide emissions. Malaysia exhibits intriguing trends with shallow minimum values, including −41.005 units for CO_2 emissions, −74.242 units for GDP impact, and −74.141 units for energy intensity impact. These figures suggest significant periods of emission reductions. In Indonesia, the maximum values for these components are very high, with a CO_2 effect reaching a peak of 94.709 units. In summary, this research emphasizes that Indonesia plays a significant role in the area's carbon dioxide (CO_2) emissions patterns. Indonesia's contributions to CO_2 emissions are significant and vary over time, whereas Brunei and Myanmar have more consistent and lesser effects. Malaysia's results indicate the possibility of substantial reductions in CO_2 emissions under certain circumstances.

Table 1: Descriptive analysis ASEAN CO_2, population, GDP and energy intensity

Description	Brunei	Cambodia	Indonesia	Malaysia	Myanmar	Philipines	Singapore	Thailand	Vietnam
Mean									
CO_2	0.274	0.845	20.476	8.619	1.126	4.465	1.771	9.914	7.607
Population effect	0.169	0.130	5.991	3.761	0.191	2.257	1.238	1.986	1.329
GDP effect	−0.086	0.409	14.126	6.099	0.879	2.537	2.163	8.243	4.939
Energy intensity effect	0.220	−0.086	−5.647	−3.574	−0.541	−1.529	−0.536	0.233	−1.032
CO_2 effect	−0.028	0.392	6.006	2.334	0.597	1.201	−1.095	−0.549	2.371
Standard deviation									
CO_2	0.926	1.051	22.530	13.048	3.450	7.522	3.510	13.400	13.868
Population effect	0.042	0.065	3.070	2.340	0.069	0.596	1.027	0.731	0.949
GDP effect	0.316	0.278	18.016	7.453	0.941	3.864	2.457	10.059	5.658
Energy intensity effect	1.254	0.816	20.416	9.441	1.090	3.743	8.589	7.512	5.429
CO_2 effect	1.060	0.828	23.831	15.231	2.338	5.275	7.984	7.291	9.069
Minimum									
CO_2	−1.548	−0.001	−14.141	−41.005	−5.017	−11.909	−6.301	−29.894	−10.375
Population effect	0.034	0.077	1.405	0.595	0.096	1.393	−1.157	0.982	0.531
GDP effect	−1.315	−0.113	−74.242	−19.801	−1.215	−6.477	−4.222	−28.031	−4.007
Energy intensity effect	−3.327	−1.391	−74.141	−34.666	−2.610	−9.785	−34.214	−21.594	−21.761
CO_2 effect	−2.421	−1.678	−55.866	−65.574	−4.345	−10.903	−21.240	−20.585	−8.338
Maximum									
CO_2	4.786	3.827	83.796	40.102	19.012	23.470	15.757	34.383	76.418
Population effect	0.245	0.306	10.818	7.468	0.464	3.699	4.027	3.748	3.986
GDP effect	0.635	1.067	36.811	19.194	2.853	11.897	9.960	30.067	21.427
Energy intensity effect	3.662	3.110	56.858	30.056	3.996	7.363	11.799	22.234	13.665
CO_2 effect	2.952	2.422	94.709	33.878	11.699	14.942	23.312	13.759	56.673

ASEAN: Association of Southeast Asian Nations

4.1. LMDI Decomposition Factors

A decomposition model is required to accurately analyze the various impacts of changes in activity, structure, and industrial intensities on energy consumption. The following diagram, labelled as Figure 1, displays the CO_2 decomposition factors for different ASEAN nations from 1971 to 2017 (or 1995 to 2017, specifically for Cambodia). The graphs analyze the variations in CO_2 emissions (Delta CO_2) by categorizing them into three factors: population effects, GDP effects, and energy intensity effects. In the case of Indonesia, the growth in CO_2 emissions is mainly influenced by the effects of GDP, which contributes the most substantially (649.78 units). This is followed by the impacts of CO_2 intensity (276.30 units).

However, the increase in population has a modest reducing effect on emissions (−275.54 units). Thailand has a similar trend where the most significant influence on GDP is seen, with a magnitude of 379.20 units. At the same time, there is a tiny decrease resulting from the impacts of CO_2 intensity, amounting to −25.24 units. Malaysia's GDP effects contribute significantly to its overall performance, with a value of 280.55 units. Additionally, there is a noteworthy decrease in intensity effects, amounting to −164.40 units. Both Vietnam and the Philippines have significant positive contributions from GDP and CO_2 intensity impacts.

Vietnam's GDP effects amount to 227.18 units, while the Philippines' effects reach 116.68 units. By comparison, Brunei and Singapore have far lesser magnitudes, with Brunei's GDP impact measuring 10.09 units and Singapore's measuring 99.51 units. Additionally, both countries see decreases in CO_2 intensity effects. Myanmar and Cambodia both demonstrate favourable impacts from GDP and CO_2 intensity effects. It is worth noting that Cambodia's data began in 1995. In most ASEAN nations, the main driver of CO_2 emissions increases is the overall influence of GDP effects. On the other hand, improvements in energy intensity have varying benefits, sometimes leading to significant reductions in emissions.

Figure 2 displays nine graphs, each specifically focused on a distinct Southeast Asian nation: Brunei Darussalam, Cambodia, Indonesia, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam. The graphs depict each country's "Index Divisia Mean Logarithm," which seems to be a metric associated with carbon emissions and energy consumption. Upon examining the first row of graphs, it becomes evident that Brunei, Cambodia, and Indonesia exhibit discernible patterns.

The graph representing Brunei's CO_2 impact exhibits notable variations, characterized by distinct spikes and dips occurring periodically. One striking feature of Cambodia's graph is a sudden surge in energy intensity, contrasting with the usually consistent patterns. Indonesia's graph exhibits more stable patterns throughout its variables, demonstrating fewer pronounced oscillations than its neighbouring countries. The second row, which includes Malaysia, Myanmar, and the Philippines, displays a greater diversity of tendencies.

The graph of Malaysia is notably remarkable, displaying drastic oscillations, including a substantial negative plunge within a specific time, indicating a significant occurrence or alteration in measurement.

The graph of Myanmar shows a progressive upward trend in several variables over time, indicating economic or environmental improvements. The graph of the Philippines also exhibits some upward patterns, namely in terms of GDP and CO_2 impacts,

Figure 1: Delta ASEAN CO_2

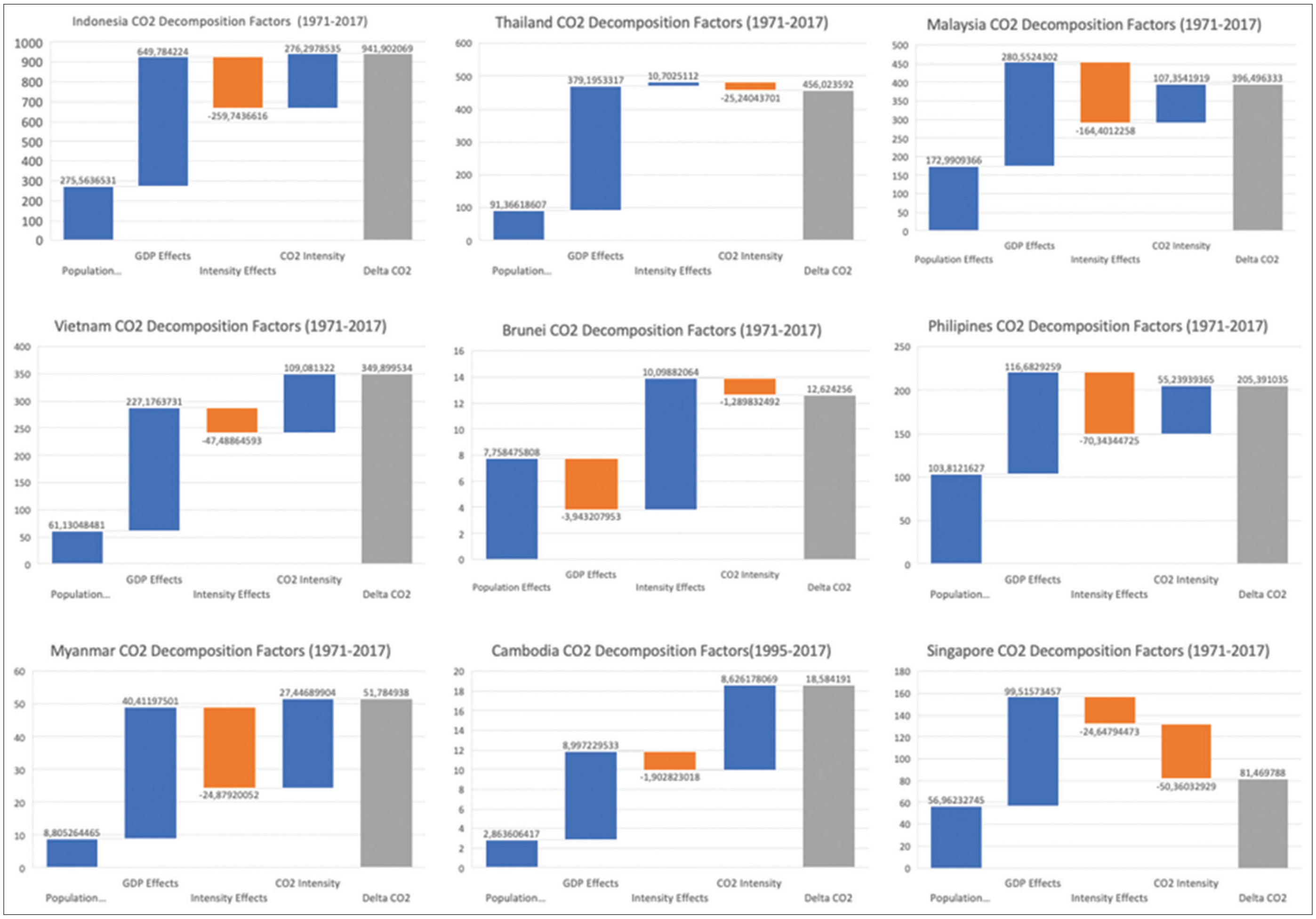
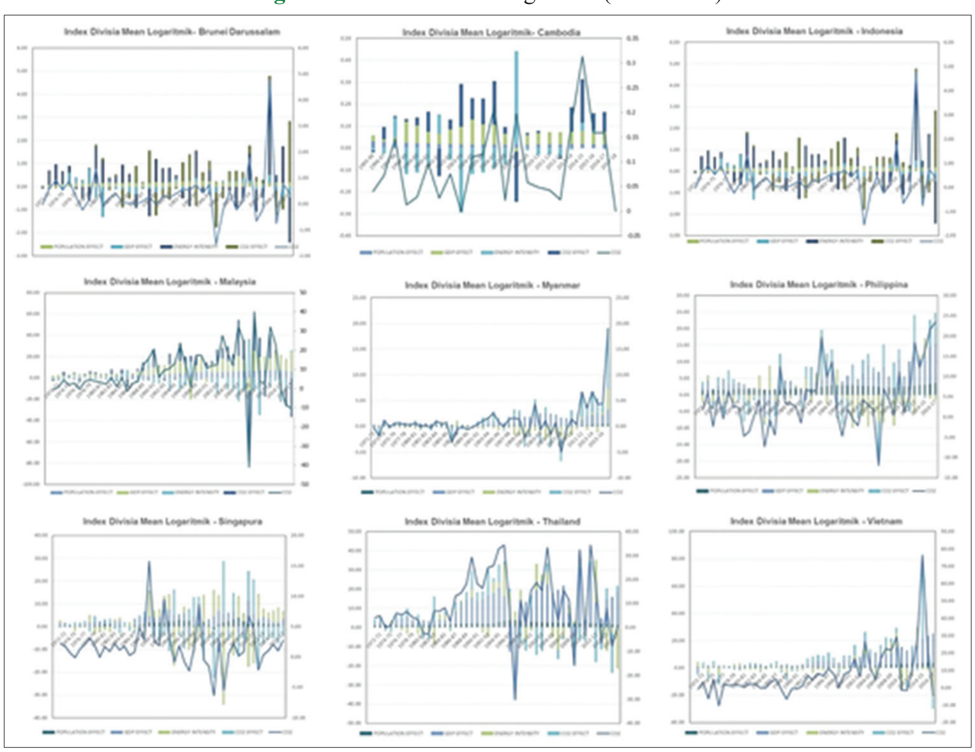


Figure 2: ASEAN Index Logaritma (1971-2019)



suggesting a correlation between economic expansion and heightened emissions. The last row, including Singapore, Thailand, and Vietnam, displays similarly intriguing patterns. The graph of Singapore displays cyclic patterns in its variables, indicating the influence of the country's meticulously controlled economy and environment. Thailand's graph displays periods of significant volatility in its measurements, characterized by abrupt fluctuations in several variables. Vietnam's graph exhibits a remarkable surge in one of its variables (perhaps the CO_2 impact) towards the conclusion of the time frame, suggesting a substantial shift in the country's emissions or energy use.

4.2. ARIMAX Model Fit

The study focus on ARIMAX (0,1,1) and ARIMAX (1,1,1) models for refining time series forecasts is supported by both theoretical and empirical evidence. These models balance simplicity and effectiveness, making them suitable for capturing key dynamics like trends and shocks in the data. The ARIMAX (0,1,1) model, with its moving average component, quickly adjusts for recent disturbances, while the ARIMAX (1,1,1) model adds an autoregressive component to account for past values, providing a robust fit. Studies in environmental sciences, such as those by Wang et al. (2021), have shown that ARIMAX models are effective in forecasting climate-related variables like CO_2 emissions. This makes ARIMAX (0,1,1) and ARIMAX (1,1,1) logical choices for initial model assessment and refinement. Table 2 displays ARIMA models with orders (0,1,1) and (1,1,1) for nine countries: Brunei, Cambodia, Malaysia, Indonesia, Myanmar, Philippines, Singapore, Thailand, and Vietnam.

In general, the models demonstrate strong alignment in most nations, exhibiting high R-squared values ranging from 0.843 to 0.995. These values indicate that the models effectively account for a significant proportion of the variability seen in the data. The stationary R-squared values, which quantify the degree of improvement compared to a mean model, exhibit a significant range from 0.028 to 0.617.

The results of the Ljung-Box Q test provide valuable information on the appropriateness of the model. Most models exhibit non-significant findings ($P > 0.05$), suggesting the absence of substantial autocorrelation in the residuals, which is a desired outcome. Nevertheless, the statistical analysis of the Philippines models reveals noteworthy outcomes ($P < 0.05$ for ARIMA 0,1,1 and $P < 0.10$ for ARIMA 1,1,1), indicating the presence of residual autocorrelation that warrants more examination.

The abnormal items consist of Indonesia's persistently low stationary R-squared, Singapore's very low stationary R-squared despite a high R-squared, and the Philippines' notable Ljung-Box test findings. These irregularities need a more thorough analysis of these nations' data and model parameters. The wide disparity between the high R-squared and low stationary R-squared values, seen in some instances such as Singapore, indicates that while the models effectively capture general patterns, more is needed to enhance the explanation of short-term fluctuations compared to a basic mean model. This suggests that some series closely resemble random walks with a trend, making ARIMA models less effective in providing significant enhancements than simpler models. Table 3 compares ARIMA models (0,1,1) and (1,1,1) for nine countries: Brunei, Cambodia, Indonesia, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam.

The statistical fit measures consist of Stationary R-squared, R-squared, RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error), MaxAPE (Maximum Absolute Percentage Error), MAE (Mean Absolute Error), MaxAE (Maximum Absolute Error), and Normalized BIC (Bayesian Information Criterion). In the case of Brunei, the ARIMA (1,1,1) model demonstrates somewhat superior performance compared to the ARIMA (0,1,1) model. This is evident from the higher Stationary R-squared value of 0.138 compared to 0.077 and the lower RMSE value of 0.912 compared to 0.932. Nevertheless, both models have high MaxAPE values (35.134 and 30.616), suggesting the presence of outliers or substantial deviations in the data. Cambodia consistently exhibits strong model performance, as both the ARIMA (0,1,1) and (1,1,1) models reveal equal R-squared values of 0.988 and display comparable levels of errors. The elevated MaxAPE values (88.624 and 88.076) indicate infrequent but significant prediction mistakes.

The data from Indonesia shows an anomaly with very high RMSE (Root Mean Square Error) and MaxAPE (Maximum Absolute Percentage Error) values (103.309 and 3672.772 for ARIMA [0,1,1]). These values suggest that the model fit is weak, and there may be difficulties with the data. Malaysia has a strong performance with a high R-squared value of 0.995 and few mistakes, suggesting that the model fits well. The performance of Myanmar's models is satisfactory, while the high MaxAPE (44.126) indicates some difficulties in making accurate predictions. The metrics of the Philippines are generally stable, but the high MaxAPE value of 19.182 suggests the occurrence of occasional significant mistakes. Singapore's metrics strongly align with the model, as shown by the low Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values. However, the high Maximum Absolute Percentage Error (MaxAPE) of 23.948 shows the presence of probable outliers. Thailand has exceptional model performance, as seen by a high R-squared value of 0.994 and low RMSE and MAE values. However, the high MaxAPE value of 17.753 is a cause for worry. Vietnam's models consistently demonstrate strong performance, but high MaxAPE values (34.180 and 36.833) suggest occasional significant prediction mistakes.

Most nations have a robust model fit, as seen by high R-squared values. However, the Stationary R-squared and MaxAPE values highlight notable difficulties in establishing stationarity and managing outliers. The investigation shows that Malaysia and Thailand exhibit the most dependable ARIMA model that fits all criteria, indicating consistent and foreseeable time series data. On the other hand, the exceptionally high RMSE and MaxAPE values in Indonesia are considered outliers, suggesting the presence of data abnormalities or shortcomings in the model. The elevated MaxAPE values in several nations indicate sporadic significant inaccuracies in predictions, necessitating more scrutiny of data quality or refining of the model. The consistent performance across various measures in Cambodia, Myanmar, and Vietnam suggests that the model fits well. However, the high MaxAPE values reflect the existence of outliers or rapid shifts in the data.

Table 2: Model fit stastistics ARIMA (0,1,1) and ARIMA (1,1,1)

Model	Number of predictors	Model Fit Statistics		Ljung-Box Q			Number of outliers
		Stationary R-squared	R-squared	Statistics	DF	Sig.	
CO_2Bru-Model_1 - ARIMA 0,1,1	3	0.077	0.949	18.532	17.000	0.356	0
CO_2Bru-Model_1 - ARIMA 1,1,1	3	0.138	0.952	16.348	16.000	0.429	0
CO_2Cam-Model_1 ARIMA 0,1,1	3	0.577	0.988	19.746	17.000	0.287	0
CO_2Cam-Model_1 ARIMA 1,1,1	3	0.578	0.988	18.295	16.000	0.307	0
CO_2Mal-Model_1 ARIMA 0,1,1	3	0.342	0.995	13.401	17.000	0.709	0
CO_2Mal-Model_1 ARIMA 1,1,1	3	0.426	0.995	12.242	16.000	0.727	0
CO_2Indo-Model_1 ARIMA 0,1,1	3	0.048	0.843	1.464	17.000	1.000	0
CO_2Indo-Model_1 ARIMA 1,1,1	3	0.048	0.843	1.412	16.000	1.000	0
CO_2Myan-Model_1 - ARIMA 0,1,1	3	0.602	0.955	20.187	17.000	0.265	0
CO_2Myan-Model_1 - ARIMA 1,1,1	3	0.617	0.957	19.174	16.000	0.260	0
CO_2Phi-Model_1 - ARIMA 0,1,1	3	0.431	0.988	31.495	17.000	0.017	0
CO_2Phi-Model_1 - ARIMA 1,1,1	3	0.447	0.988	25.854	16.000	0.056	0
CO_2Sin-Model_1 - ARIMA 0,1,1	3	0.028	0.983	20.722	17.000	0.239	0
CO_2Sin-Model_1 - ARIMA 1,1,1	3	0.032	0.984	20.911	16.000	0.182	0
CO_2Tha-Model_1 - ARIMA 0,1,1	3	0.118	0.994	24.985	17.000	0.095	0
CO_2Tha-Model_1 - ARIMA 1,1,1	3	0.182	0.995	25.272	16.000	0.065	0
CO_2Viet-Model_1 - ARIMA 0,1,1	3	0.472	0.991	10.823	17.000	0.866	0
CO_2Viet-Model_1 - ARIMA 1,1,1	3	0.507	0.992	10.254	16.000	0.853	0

Table 3: Statistics fit ARIMA (0,1,1) and ARIMA (1,1,1)

Fit Statistic	Brunei	Cambodia	Indonesia	Malaysia	Myanmar	Philippines	Singapore	Thailand	Vietnam
Stationary R-squared - ARIMA 0,1,1	0.077	0.577	0.048	0.342	0.602	0.431	0.028	0.118	0.472
Stationary R-squared - ARIMA 1,1,1	0.138	0.578	0.048	0.426	0.617	0.447	0.032	0.182	0.507
R-squared - ARIMA 0,1,1	0.949	0.988	0.843	0.995	0.955	0.988	0.983	0.994	0.991
R-squared - ARIMA 1,1,1	0.952	0.988	0.843	0.995	0.957	0.988	0.984	0.995	0.992
RMSE - ARIMA 0,1,1	0.932	0.622	103.309	11.093	2.281	5.946	3.626	13.187	10.554
RMSE - ARIMA 1,1,1	0.912	0.629	103.875	10.487	2.265	5.932	3.664	12.856	10.323
MAPE - ARIMA 0,1,1	8.015	10.622	57.593	4.235	10.011	4.502	4.003	4.478	8.092
MAPE - ARIMA 1,1,1	7.768	10.710	58.202	4.669	9.906	4.365	4.004	4.850	8.396
MaxAPE - ARIMA 0,1,1	30.616	88.624	3672.772	16.862	44.126	19.182	23.948	17.753	34.180
MaxAPE - ARIMA 1,1,1	35.134	88.076	3670.748	17.869	38.802	19.970	23.758	19.617	36.833
MAE - ARIMA 0,1,1	0.557	0.301	30.644	6.604	1.513	4.152	2.118	8.829	6.217
MAE - ARIMA 1,1,1	0.544	0.304	30.797	6.362	1.503	4.036	2.137	8.766	6.226
MaxAE - ARIMA 0,1,1	4.382	2.607	940.141	49.211	6.714	15.967	13.844	41.016	48.847
MaxAE - ARIMA 1,1,1	4.286	2.591	939.623	46.062	5.904	15.207	13.734	36.127	43.715
Normalized BIC - ARIMA 0,1,1	0.276	(0.534)	9.519	5.229	2.065	3.981	2.993	5.575	5.129
Normalized BIC - ARIMA 1,1,1	0.316	(0.429)	9.579	5.200	2.134	4.060	3.096	5.607	5.168

5. CONCLUSION

The study revealed that the ASEAN area has substantial obstacles in achieving a harmonious equilibrium between economic expansion and environmental sustainability. The LMDI decomposition study demonstrates that the increase in GDP has been the main factor influencing the rise in CO_2 emissions across ASEAN nations, but the degree of impact varies. This is consistent with the observed shift from agricultural to industrial and service-based economies that has been happening since the 1970s. Nevertheless, the data indicates a consistent decline in energy intensity over time, indicating improvements in energy efficiency. The results are further supported by the ARIMAX modelling, which suggests that while economic growth continues to be a significant predictor of emissions, there are possibilities for decoupling via implementing better energy practices and transitioning towards activities with lower carbon intensity.

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The findings emphasize the immediate need for ASEAN nations to implement comprehensive decarbonization policies.

The models emphasize the need for policy implications to prioritize the acceleration of the shift towards renewable energy sources, enhancing energy efficiency in various sectors, and implementing efficient carbon pricing systems. Based on the ARIMAX predictions, it is shown that without substantial actions, emissions are projected to increase in the majority of ASEAN nations. Nevertheless, the models also suggest that specific measures, such as augmenting the proportion of renewables in power production and encouraging the use of electric cars, can substantially modify these patterns. The study's results highlight the significance of regional cooperation in building carbon capture and storage (CCS) corridors and formulating a national hydrogen strategy. Furthermore, the study provides evidence for significant expenditures in research and development to enhance carbon capture efficiency and tackle sustainability concerns in new clean energy systems.

The practical ramifications of this study are diverse and complex. The LMDI and ARIMAX models provide policymakers with a data-driven framework to evaluate the possible influence of different policy actions on CO_2 emissions. This may facilitate the creation of more focused and efficient decarbonization plans. For companies, especially those in industries that use much energy, the results emphasize the significance of allocating resources towards energy efficiency initiatives and shifting to cleaner energy sources to maintain competitiveness in a market that is becoming more aware of carbon emissions. Additionally, the models may be used as instruments for firms to predict their emissions and establish reduction objectives founded on scientific principles. Investors should consider carbon risks when making investment choices, especially in ASEAN nations, where policy landscapes quickly change in response to climate change problems. This study emphasizes the increasing significance of evaluating these risks.

In order to enhance the accuracy of the statistical results, the next future study should prioritize a thorough review and selection procedure for the model. To evaluate the performance of the ARIMA (0,1,1) and (1,1,1) models in each nation, we should do formal model comparisons using metrics such as AIC and BIC. Additionally, the study should investigate simpler models where they are suitable. It is recommended that thorough residual diagnostics, including analyzing ACF and PACF plots, be done to detect any lingering patterns. This is particularly important for nations such as the Philippines, where Ljung-Box tests suggest the presence of possible concerns. Reevaluating the need for differencing, especially for nations such as Singapore with shallow stationary R-squared values, and investigating possible seasonal trends may result in more precise model specifications. In addition, using formal outlier identification techniques and conducting tests for structural breakdowns may uncover significant characteristics in the data that are not currently accounted for by the existing models.

To improve the accuracy of forecasting in nations like Indonesia and Singapore, which have poor fit or odd outcomes, it is recommended to use different time series models such as SARIMA, ETS, or state space models. By including external factors related to CO_2 emissions and using non-linear models, a more detailed understanding may be gained, mainly when dealing with intricate emission patterns. By including time series cross-validation and assessing out-of-sample predictions, a more reliable evaluation of model performance may be achieved beyond the limitations of in-sample fit statistics. Ultimately, doing a comparison study across different nations might uncover shared trends or differences that can be used to improve the model. Following these processes will result in a more nuanced comprehension of the dynamics of CO_2 emissions in each nation, which has the potential to enhance both the accuracy of models and the precision of forecasts. Additionally, it will provide significant insights for making environmental policy and management choices.

Subsequent investigations have the potential to expand upon this study in several ways. Firstly, by including more detailed data at the sector-specific level, we may better understand the factors contributing to emissions and identify practical measures to reduce them in essential sectors. Furthermore, including supplementary factors such as technical innovation indexes, investments in renewable energy, and indicators of policy stringency in the model might augment its predictive capability and provide a more thorough understanding of emission patterns. Furthermore, comparing research with other emerging areas might provide valuable insights into the distinctiveness or universality of ASEAN's emission patterns. Ultimately, including scenario analysis considering various policy and technology adoption paths might significantly improve the model's usefulness for long-term planning and decision-making. Exploring these prospective areas of study will not only enhance our comprehension of emission dynamics in quickly growing economies but also aid in developing more efficient global measures to mitigate climate change.

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