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The Impact of Agricultural Sector Growth on Total National Greenhouse Gas Emissions in Southeast Asia

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ABSTRACT

The agricultural sector plays a significant role in greenhouse gas emissions, particularly in developing countries within the ASEAN region. Despite ASEAN's status as a group of emerging economies, environmental pressures continue to increase alongside economic and demographic growth. This study aims to examine the determinants of greenhouse gas emissions in six ASEAN countries—Indonesia, Vietnam, Thailand, Myanmar, the Philippines, and Malaysia—using panel data from 1997 to 2019 obtained from the World Bank's World Development Indicators (WDI). Employing a robust fixed-effects model to address heteroskedasticity and autocorrelation, the results reveal that forest area and population size have a positive and statistically significant impact on greenhouse gas emissions, while fertilizer consumption, agricultural land, livestock production, and gross domestic product (GDP) are not statistically significant. These findings indicate that environmental degradation in ASEAN is driven by land-use dynamics and demographic pressures. The positive effect of forest area suggests that increases in forest coverage do not necessarily translate into lower emissions, likely due to forest degradation, deforestation, and land conversion. Meanwhile, the significant role of population highlights the increasing demand for resources, energy, and food as key drivers of emissions. Therefore, this study emphasizes the importance of

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ARTICLE INFO

Received: 19 March 2026 | Revised: 22 April 2026 | Accepted: 27 April 2026 | Published Online: 8 May 2026

DOI: https://doi.org/10.30564/jees.v8i5.13315

CITATION

Nurjati, E., Adityawati, S., 2026. The Impact of Agricultural Sector Growth on Total National Greenhouse Gas Emissions in Southeast Asia. Journal of Environmental & Earth Sciences. 8(5): 111–122. DOI: https://doi.org/10.30564/jees.v8i5.13315

strengthening sustainable land-use management, improving forest governance, and enhancing resource efficiency.

Keywords: Agricultural Land; Total Population; Fertilizer Consumption; Livestock Production

1. Introduction

The increase in greenhouse gas emissions is one of the primary causes of global warming and climate change [1,2]. Interestingly, greenhouse gas emissions rise alongside the growth of the agricultural sector [3]. Activities within the food value chain system, ranging from pre- to post-production processes such as manufacturing, transportation, processing, and waste disposal, significantly contribute to the increase in greenhouse gas emissions [4]. According to data from the Environmental Protection Agency [5]. The agricultural sector accounts for 10% of greenhouse gas emissions, with the majority stemming from livestock, crop farming, and rice production. One agricultural practice that contributes to the rise in greenhouse gas emissions is the use of chemical fertilizers [6–9]. FAOSTAT [10] reports that the use of chemical fertilizers in each country tends to increase over time. The limited implementation of bio-circular economy practices in agriculture also contributes to high greenhouse gas emissions, as waste utilization practices have yet to be widely adopted [11].

Demographic bonuses lead to an increase in the labor force, which in turn helps reduce poverty levels, positively impacting economic growth [12,13]. However, this situation also adversely affects the increase in carbon emissions, as higher consumption levels and environmental stress accompany population growth [14,15]. The growing population necessitates greater efforts to meet food consumption needs [16], a trend observed globally and particularly in Southeast Asia, where agricultural expansion and food security are closely tied to demographic growth.

Agricultural extensification is one solution to meet food consumption needs and strengthen food security systems [17]. Unfortunately, food system strengthening programs through agricultural area expansion also contribute to the increase in greenhouse gas emissions and exacerbate global warming [18,19]. Net carbon fluxes from land use and land-use change contribute 12.5% of total anthropogenic carbon [20]. Deforestation, partially caused by land conversion, significantly contributes to greenhouse gas emissions and climate change. Increased food production is a key driver of deforestation [21].

Besides the agricultural sector, the livestock sector is also important as it impacts the increase in greenhouse gas emissions [22]. Livestock sector development affects agricultural land expansion, deforestation, surface water eutrophication, and nutrient imbalance [23]. The livestock sector, through methane and nitrous oxide emissions, contributes 9% of total greenhouse gas emissions [24]. Cattle farming and dairy production account for 60% of total livestock sector emissions [22,25]. Livestock waste and feed significantly influence the increase in greenhouse gas emissions in the livestock sector [22]. Moreover, other significant sources of greenhouse gas emissions in the livestock sector include enteric fermentation, manure management, and fossil fuel use [23]. Proper management of livestock waste is crucial as it directly affects the increase in N2O emissions and indirectly impacts the rise in CH4 emissions [26,27].

Interestingly, greenhouse gas emissions are more prevalent in developing countries than in developed ones. The high emissions in developing countries are driven by increased investments in these regions and the lack of circular bio-economy practices, leading to environmental pollution. The agricultural sector significantly impacts high greenhouse gas emissions in developing countries [7]. The growth of developing countries has led to a 44% increase in global greenhouse gas emissions [28].

Southeast Asia is predominantly composed of developing countries that have experienced substantial economic growth in recent decades. However, pollution levels have also multiplied [29]. Electricity consumption, population growth, urbanization, and industrialization are factors contributing to the increase in greenhouse gas emissions in Association of Southeast Asian Nations (ASEAN) [30,31]. Moreover, the agricultural sector is a crucial factor in the increase in greenhouse gases. The rise in agricultural productivity positively correlates with increased carbon emissions [32–34]. This situation presents a dilemma in balancing food consumption needs with the growing population.

Given these issues, it is crucial to identify the impact of agricultural sector development on the increase in greenhouse gas emissions in Southeast Asia. The selection of agricultural emission determinants in this study is grounded in established global frameworks and empirical literature. The Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories [35] identify key sources of greenhouse gas emissions in the agricultural sector, including fertilizer use, livestock production, and land-use change. Building on this framework, Tubiello et al. [4] provide a comprehensive emissions database (FAOSTAT) that operationalizes these sources and highlights the central role of agricultural intensification in driving emissions, particularly through fertilizer-induced nitrous oxide (N_2O) and livestock-related methane (CH_4). Furthermore, Timothy D. Searchinger et al. [36] emphasize that agricultural expansion and land-use change are critical drivers of emissions, especially in developing regions where deforestation and land conversion remain prevalent. Drawing on these foundations, this study focuses on key agricultural determinants—fertilizer consumption, agricultural land area, livestock production, and total population—to examine their impact on greenhouse gas emissions in Southeast Asia. This integrated approach ensures that the empirical model is both theoretically grounded and consistent with internationally recognized emission accounting frameworks.

2. Materials and Methods

2.1. Analytical Framework

Agricultural activities play an important role in global greenhouse gas (GHG) emissions. Several components of the agricultural sector, including fertilizer use, agricultural land expansion, livestock production, forest area, and population growth, are frequently identified as key drivers of emissions. In addition, gross domestic product (GDP) is incorporated as an important independent variable, as it reflects the level of economic development and the scale of production and consumption activities that may intensify environmental pressure. Higher GDP levels are often associated with increased energy use, agricultural intensification, and land-use change, all of which can contribute to rising emissions.

Forest area is an independent variable because of its dual role in the carbon cycle. On the one hand, forests act as significant carbon sinks by absorbing carbon dioxide from the atmosphere, thereby helping to mitigate GHG emissions. On the other hand, reductions in forest area—often driven by agricultural expansion—lead to deforestation, which releases stored carbon and increases emissions. Therefore, changes in forest area capture both mitigation and emission dynamics associated with land-use change.

Chemical fertilizers are widely used to increase agricultural productivity; however, their excessive use contributes significantly to greenhouse gas emissions. Although fertilizers enhance crop yields, they also generate nitrous oxide emissions that contribute to climate change [37,38]. Previous studies suggest that combining organic and chemical fertilizers can reduce environmental impacts while maintaining productivity [6,39,40].

Agricultural land expansion also contributes to greenhouse gas emissions. Research in China shows that long-term expansion of agricultural land has increased GHG emissions due to land-use changes and biomass burning [4]. Compared to natural ecosystems, agricultural land generates higher levels of nitrous oxide emissions [41,42].

Livestock production is another important source of greenhouse gas emissions. The livestock sector contributes significantly to methane emissions from ruminant digestion and nitrous oxide emissions from manure management [24]. Differences in livestock management systems may influence emission levels, with integrated systems generally producing lower emissions [34,43].

Population growth also influences greenhouse gas emissions through increased energy consumption [44]. Countries with large populations tend to contribute significantly to global emissions growth due to increased economic and consumption activities [45].

Based on the previous literature, **Figure 1** illustrates the following hypotheses:

H1. *Chemical fertilizer has a significant association with greenhouse gas emissions.*

H2. *Agricultural land has a significant association with greenhouse gas emissions.*

H3. *Livestock production has a significant association with greenhouse gas emissions.*

H4. *Total population has a significant association with greenhouse gas emissions.*

H5. *Forest area has a significant association with greenhouse gas emissions.*

H6. *GDP has a significant association with greenhouse gas emissions.*

Figure 1 illustrates the analytical framework of this study.

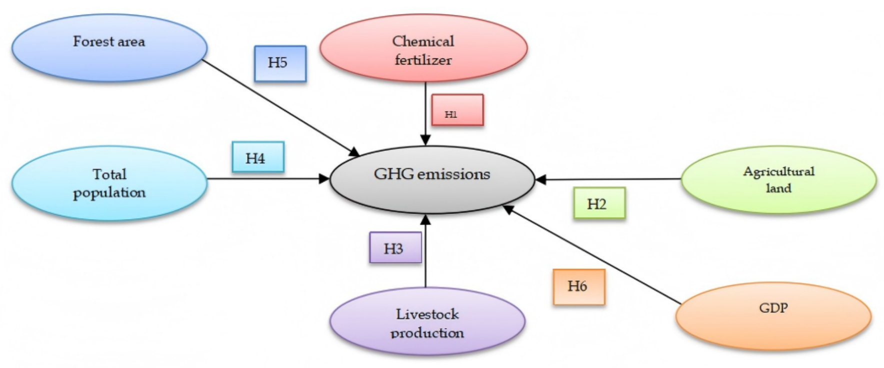

Figure 1. Conceptual Framework.

2.2. Methods

The study employs an econometric approach by collecting panel data from Southeast Asian countries spanning from 1997 to 2019. Six Southeast Asian countries are included in this research: Indonesia, Vietnam, Thailand, Myanmar, the Philippines, and Malaysia. These countries are classified as emerging and developing economies according to the International Monetary Fund (IMF) in 2023. The selection of countries is based on data availability and completeness for all variables over the study period. The exclusion of several ASEAN countries, such as Cambodia and Laos, due to data limitations may affect the representativeness of the results, particularly in the context of agricultural emissions and land-use change.

The econometric model used in this study is adapted from the production function model. Carbon emissions are the dependent variable, while four other variables serve as independent variables: fertilizer consumption, agricultural land, livestock production, forest area, population size, and GDP. Equation 1 describes the influence of key variables in the agricultural sector.

$$\begin{aligned} \ln E_{it} = \alpha_i + \beta_1 \ln F_{it} + \beta_2 \ln AL_{it} + \beta_3 \ln LP_{it} \\ + \beta_4 \ln FA_{it} + \beta_5 \ln TP_{it} + \beta_6 \ln GDP_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

Where: β_1, β_2, β_3, β_4. β_5 and β_6 represent coefficients, *i* denotes the country, and *t* represents the time period. *E* stands for the total greenhouse gas emissions in kilotonnes of CO_2 equivalent, which includes total CO_2 emissions excluding short-cycle biomass combustion (such as the burning of agricultural waste and savanna burning) but includes other biomass burning (such as forest fires, post-burning decay, peat fires, and decay of drained peatlands), all anthropogenic CH4 sources, N_2O sources, and F-gases (HFCs, PFCs, and SF6). F is the fertilizer consumption (kilograms per hectare of arable land) and it measures the quantity of plant nutrients used per unit of arable land. Fertilizer products cover nitrogenous, potash, and phosphate fertilizers (including ground rock phosphate). AL represents agricultural land (% of land area), referring to the portion of land that is arable, under permanent crops, and under permanent pastures. LP is the livestock production index (2014–2016 = 100), which includes meat, milk, dairy products, and other livestock products. Since the base period (2014–2016) falls within the study period (1997–2019), this may compress variation in the later years, potentially introducing bias in the coefficient estimates. While this choice was made based on data availability, this limitation is acknowledged, and caution is recommended when interpreting the results related to livestock production. FA is forest area (% of land area), which is the share of total land area that is under natural or planted stands of trees of at least 5 meters in situ, whether productive or not, and excludes tree stands in agricultural production systems (for example, in fruit plantations and agroforestry systems) and trees in urban parks and gardens. TP denotes the total population, which refers to the de facto population count, including all residents regardless of legal status or citizenship. GDP is gross domestic product per capita (current

US$), which is the total income earned through the production of goods and services in an economic territory during an accounting period. All data were obtained from the World Development Indicators [46].

To assess the impact of the independent variables on the dependent variable, the Ordinary Least Squares (OLS) method, Fixed Effect Model (FEM), and Random Effect Model (REM) were employed. To determine the best model among the three, the Chow test and the Hausman test were conducted through FEM hypothesis testing, comparing REM versus FEM. When assuming that all coefficients are constant over time and across individuals, and assuming no significant country-specific or temporal effects, the data can be pooled and an Ordinary Least Squares (OLS) regression model can be run:

$$\begin{gathered} \mathrm{lnE_{it}} = \alpha_\mathrm{i} + \beta_1 \mathrm{lnF_{it}} + \beta_2 \mathrm{lnAL_{it}} + \beta_3 \mathrm{lnLP_{it}} \\ + \beta_4 \mathrm{lnFA_{it}} + \beta_5 \mathrm{lnTP_{it}} + \beta_6 \mathrm{lnGDP_{it}} + \varepsilon_\mathrm{it} \end{gathered} \tag{2}$$

Where *i* stands for country, *t* represents the *t*-th time period, and ε_it denotes the error term, which is assumed to be white noise and varies across both countries and time. Furthermore, using a panel data model with the incorporation of individual effects has several advantages; for instance, it allows us to account for individual heterogeneity. Therefore, by pooling countries together, the unobserved individual effects are incorporated into the equation below:

$$\begin{gathered} \mathrm{lnE_{it}} = \alpha_\mathrm{i} + \beta_1 \mathrm{lnF_{it}} + \beta_2 \mathrm{lnAL_{it}} + \beta_3 \mathrm{lnLP_{it}} \\ + \beta_4 \mathrm{lnFA_{it}} + \beta_5 \mathrm{lnTP_{it}} + \beta_6 \mathrm{lnGDP_{it}} + \varepsilon_\mathrm{it} + w_\mathrm{it} \end{gathered} \tag{3}$$

The difference between the surveyed OLS regression and the model that accounts for unobserved individual effects lies precisely in μ_i. When considering the random effects model, the equation below remains the same, but in this case, μ_i is assumed to have a mean of zero, independent of the individual error term ε_it, with a constant variance σ, and independent from the explanatory variables.

If there is no correlation between countries, individual effects, and unobserved determinants of growth, the most appropriate approach for analysis is to use the random effects panel model. Conversely, if there is a correlation between countries, individual effects, and growth determinants, the fixed effects panel model is the most appropriate method for analysis.

To test for the possibility of correlation, we use the Hausman test. This test examines the null hypothesis of no correlation between unobserved individual effects and growth determinants against the alternative hypothesis of the existence of correlation. If the null hypothesis is not rejected, we can conclude that the correlation is not relevant, and therefore, the random effects panel model is the most appropriate approach to analyze the relationship between economic growth and its determinants. On the other hand, if the null hypothesis is rejected, we can conclude that the correlation is relevant, and thus, the fixed effects panel model is the most appropriate method to analyze the relationship between economic growth and its determinants.

3. Results

3.1. Greenhouse Gas Emission Trends in ASEAN

This study aims to identify the factors influencing the increase in greenhouse gas emissions in Southeast Asia. The variables suspected to contribute to the rise in fertilizer consumption, agricultural land, livestock production, forest area, population size, and GDP. **Figure 2** illustrates that Southeast Asian countries, namely Indonesia, Vietnam, Thailand, Myanmar, the Philippines, and Malaysia, have all experienced an increase in total greenhouse gas emissions from 1997 to 2019.

3.2. Descriptive Statistics

Table 1 presents the descriptive statistics for both dependent and independent variables across the six ASEAN countries over the study period. The average level of greenhouse gas emissions (E) varies substantially among countries, ranging from approximately 90,892 in Myanmar to 767,568 in Indonesia, indicating that Indonesia is the largest emitter in the sample, followed by Thailand and Vietnam. In terms of fertilizer use (F), Vietnam records the highest average value, while the Philippines shows the lowest, suggesting significant differences in agricultural intensity. Agricultural land (AL) and livestock production (LP) also display variation, with Thailand and Indonesia generally exhibiting higher averages compared to other countries. Meanwhile, forest area (FA) tends to be relatively stable across countries, although Malaysia records the highest average among the group. For total population (TP), Indonesia dominates with the largest average population size (2.38×10^8), reflecting its demographic scale relative to the other ASEAN countries. Similarly, gross domestic product (GDP) varies widely, with Malaysia and Vietnam showing relatively high average values, while Myanmar records the lowest.

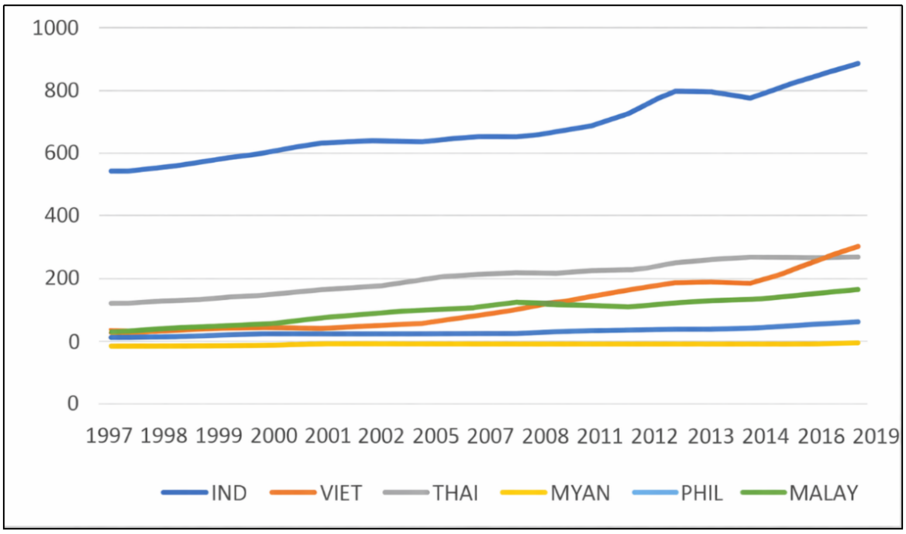

Figure 2. Comparison of Total Greenhouse Gas Emissions in Six ASEAN Countries, 1997–2019 [10].

Table 1. Descriptive Statistics for Each Variable in Six ASEAN Countries.

	Variable	**N**	**Mean**	**SD**	**Min**	**Max**		**Variable**	**N**	**Mean**	**SD**	**Min**	**Max**
	E	23	767,568.5	100,454.1	632,997	1,002,369		E	23	234,087.1	92,980.98	112,967	450,149
	F	23	2.16×10^9	1.13×10^9	1.39×10^8	3.89×10^9		F	23	3.57×10^9	9.05×10^8	4.25×10^8	4.84×10^9
Indonesia	AL	23	28.609	2.87	24	33	**Vietnam**	AL	23	32.87	4.52	24	40
	LP	23	85.304	35.303	46	167		LP	23	73.304	25.841	34	112
	FA	23	53.13	2.437	49	59		FA	23	413.913	366.481	34	46
	TP	23	2.38×10^8	2.02×10^7	2.05×10^8	2.70×10^8		TP	23	8.59×10^7	6,015,939	7.61×10^7	9.58×10^7
	GDP	23	3.16×10^9	2.15×10^9	3.63×10^8	8.81×10^9		GDP	23	3.47×10^9	2.09×10^9	7.11×10^7	9.26×10^9
	Variable	**N**	**Mean**	**SD**	**Min**	**Max**		**Variable**	**N**	**Mean**	**SD**	**Min**	**Max**
	E	23	330,478.3	57,430.78	238,004	422,087		E	23	90,891.83	19,058.81	65,128	133,251
	F	23	2.87×10^9	3.54×10^9	1.27×10^7	9.98×10^9		F	23	2.76×10^9	2.17×10^9	1.80×10^8	7.61×10^9
Thailand	AL	23	40.957	2.531	38	45	**Myanmar**	AL	23	18.217	1.413	16	20
	LP	23	85.13	12.088	68	102		LP	23	51.87	31.252	13	108
	FA	23	38.348	0.832	37	39		FA	23	493.913	3.354	44	55
	TP	23	6.70×10^7	3,223,596	6.10×10^7	7.13×10^7		TP	23	4.87×10^7	2,702,358	4.40×10^7	5.30×10^7
	GDP	23	3.93×10^9	2.15×10^9	2.47×10^8	7.61×10^9		GDP	23	2.17×10^9	1.73×10^9	1.01×10^9	7.58×10^9
	Variable	**N**	**Mean**	**SD**	**Min**	**Max**		**Variable**	**N**	**Mean**	**SD**	**Min**	**Max**
	E	23	163,961.1	31,422.04	131,946	234,283		E	23	229,340.4	56,921.63	138,586	313,024
	F	23	1.52×10^9	2.39×10^8	1.05×10^9	2.13×10^9		F	23	1.63×10^9	5.79×10^8	1.41×10^8	2.30×10^9
Philippines	AL	23	39.957	1.87	37	42	**Malaysia**	AL	23	23	1.977	21	26
	LP	23	82.087	15.386	55	102		LP	23	73.522	19.961	48	105
	FA	23	23.826	0.717	23	25		FA	23	58.913	0.848	58	61
	TP	23	9.14×10^7	1.15×10^7	7.27×10^7	1.10×10^8		TP	23	2.74×10^7	3,619,880	2.12×10^7	3.28×10^7
	GDP	23	2.29×10^9	2.56×10^9	1.10×10^8	9.83×10^9		GDP	23	4.58×10^9	3.26×10^9	1.09×10^7	9.86×10^9

3.3. Determinants of Greenhouse Gas Emissions in ASEAN

This study begins by estimating three panel data models, namely, pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). **Table 2** reports the estimation results of the pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE) models. The explanatory variables considered in this study include fertilizer consumption, agricultural land, livestock production, forest area, population size, and gross domestic product (GDP). The results indicate that the coefficients obtained from the OLS and RE estimations are identical, whereas the FE model yields different coefficient magnitudes for several variables. This discrepancy suggests the presence of unobserved country-specific heterogeneity that is not captured in the OLS and RE frameworks. Notably, the coefficient associated with population size is considerably larger in the FE model, highlighting the importance of controlling for individual effects.

Table 2. The Comparison of OLS, Fixed Effects, and Random Effects Estimation Results.

Variable	OLS	FE	RE
F	−0.0476**	0.0101	−0.0476**
AL	1.5358***	0.6958***	1.5358***
LP	0.2911***	0.1376***	0.2911***
FA	1.9408***	1.3686***	1.9408***
TP	0.5267***	1.3208***	0.5267***
GDP	−0.0082	0.0003	−0.0082
Constant	−9.6730***	−19.8425***	−9.6730***
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Observations	138	138	138
R-squared	0.9185	0.8936*	0.9185
Prob > F/chi^2	0.0000	0.0000	0.0000

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Agricultural land, livestock production, forest area, and population size are consistently significant across all model specifications, while fertilizer consumption and GDP are not statistically significant in the FE model. All models are jointly significant at the 1% level, as indicated by the Prob > F/chi^2 values of 0.0000. Furthermore, the models demonstrate strong explanatory power, with R-squared values exceeding 0.89 across specifications.

To determine the appropriate panel data model, a series of model selection tests was conducted. First, the Chow test was applied to compare the Pooled OLS model and the Fixed Effects (FE) model. The result shows a probability value of Prob > F = 0.0000, indicating that the null hypothesis of the Pooled OLS model is rejected. Therefore, the Fixed Effects model is preferred over the Pooled OLS model.

Subsequently, the Hausman test was employed to choose between the Fixed Effects (FE) and Random Effects (RE) models. The test result yields a probability value of Prob > chi^2 = 0.0000, leading to the null hypothesis of the Random Effects model being rejected. Thus, the Fixed Effects model is selected as the most suitable specification for this study.

Following the selected models, a series of classical assumption tests is conducted to assess the validity and reliability of the estimations. The results of the multicollinearity test indicate that all explanatory variables have Variance Inflation Factor (VIF) values below the threshold of 10 (see **Table 3**), suggesting the absence of serious multicollinearity among the independent variables.

Table 3. VIF values.

Variable	VIF	1/VIF
F	3.81	0.2625
LP	2.30	0.4343
AL	1.93	0.5169
FA	1.22	0.8166
GDP	1.06	0.9434
E	1.02	0.9758
Mean VIF	**1.89**	

However, further diagnostic tests reveal potential violations of standard assumptions. The Modified Wald test indicates the presence of heteroskedasticity, as evidenced by a probability value of Prob > chi^2 = 0.0000, leading to the rejection of the null hypothesis of homoskedasticity. In addition, the autocorrelation test shows a probability value of Prob > F = 0.0047, indicating the presence of serial correlation in the panel data.

These findings suggest that, although the model is free from multicollinearity, it suffers from heteroskedasticity and autocorrelation, which may lead to inefficient and biased standard errors if left unaddressed. Therefore, an appropriate correction is required to obtain robust and reliable estimates.

To address these issues, the model is re-estimated using robust standard errors. The results of the Fixed Effects model with clustered robust standard errors provide consistent and reliable estimates. **Table 4** reports the estimation results of the Fixed Effects model with clustered robust standard errors at the country level. The results indicate that population size is the only variable that is statistically significant at the 1% level, with a positive coefficient of 1.3208. This implies that a 1% increase in population size leads to an approximate

1.32% increase in greenhouse gas emissions, ceteris paribus. In addition, forest area shows a positive effect and is weakly significant at the 10% level, suggesting a potential association with emissions, although the evidence is less robust. On the other hand, fertilizer consumption, agricultural land, livestock production, and GDP are not statistically significant, indicating that their effects on greenhouse gas emissions are not robust after controlling for heteroskedasticity and autocorrelation. The signs of the coefficients, however, remain consistent with the baseline model. Furthermore, the model demonstrates strong explanatory power, as reflected by a within R-squared value of 0.8936, indicating that approximately 89.36% of the variation in greenhouse gas emissions within countries is explained by the independent variables. The joint significance test also confirms that the model is statistically valid, with an F-statistic of 83.34 and a probability value of 0.0001.

Table 4. Fixed Effects Estimation with Clustered Robust Standard Errors.

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
F	0.0101	0.0102	0.99	0.368
AL	0.6958	0.6321	1.10	0.321
LP	0.1376	0.0885	1.55	0.181
FA	1.3686*	0.6571	2.08	0.092
TP	1.3208***	0.2783	4.75	0.005
GDP	0.0003	0.0050	0.06	0.954
Constant	−19.8425**	5.1369	−3.86	0.012
Observations	138			
Number of groups	6			
Within R-squared	0.8936			
F-statistic (joint)	83.34			0.0001

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

4. Discussion

The descriptive findings reveal substantial variation in greenhouse gas emissions across the six ASEAN countries, with Indonesia recording the highest emissions and Myanmar the lowest. Indonesia's high emission levels are closely associated with its rapid economic expansion, particularly in the industrial and agricultural sectors, which remain highly dependent on non-renewable energy sources. In addition, population growth contributes to increased demand for food and energy, thereby intensifying environmental pressure and emissions [15,47,48].

The empirical results from the Fixed Effects model with clustered robust standard errors indicate that population size is the most robust determinant of greenhouse gas emissions, showing a positive and statistically significant effect at the 1% level. Specifically, a 1% increase in population leads to an approximate 1.32% increase in emissions. This finding confirms that demographic pressure plays a central role in driving emissions in ASEAN countries. As the population increases, the demand for agricultural products, energy, and natural resources rises, leading to higher emissions through intensified production systems and land-use pressures. This mechanism is widely supported in the literature, which emphasizes the strong linkage between population growth, food demand, and environmental degradation [49–51].

In addition, forest area exhibits a positive effect and is weakly significant at the 10% level. This result suggests that changes in forest area are associated with variations in emissions, potentially reflecting the role of deforestation and land-use change in Southeast Asia. In this context, forest area may capture not only the extent of forest resources but also underlying processes such as forest conversion, peatland degradation, and biomass burning, all of which are major sources of greenhouse gas emissions in the region [52–54]. This finding highlights the importance of sustainable forest management and the need to control deforestation as part of climate mitigation strategies.

The finding that forest area has a positive effect on greenhouse gas emissions suggests a relationship that is not straightforward and requires careful interpretation. In theory, an increase in forest area should enhance carbon sequestration and reduce emissions. However, in the ASEAN context, this result likely reflects the heterogeneous nature of forest conditions, where not all forested areas function effectively as carbon sinks. First, the forest area variable may not fully capture the quality and condition of forests. In many ASEAN countries, increases or relatively large shares of forest area can coexist with intensive deforestation dynamics, such as logging, forest degradation, and land conversion for agriculture (e.g., oil palm plantations). As a result, even when forest area appears substantial, ongoing degradation and biomass loss can lead to higher emissions. In this context, the variable may proxy land-use pressure rather than effective carbon sequestration [52–54].

Furthermore, the positive relationship can be explained by land-use change dynamics that are particularly prominent in Southeast Asia. Agricultural expansion and resource extraction frequently occur within or adjacent to forested areas, triggering deforestation, peatland drainage, and biomass burning—all of which significantly increase emissions. In many cases, areas remain administratively classified as forest land despite experiencing partial conversion or degradation, creating a mismatch between statistical forest coverage and actual environmental performance. Therefore, these findings imply that increasing forest area alone is insufficient to reduce emissions, and must be accompanied by sustainable forest management, strict conservation policies, and efforts to improve forest quality and integrity.

On the other hand, fertilizer consumption, agricultural land, livestock production, and GDP are not statistically significant in the robust specification. This indicates that their effects on emissions are not robust after correcting for heteroskedasticity and autocorrelation. Nevertheless, the positive coefficients of these variables remain consistent with the existing literature, which identifies agricultural expansion, livestock activities, and fertilizer use as important contributors to emissions through methane and nitrous oxide release [22,37,55,56]. The lack of statistical significance may reflect differences in country-specific conditions, technological adoption, or policy frameworks across ASEAN countries.

Overall, the findings suggest that population size and forest-related dynamics are the most influential factors affecting greenhouse gas emissions in ASEAN countries. While other agricultural variables remain theoretically relevant, their impacts are less robust when econometric issues are addressed. These results underscore the importance of integrating demographic and land-use policies into environmental strategies, particularly through sustainable forest management, improved land-use planning, and resource-efficient agricultural practices to mitigate emissions in the region.

5. Conclusions

This study concludes that greenhouse gas emissions in ASEAN countries are primarily influenced by structural and environmental factors, with forest area and population size emerging as significant determinants under the robust fixed-effects estimation. The positive and significant impact of population size indicates that demographic pressure remains a key driver of emissions through increased demand for food, energy, and economic activities. Meanwhile, the positive relationship between forest area and emissions highlights that forest expansion alone does not guarantee environmental improvement, particularly when forest quality, degradation, and land-use dynamics are not adequately addressed.

Overall, the findings emphasize that environmental outcomes in ASEAN are shaped not only by the scale of resources but also by how they are managed. The insignificance of fertilizer consumption, agricultural land, livestock production, and GDP suggests that their impacts may be conditional on efficiency, technology, and policy frameworks rather than purely quantitative increases. Therefore, policy efforts should focus on promoting sustainable land-use practices, improving forest governance, and enhancing resource efficiency to effectively mitigate emissions. Integrating environmental considerations into development planning is essential to ensure that economic and demographic growth does not come at the expense of environmental sustainability.

Author Contributions

Conceptualization, methodology, formal analysis, data curation: E.N.; writing original draft preparation: E.N. and S.A.; validation, visualization, writing—review and editing and supervision: S.A. Both authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable. This study used secondary data obtained from publicly available databases and did not involve human participants or animals.

Informed Consent Statement

Not applicable. This study used secondary data obtained from publicly available databases and did not involve human participants.

Data Availability Statement

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Acknowledgments

The authors would like to thank all parties who indirectly supported this research.

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

The authors used AI-assisted tools (Grammarly) for language editing. All content, analysis, and conclusions remain the authors' original work.

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