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Exploring the Spatial Dynamics of FEW Nexus Policies and Their Impact on Income Inequality Using Spatial Econometric Models: Evidence from Southeast Asian Countries

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ABSTRACT

This research investigates the spatial dynamics of Food, Energy, and Water (FEW) Nexus policies in Southeast Asian countries, analyzing their impact on income inequality. Utilizing spatial econometric models, the study explores intricate spatial patterns and employs spatial lag models along with a panel Granger causality test. Examining data from variables such as population, urbanization, life expectancy, GDP, HDI, CO_2 Emission and energy consumption, our findings reveal significant spatial dependencies and causal relationships. The study enhances understanding of spatial dimensions in policy impacts for sustainable development, offering valuable insights for targeted FEW Nexus interventions to address income inequality in Southeast Asia.

Keywords: Income Inequality, Spatial Lag Models, FEW Nexuses Policies
JEL Classification: O15, Q56, I31

1. INTRODUCTION

The United Nations World Organization (UN, 2020) has highlighted a recurrent difficulty that South Asian countries have faced recently: a startling 70% of their population lives in places where wealth inequality has increased over the last three decades. Of the nations in contention, income inequality increased noticeably between 2014 and 2018. Real income for those in the lowest deciles fell throughout this time, whereas income for those in the top deciles increased, albeit more slowly. A complex pattern of wealth disparity emerges within the urban fabric of South Asian nations, especially in self-represented cities like Delhi, Mumbai, Karachi, Dhaka, and Colombo. There is only one statistically significant change, as reported by the (UN, 2020), and it was seen in a metropolis like Colombo. The fact that different cities have different Gini coefficients further complicates the picture. As of December 2019, Karachi has the lowest Gini coefficient (0.401), while Colombo had the highest coefficient (0.485), indicating a more significant income inequality.

But it’s important to recognize that provincial and national conditions may differ from one another. Gupta and Nagar (2018) highlight the impact of both external and internal factors on the diverse socioeconomic environments seen in various regions of South Asian nations. This requires a sophisticated comprehension of the complex network of factors causing income disparity and calls for customized policy solutions that consider the difficulties faced by each locality. The mechanisms at work can be understood through theoretical frameworks on income inequality, especially Kuznets’ (1955) hypothesis. According to Kuznets’ theory, income disparities tend to get worse as economies grow until they pass a particular developmental threshold. The observed rise in income disparity in South Asian countries has been largely attributed to the disproportionate concentration of resources, particularly human capital. The incapacity of current strategies to adequately address the complex structure of inequality is the fundamental cause of this structural problem.

Expanding upon Kuznets' theory, contemporary research has aimed to confirm its relevance in poor regions of South Asian nations. According to Gupta et al. (2021), reducing income disparity is largely dependent on the current rate of economic growth. In addition, the 2008 removal of labor flexibilization in the private sector created a more advantageous environment with better worker benefits, which helped to lower inequality levels. This study undertakes a critical investigation of the factors influencing income disparity in South Asian cities considering this intricate situation. The study uses sophisticated analytical tools, such as descriptive analysis techniques and spatial panel econometrics, such as the spatial lag panel model[1] (SLM) and makes use of a comprehensive panel dataset that spans several cities over a 10-year period. By these spatial models, the research seeks to identify the factors that contribute to the problem of income disparity and to explore its temporal and spatial dimensions.

This study's ultimate objective transcends purely academic to include the practical domain of policy formulation. Through identifying the complex interactions that lead to income disparity, the research hopes to provide useful information for specific policies intended to reduce the gaps that already exist in the cities that are being examined. By addressing the lived reality of South Asian countries, it aims to make a relevant contribution to the continuing discourse on income disparity, extending beyond academic frameworks. The study will explore the empirical data from pertinent literature as it develops, describing information sources and the econometric model, presenting findings, and concluding with research-derived insights.

2. EMPIRICAL LITERATURE

There are four main sections to the literature review. The first section summarizes previous research that has investigated the inverted-U hypothesis and looked at the connection between income inequality and economic growth. Subsequently, studies that explore the relationship between human capital and income inequality are included in the second section. Studies examining the relationship between financial development and income inequality are compiled in the third part. Finally, research that explores the remaining factors of inequality specifically, research that looks at them from a spatial perspective is included in the closing section. This paper lays the groundwork for an investigation into the spatial dynamics of FEW Nexus Policies and their effects on income inequality in the context of Southeast Asian nations using cutting-edge spatial econometric models.

2.1. Growth in the Economy and Income Inequality

The research that has already been written has thoroughly examined the complex relationship between economic development and income disparity. One popular theory used to examine this dynamic is the well-known inverted U-shaped hypothesis of Kuznets. The idea, which dates back to Kuznets' groundbreaking study in 1955, holds that as per capita income rises in the early phases of economic development, income disparity gets worse. But as a nation's economy grows, the theory predicts that income disparity would decline as long as per capita income keeps rising (Lyubimov, 2017).

Sayed and Peng (2020) provide a longitudinal perspective that supports this idea by showing that, over time, economic growth as measured by GDP per capita first causes an increase in income disparity until it peaks at $4600. After that, income disparity starts to decrease and reaches a minimum of $22,355 USD before rising once more. Wu et al. (2018) add nuance to this viewpoint by using hierarchical linear models (HLM) for China's provinces, which show that while local income disparity has a negative impact on people's life satisfaction, local economic growth rates have a favorable impact.

Wu and Yao (2015) and Yang and Greaney (2017) contend that, in contrast to the conventional interpretation of the Kuznets curve, government efforts to achieve a short-term balance between growth, equality, and state ownership may compromise long-term equality because of state ownership and asymmetric growth patterns. This results in a delayed inflection point for China on the inverted U-shaped Kuznets curve. Adam (2015) highlights the importance of tax structure, showing that taking labor income taxes into account instead of capital taxes results in more unequal capital-dependent economies. In response to the trickle-down theory, Akinci and Chahrour (2018) contend that rising wealth has a beneficial impact on falling wealth and vice versa. It is notable, nevertheless, that the richer get a larger portion of the transfer of income from the poor. Numerous studies conducted in a variety of circumstances have produced similar results. For example, Asteriou et al. (2014) studied 27 countries in the European Union, and Lim and McNelis (2016) studied 214 countries globally.

Mieres Brevis (2020) questions the conventional Kuznets inverted U-shape in Chile by discovering an inverse behavior through a regional-level investigation. The concentration of the indigenous population, human capital, initial income levels, and regional economic activity all stand out as important factors influencing income inequality in Chile. In a similar Chroufa and Chtourou (2022) validate the fulfillment of Kuznets' inverted-U hypothesis when examining GDP per capita growth in linear terms. Several research, such as those by Adrián Risso and Sánchez Carrera (2019), Mijs (2021), Sampson (2016), still employ the Kuznets inverted-U hypothesis in their analyses. This collection of work emphasizes the complex phenomenon's varied nature across various global contexts and advances a nuanced understanding of the complex relationship between economic development and income disparity.

2.2. Human Capital and Disparities in Income

In the modern knowledge-driven economy, human capital is a crucial economic resource, and improvements in education are frequently linked to both economic growth and the reduction of inequality (Odoardi and Pagliari, 2020). Notable results have been obtained from an investigation of the relationship between human capital and income inequality in the context of South Asian

1 Statistical model used to analyze the relationship between a dependent variable and independent variables, while considering both the spatial and temporal dependence in the data.

nations. In their research, Abrigo et al. (2018) found that investing in human capital had a significant effect on lowering inequality in Asian countries. According to Murphy and Topel (2016), human capital primarily affects growth and inequality through its impact on worker income. Higher labor productivity therefore drives up production and income.

Suhendra et al. (2020) and Quito et al. (2023) offer opposing viewpoints as well, arguing that human capital augmentation works as a catalyst to reduce income inequality by raising the chances of people being accepted into the labor market and earning more money. In the meantime, an asymmetric approach reveals a long-term cointegration link between human capital, economic disparity, and energy consumption in Sehrawat's (2021) investigation of inequality in India between 1970 and 2014. Therefore, increasing educational attainment becomes essential for reducing both educational and income inequality (Lee and Lee, 2018).

Parallel to this, Lee and Vu's (2020) research on 113 nations produces informative findings that are unique to South Asian contexts. Their results highlight the fact that nations with complex product-oriented economies have lower inequality rates. Moreover, countries that effectively combine industrial policies that diversify toward higher-end products with social policies that improve human capital quality tend to have lower levels of economic disparity. The study also suggests that nations with strong institutions develop productive capacities faster, which increases economic complexity and improves wealth distribution (Ajewole et al.2020).

The complex relationship between educational investments, labor productivity, and wealth distribution is clarified by these research findings, particularly in the dynamic setting of South Asian countries where human capital is highly valued. The sophisticated knowledge gained from this research adds to the continuing conversation about developing policies that support both the development of education and the realization of the economic potential inherent in human capital, with the goal of achieving more prosperity and equity in the area.

2.3. Economic Growth and Income Inequality

In recent decades, income inequality has become a major worry that has an impact on the economic stability of both industrialized and developing countries. The seriousness of this problem is highlighted by instances of poor economic governance, conflicting economic ideologies, and policy failures (Kavya and Shijin, 2020). When considering this in the context of South Asian nations, the effects of economic inequality become even more apparent, highlighting the pressing need for efficient policy solutions. According to insights from Kaidi et al. (2019), financial development is essential for both directly and favorably narrowing the wealth gap and for easing poverty. A different perspective is offered by Seven and Coskun (2016), who contend that although financial development may spur economic progress, low-income populations in emerging nations may not always profit from it. These differing viewpoints draw attention to the intricate relationship that exists between income distribution and financial development, especially in the context of South Asian nations that aim for inclusive growth.

The study by Law and Singh (2014), which included a panel of 81 nations, adds subtlety to this issue by introducing the idea of a threshold effect of institutional quality on the relationship between income inequality and financial development. According to their findings, financial development only serves to lessen income disparity up until it reaches a particular institutional quality level. Financial progress has no effect on income disparity until this barrier is crossed. This emphasizes how important institutional quality is in determining how financial development unfolds and how that development affects the distribution of income. A more equitable distribution of income relates to financial institutions of greater quality (Law and Singh, 2014). Examining this relationship in more detail, Jauch and Watzka (2016) provide evidence in favor of theoretical models that state that financial development will have a detrimental effect on income inequality as determined by the Gini coefficient across their panel of 38 nations. While it is not statistically significant for net income inequality, the negative correlation at the 10% confidence interval is more remarkable for gross income disparity. This suggests that depending on the economic variables considered, the effect of financial development on income inequality may differ.

2.4. Spatial Studies and Other Determinants of Income

According to UN estimates, Africa and Asia are the two regions in the world that are urbanizing the fastest, with 56% and 64% of their respective areas expected to be urban by 2050. Additionally, these areas struggle with rising income inequality. Divergent viewpoints exist among academics regarding the connection between income disparity and urbanization. According to Sulemana et al. (2019), the influence varies depending on the developmental stage and is not linear. They discover evidence of a positive correlation between urbanization and income inequality after analyzing 48 African nations (Adams and Klobodu, 2019). Ha et al. (2020) report findings from Vietnam that point to an inversely curved link between income disparity and urbanization. Urbanization appears to have a long-term positive impact on income disparity, although its short-term effects are negligible. On the other hand, research by Wang et al. (2019) in Chinese provinces suggests that more urbanization greatly reduces the income gap between urban and rural areas. This highlights how urgently the pattern of inequality reduction during China's ongoing urbanization development needs to be adjusted.

Nevertheless, these results are contested by Lee et al. (2020), who refute claims that globalization and urbanization have a favorable effect on income. They argue that these factors are part of the reason why income disparities are widening. The divergence of scholarly perspectives highlights the intricate nature of the correlation between urbanization and economic inequality. It is crucial to traverse this complexity and consider the various economic and social elements at play as these regions continue to rapidly urbanize to develop effective policies that address and maybe ameliorate growing income inequality.

Two main claims made in a study by Ragoubi and El Harbi (2018) provide insight into the connection between income disparity and entrepreneurship. First, they provide a compelling case for the Kuznets curve theory, which is consistent with an inverted U-shaped relationship. Secondly, they suggest that the degree of economic growth of a nation negatively moderates the relationship between income disparity and entrepreneurship. The complex relationships between entrepreneurship and income distribution are highlighted by this study. Quito et al. (2023) on the other hand, use a spatial model technique to explore Spain's provinces. According to their findings, local politics, economic variables, and human capital account for most of the explanations for inequality in each area. The application of regionally weighted Bayesian regressions highlights the concentrated character of these dynamics and provides more evidence for the existence of spatially diverse effects.

Using spatial models, Chen et al. (2019) investigate how banks' liquidity risk interacts with inequality. Their study reveals evidence of spatial dependence in liquidity spillovers, which enables banks to steer liquidity through credit lines customized to the unique requirements of each province. This demonstrates how financial systems and regional inequality are intertwined, necessitating focused policy measures. Lastly, the study conducted by Mastronardi and Cavallo (2020) focuses on income disparity at the local level in Italy. According to their findings, there is greater disparity in crowded urban areas where postsecondary education is common, and the population is younger. On the other hand, inland regions show a more evenly distributed income, which may be explained by a poor social and economic framework that leads to lower income levels and job opportunities, especially in the agriculture industry. The regional differences in the distribution of income within a nation and the complex variables influencing these differences are highlighted in this study.

3. METHODOLOGY AND DATA

The dataset utilized for this analysis consists of a wide range of variables obtained from reliable sources, with the aim of investigating socio-economic dynamics in Southeast Asia. The Human Development Index (HDI)[2] data were gathered from the United Nations, while Gini coefficients, which measure income disparity, were sourced from the World Income Disparity (WID)[3] database. Additional relevant socio-economic statistics were obtained from the World Development Indicators (WDI)[4] repository. From 2000 to 2021, this dataset covers a wide time to accurately represent long-term patterns and transformations in the region. The integration of data from multiple credible sources guarantees the strength and dependability of the study.

In addition, coordinates and pertinent spatial data were obtained from the Integrated Public Use Microdata Series (IPUMS)[5] site to facilitate spatial analysis and geographical integration. This incorporation enables the investigation of spatial dynamics and enables the analysis of geographic patterns and regional interconnections within Southeast Asia. The dataset is broad and includes characteristics related to human development, income inequality, and other socio-economic features. This allows for a full knowledge of the various factors that influence the socio-economic landscape of the region.

The research employs a multi-faceted econometric methodology to analyze the spatial dynamics of FEW Nexus policies and their impact on income inequality. The descriptive analysis provides an overview of the economic indicators, highlighting trends and variations across countries and time periods. To account for spatial dependencies in the data, the study utilizes spatial panel econometrics, specifically the spatial lag model (SLM). These models allow for the consideration of both spatial autocorrelation and spillover effects, offering a more accurate representation of the complex interplay between economic variables. The spatial lag model (SLM) captures the direct spatial effects, accounting for the influence of neighboring regions on income inequality. By integrating these advanced spatial econometric models, the research aims to provide a nuanced understanding of how FEW Nexus policies contribute to income inequality over time and across different geographical locations within Southeast Asian countries. The findings are expected to contribute valuable insights to policymakers and researchers seeking effective strategies to address income inequality in the context of sustainable development and the FEW Nexuses.

When carrying out geographical research, one of the most important steps is to perform spatial modeling. It works in conjunction with a geographic information system (GIS)[6] to appropriately analyze and show data in a graphical format for the benefit of human users. The evaluation of geographical data may make use of models, as well as certain concepts and processes. The fact that it is visual makes it easier for researchers to quickly interpret the data and come to conclusions, both of which would be more challenging if they were just given numerical and textual data. A lengthy analytical process may be broken down into several discrete phases, each of which corresponds to a different step in the manipulation of information. Coverage is the foundation of spatial modeling, which is also object-oriented and focuses on the functioning or look of the actual environment as its primary focus (Higdon et al., 2022). The model that was created is meant to be a representation of a group of things or a process that occurs in the actual world. By superimposing a map with various spatial data, such as highways, dwellings, the route of the tornado, and even its strength at various areas, spatial modeling, for example, may be utilized to evaluate the projected path of tornadoes. This is accomplished by superimposing the map with the data. Because of this, experts can determine the exact route of damage that a storm has left behind. It is possible to use this model to highlight route correlations and geographic features in comparison to other models of neighboring cyclones (Mollalo et al., 2020).

An important idea in the field of spatial modeling is scale, which refers to the geographic range across which ecological processes operate (Chang et al., 2019). Scale specifies the scope of ecological

2 https://hdr.undp.org/data-center/human-development-index#/indicies/HDI
3 https://wid.world/data/
4 https://databank.worldbank.org/source/world-development-indicators
5 https://international.ipums.org/international/geography_gis.shtml

6 It is a tool that integrates hardware, software, and data to create visual representations and insights into spatial relationships and patterns.

processes. It is vital to select a scale that is right for the problem at hand since the processes that are influencing the various species may have varying impacts on them depending on their size. Because of this, it is essential to choose a scale that is appropriate for the problem at hand. There are a lot of different processes going on at different sizes (Leyk et al., 2019).

One of the most important qualities that scattered creatures in a landscape must possess is the ability to create spatial patterns. Patterns are the result of ecological processes and the behavioral reactions of creatures in their environment. There are three general distribution categories that can be used to classify patterns: (1) gradients, which display a smooth directional shift over space; (2) patches, which display clusters of homogenous features separated by gaps; and (3) noise, which refers to random fluctuations that the model cannot account for. Patterns can be categorized using these three general distribution categories. It is possible to detect the pattern by the examination of both the point pattern and the surface pattern. The first category explains the pattern's distribution type and possible chain of events that led to it. The strategy known as "nearest neighbor" is the one that is used the most frequently. The second category of data focuses on geographically continuous data and statistical methods such as correlograms and variograms that can be used to quantify the intensity and size of the spatial relationship within the data. These approaches may be used to determine whether a data set is geographically continuous. The idea of spatial autocorrelation is essential because it demonstrates the potential that neighboring samples are more like one another than would be predicted by random chance. The spatial autocorrelation is said to be positive when the sample values are more like one another than would be anticipated by chance; conversely, the spatial autocorrelation is said to be negative. A very high proportion of ecological data demonstrates some degree of autocorrelation in space. In most cases, this lessens as the distance increases. Those that are closer together have a greater chance of having positive autocorrelation than those that are further away do because the variables that drive species behavior, including as environmental effects, communication, and interactions, are increasingly similar with proximity (Gaynor et al., 2019).

When dealing with geographical models, it is required to obtain and maintain data about the space that the models represent. The amount of data that is currently available in geographical contexts has expanded because of technological advancements in satellite remote sensing. The Television and Infrared Spacecraft (TIRS) was the very first spacecraft that ever saw Earth from space.

3.1. Regression Model

A statistical technique known as linear regression may be used to represent the relationship that exists between a continuous answer and one or more explanatory factors (also referred to, respectively, as dependent variables and independent variables). When there is just one explanatory variable, simple linear regression is utilized, but when there are many explanatory factors, multiple linear regression is utilized. This phrase is more specific than its counterpart, multivariate linear regression, because it refers to the prediction of numerous connected dependent variables rather than just one. The multivariate linear regression term relates to the prediction of just one dependent variable (Maulud and Abdulazeez, 2020). The econometric model is given below.

$$Y_{EI}=\beta_0+\beta_1 TP+\beta_2 UP+\beta_3 LEB+\beta_4 PGR+\beta_5 GDP+\beta_6 HDI+\beta_7 REC+\beta_8 UR+\beta_9 Other_{Gases}+\beta_{10} UR+u_t \quad (1)$$

The equation suggests that you are exploring how variations in the total population, urban population, life expectancy at birth, population growth rate, GDP, HDI, energy consumption, other gases and unemployment rate are associated with variations in education inequality.

The error term (u_t) captures unobserved factors or random variations in education inequality that are not explained by the included variables. This equation allows you to estimate the impact of each explanatory variable on education inequality while accounting for other factors.

The purpose of linear regression is to model connections by utilizing linear predictor functions and then utilize the data to estimate the values of the model's unknown parameters. Linear predictor functions are used to model connections. Linear models are what we're going to be discussing in this section. There is a common misconception that the answer is an affine function of the values of the explanatory factors, which leads to the frequent application of conditional means, medians, and other quantiles (Bertelsen, 2019). The focus of linear regression analysis, as it is with all other kinds of regression analysis, is on the conditional probability distribution of the answer given the values of the predictors. This is also the case with all other kinds of regression analysis. The combined probability distribution of all these variables is the focus of multivariate analysis (Rath et al., 2020).

When it comes to regression analysis, linear regression was the first to receive significant attention from scholars and was also the first to be applied in practical settings. This is because it is easier to identify the statistical characteristics of the consequent estimators, as well as the fact that it is simpler to adapt models that rely linearly on their unknown parameters as opposed to models that rely non-linearly on their parameters.

3.2. Lag Model

A spatial lag model is a sort of spatial econometric model that integrates spatial dependency into a regression framework. This type of model is also known as a spatial lag regression model. It does this by introducing a lagging version of the dependent variable as an extra explanatory variable. This allows it to take into consideration the effect that adjacent observations have on the variable that is being explained (Lam and Souza, 2020).

It is assumed, in a model known as a spatial lag model, that the dependent variable at each site is impacted not only by the features of that place but also by the characteristics of locations that are located nearby. This is represented in the regression equation by the inclusion of a factor that is spatially delayed in time (Lam and Souza, 2020).

The general form of a spatial lag model can be expressed as:

$$Y=\rho W_y+X\beta+\varepsilon \tag{2}$$

The spatial correlations between data are analyzed using the spatial weights matrix, which is denoted by W. When computing the spatial lag, it is the weights that are allocated to each surrounding observation that are specified here. The relative importance of each factor can be determined by several factors, including geographic distance, contiguity, or any number of other measurements of spatial closeness.

The estimation of a spatial lag model requires the use of proper estimation techniques, such as maximum likelihood or the generalized method of moments (GMM), to estimate the coefficients of the model. The geographical structure of the data is taken into consideration by these approaches, which also produce reliable estimations. The spatial lag model incorporates the direct and indirect impacts of surrounding observations on the dependent variable by incorporating the spatial lag component. This allows for a better understanding of geographical dependency and how it influences the connection between variables (Zeng and He, 2019).

3.3. Panel Granger Causality Test

The panel Granger causality test is a statistical tool that is utilized for the purpose of analyzing the causal link that exists between variables in an environment including panel data. Panel data is a type of data that is collected over a period and includes observations from numerous entities (such as individuals, nations, or companies). The conventional Granger causality test has been expanded into the panel Granger causality test, which takes into consideration the cross-sectional as well as the time-series aspects of the data (Odhiambo, 2021). The equation of the panel granger causality test is given below.

$$Y_{it}=\alpha_1+\beta_1 Y_{i,t-1}+\beta_2 Y_{i,t-2}+\beta_p Y_{i,t-p}+\gamma_1 X_{i,t-1}+\gamma_2 X_{i,t-2}+\gamma_p X_{i,t-p}+\mu_{it} \tag{3}$$

The purpose of the panel Granger causality test is to explore if the past values of one variable help predict the future values of another variable while controlling for any confounding variables and individual-specific effects. In other words, the test seeks to determine whether the past values of one variable assist predict the future values of another variable. The purpose of the test is to determine whether the incorporation of lagging values for one variable improves the accuracy of prediction for another variable beyond what can be explained by the latter variable's own historical values and the values of other control variables (Bayar et al., 2020).

The first stage is to provide an acceptable econometric model that reflects the connection between the variables of interest. This model should include the lags of the putative causative variable(s), any control variables, and any individual-specific effects. Once this model has been specified, the next step is to specify the panel data model. Models with fixed effects, models with random effects, and pooled models are all examples of models that are often utilized in panel data analysis.

After estimating the model, the Granger causality test may be carried out. This test can be carried out after the model has been assessed. The test consists of assessing the degree to which two nested models fit the data: one model contains lagged values of the probable causative variable(s) and other control variables, whereas the second model does not include these delayed variables and instead excludes them. The F-test or the likelihood ratio test is often used as the foundation for the comparison.

If the test statistic is statistically significant, it shows that the lagged values of the possible causative variable (or variables) contribute considerably to explaining the variation in the dependent variable, even after accounting for its own previous values and other control factors.

4. RESULTS AND DISCUSSION

Figure 1 demonstrates that Java, Indonesia, has the highest population density in Southeast Asia >140 million people call Java home, greater than the populations of any other countries in the region combined. Southeast Asia's population is expanding quickly overall. By 2025, there will be more than 700 million people living in the region. There is a strain on food, water, and energy supplies due to this fast population expansion. Degradation of the environment and growing urbanization are other results of it.

Southeast Asia is an area with a high level of urbanization, as seen by the map in Figure 2. Nonetheless, a sizable portion of the population in the region still lives in rural areas, especially in nations like Indonesia, Myanmar, and Cambodia.

It also demonstrates the wide range of differences in Southeast Asian countries' levels of urbanization. Numerous factors, such as the country's size, population density, degree of economic growth, and demographic dispersion, are to blame for this.

Figure 3 shows how life expectancy in Southeast Asia depicts a region struggling with both notable development and enduring inequities. At the top, Singapore has an impressive 82.8 years, which is a result of its strong economy, consistent investments in healthcare, and well-educated population. Its wealthy neighbor Brunei comes in close after with 78.7 years, reflecting a similar dedication to wellbeing. Thailand's rise to 75.2 years highlights the country's commitment to healthcare advancements, which pays off in the form of a continually increasing life expectancy.

Standing tall at 73.6 years, Vietnam is another success story that may be attributed to its varied efforts in reducing infectious diseases, improving healthcare accessible, and promoting economic growth. Malaysia manages to secure a commendable 73.2 year thanks to its advanced healthcare system and relative income. A more nuanced image is presented by Indonesia, a country of tremendous diversity. Although the average age across the country is 72.1 years, there are still differences between regions, which emphasizes the continuous fight for fair access to healthcare.

With a lifespan of 70.9 years, the Philippines is attempting to get over the obstacles ailing its healthcare system by making

Figure 1: Exploring the total population in Southeast Asian region

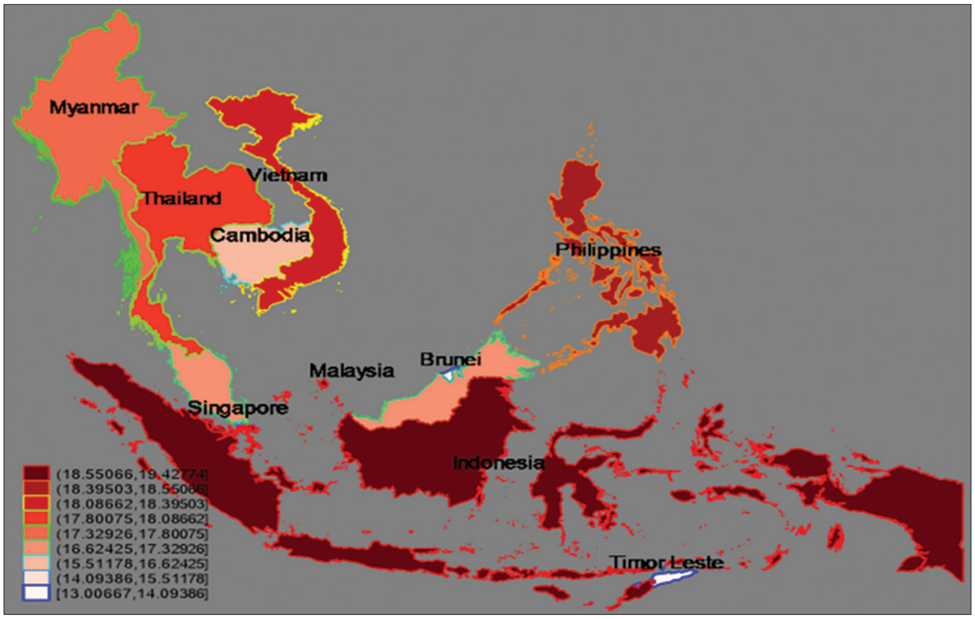


Figure 2: Explore the Urban population in Southeast Asian region

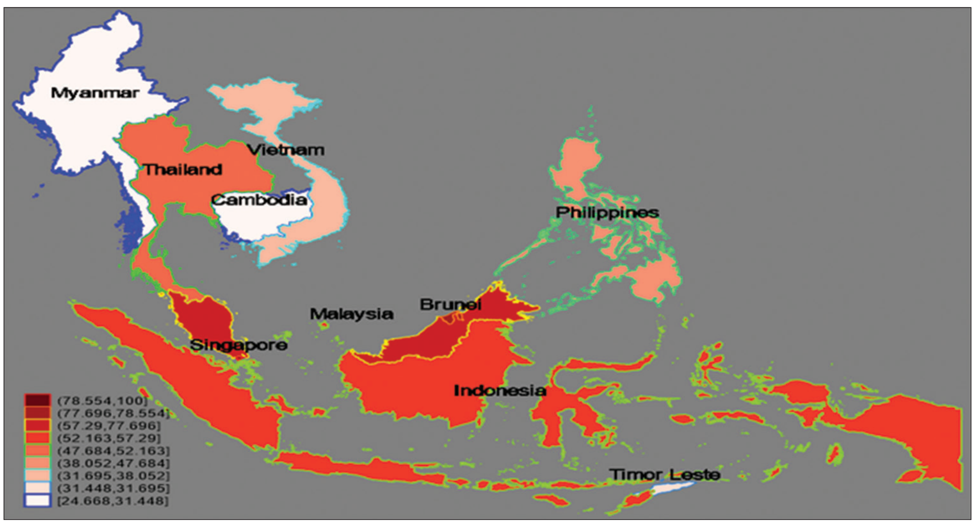
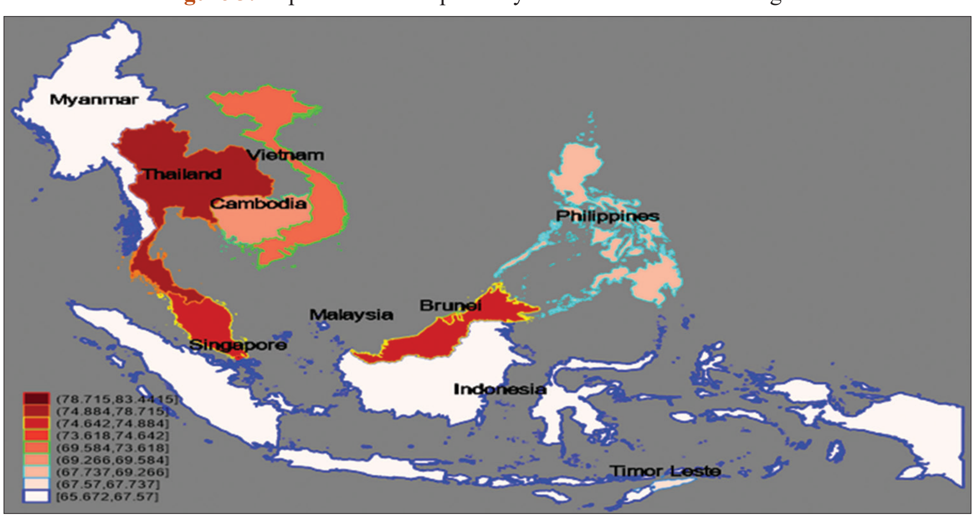


Figure 3: Explore the life expectancy in the Southeast Asian region



incremental improvements. Myanmar, which suffers from extreme poverty and has a shaky healthcare system, records 69.1 years, highlighting the difficulties that poor countries face. At 66.2 years old, Cambodia reflects these challenges with its own set of problems, including poverty, poor access to healthcare, and a high rate of infectious diseases. With 64.2 years, Timor-Leste, a country emerging from conflict, is at the bottom, serving as a sobering reminder of the long road ahead for recovery and fair healthcare distribution.

Figure 4 illustrates Southeast Asia's economic vitality, with Thailand and Indonesia in the forefront. While the Philippines and the developing economies of Cambodia and Myanmar want to establish their positions in the regional scene, Vietnam's remarkable rise is also worth mentioning. The lowest GDP indicated by the smallest country Timor-Leste.

Southeast Asia's energy landscape presents a varied mosaic of development paths in Figure 5. Leading the pack, Singapore's energy-intensive industry, small size, and reliance on imported energy allow it to consume an impressive 8759 tons of oil equivalent annually per person. With 4704 tons per person, Malaysia is just behind, driven by a strong manufacturing sector and a booming economy. Thailand, another economic giant with 3210 feet above sea level, depends largely on energy for both industrial and tourism. Vietnam's economy is growing, as seen by its impressive growth of 2501.

Transportation and industry demand account for 2024 toe per capita consumption in Indonesia. The Philippines' rising energy consumption per person at 1518 reflects its developing economy, while Myanmar and Cambodia only require moderate amounts of energy 1025 and 755 toe, respectively. Timor-Leste lags at

Figure 4: Explore the GDP in the Southeast Asian region

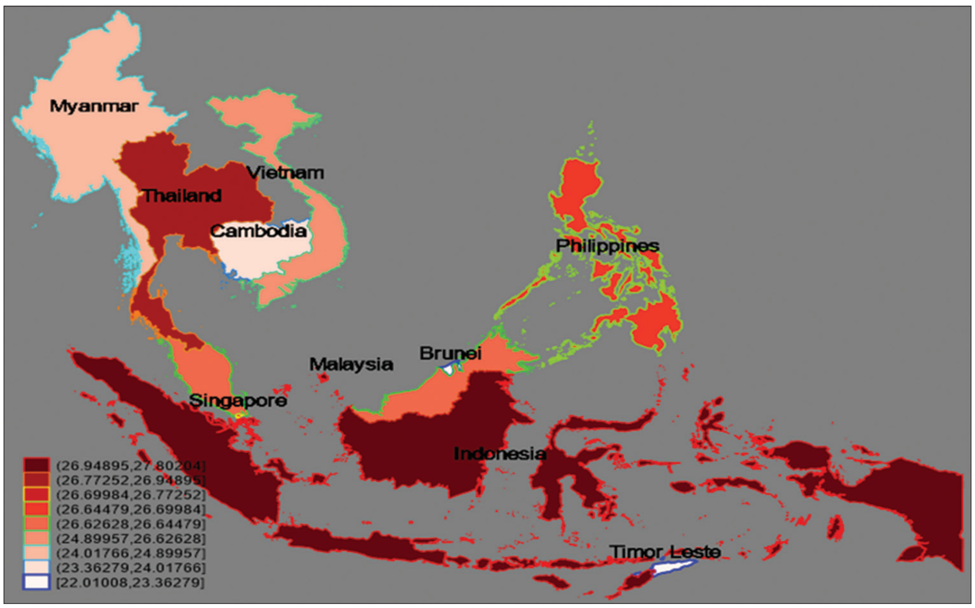
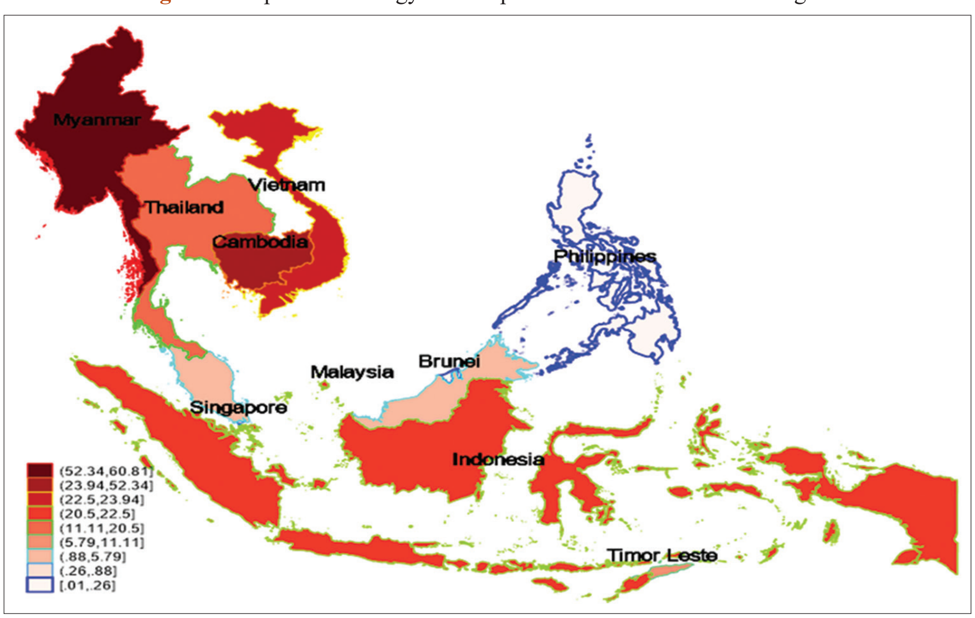


Figure 5: Explore the energy consumption in the Southeast Asian region



402, which is representative of its recent progress. This spectrum highlights the intricacy of development and the necessity of sustainable energy solutions in the face of expanding economies and environmental issues.

The above Figure 6 shows the Southeast Asia's complex map intertwines environmental challenges with economic success, with significant differences in CO_2 emissions between its countries. As the region's economic powerhouse, Indonesia leads the way with its yearly emissions of 619 million metric tons of CO_2. The significant reliance on fossil fuels for power generation and the expanding industrial sector are the main causes of this emission spike. Closely behind, Malaysia releases over 231 million metric tons, propelled by its growing palm oil fields and businesses, and Thailand releases 243 million metric tons because of its thriving tourism and manufacturing sectors.

Vietnam is releasing 208 million metric tons, mirroring growth patterns despite its rapid economic ascension. With its rapidly expanding economy, the Philippines has surpassed its low-emission classification with 178 million metric tons of emissions. On the other hand, because of their low levels of industrial activity and pervasive poverty, Myanmar and Cambodia have considerably lower emissions, coming in at 47 million and 20 million metric tons, respectively.

Despite accounting for only 6% of global CO_2 emissions, Southeast Asia's rapid economic growth and reliance on fossil fuels present serious environmental issues. It is essential to prioritize sustainable development to lessen this. In Southeast Asia, the protection of natural carbon sinks like forests, energy efficiency campaigns, and investments in renewable energy are essential steps toward a cleaner and more sustainable future.

Figure 7 indicates that the flourishing industries and urban landscapes of Southeast Asia's complicated map: the hidden emissions of HFC, PFC, and SF6, powerful greenhouse gases that are quietly affecting the region's climate while its economy grows at an accelerated rate. Significant contributors to these emissions are well-known emission hotspots, most notably East Java, Indonesia, where a high concentration of electronics and semiconductor businesses are widely distributed. Bangkok, Thailand, is also concerned about the increasing amount of these invisible pollutants because of its strong electronic production industry. Industrial emissions are also present in Peninsular Malaysia, a reflection of the region's unrelenting drive for economic growth.

Nevertheless, despite these obvious hotspots, there are significant data gaps that make it difficult to get a clear picture of the region's emissions situation. Vietnam, which appears to be less impacted, hides its emission profile behind inaccurate data. This disjointed representation emphasizes how urgently a comprehensive understanding is required. Each increase in HFC, PFC, and SF6 emissions exacerbates the warming trend in the area and quickens the dangerous course of climate change. To counter this invisible threat, coordinated action is required. Stricter laws must be implemented by governments to reduce excessive industrial emissions and promote cleaner technologies. The industrial sector needs to change its focus to sustainable methods, supporting ethical production and reducing the use of dangerous gases. Advocating for climate-conscious decisions and holding stakeholders accountable are equally important as collective individual action.

Figure 8 shows the cartographic representation of Southeast Asia illustrates stark disparities in economic prosperity, with certain regions exhibiting affluence while others grapple with acute financial constraints. Singapore is highly affluent, whereas Brunei is similarly prosperous due to its oil reserves. Thailand, Vietnam, and Malaysia possess a moderate level of affluence, however significant disparities persist between the wealthy and the impoverished. Indonesia, despite its significant economic size, exhibits substantial disparities among its population.

Figure 6: Explore the CO_2 emission in the Southeast Asian region

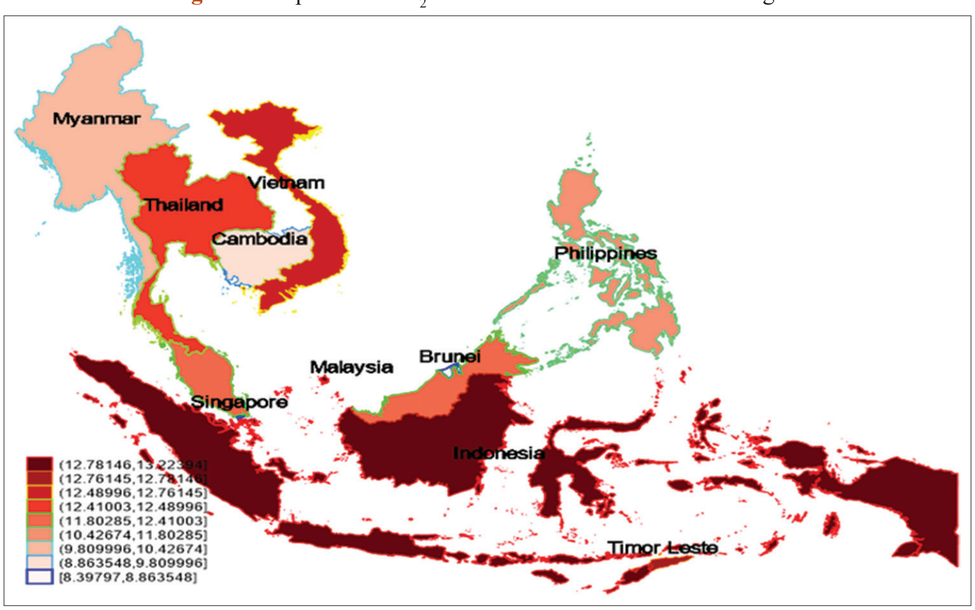


Figure 7: Explore the other gasses emission in the Southeast Asian region

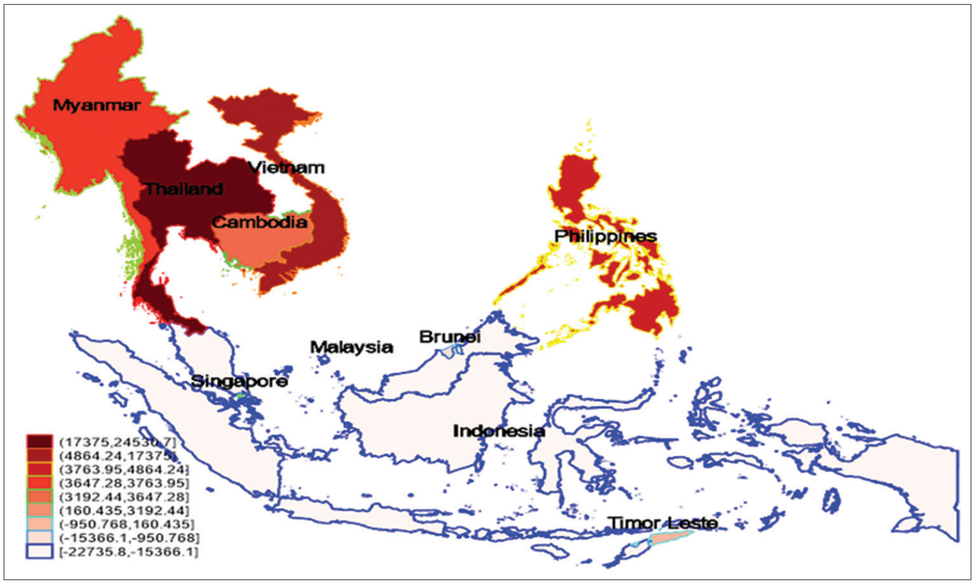
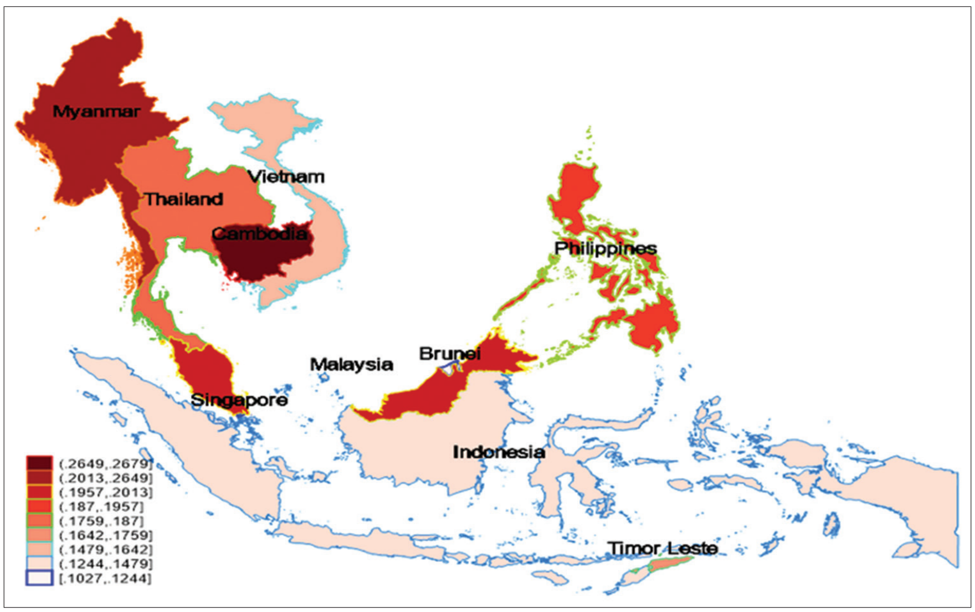


Figure 8: Explore the income inequality in the Southeast Asian region



The wealth disparity in the Philippines and Cambodia is pronounced, as a small minority control most of the financial resources. Timor-Leste exhibits the highest level of inequality, characterized by a significant disparity in the distribution of wealth among its population. This imbalance gives rise to difficulties. It engenders discontent among certain individuals and hinders the country's progress as not all individuals are afforded equitable opportunities.

To address this issue, it is imperative for governments to provide increased assistance to individuals living in poverty, establish equitable regulations pertaining to taxation, and provide educational opportunities for all individuals. Corporations ought to provide equitable compensation and ensure impartial treatment for all individuals. Individuals ought to advocate for equitable regulations that promote equal opportunities for all individuals in their lives.

The HDI map of Southeast Asia illustrates the relative performance of several countries in terms of indicators such as health, education, and living standards. Locations such as Singapore and Brunei are performing very well and are classified as very high in terms of their performance in the above Figure 9. On the other hand, countries like Thailand, Malaysia, Vietnam, and Indonesia are also performing well, but not to the same extent. Myanmar and Cambodia are geographically located in a central position, and they are currently encountering certain challenges in comparison to other countries. This map also illustrates the disparities in performance across different regions within each country.

For example, in Singapore, possessing wealth and having access to quality healthcare and education contribute significantly to their high scores. Like Singapore, Brunei likewise derives significant advantages from its abundant oil resources. Thailand

Figure 9: Explore the human development index in the Southeast Asian region

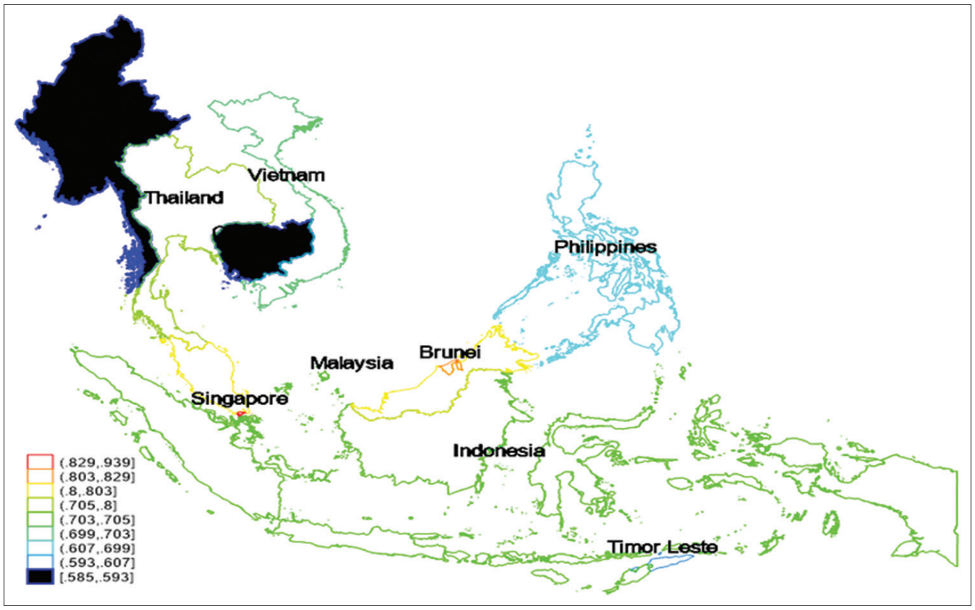
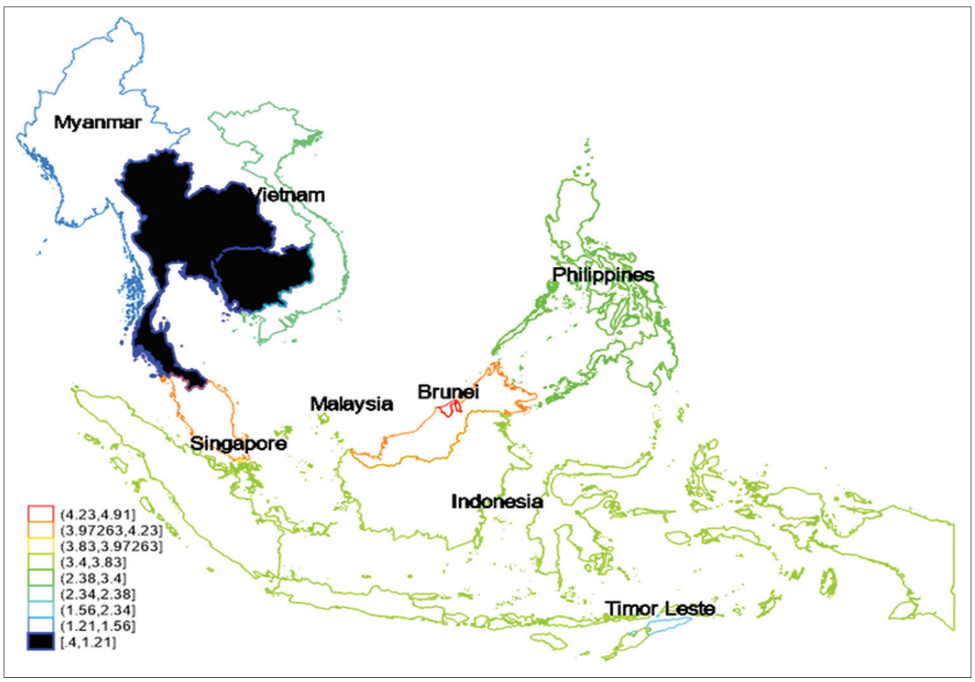


Figure 10: Explore the unemployment rate in the Southeast Asian region



and Malaysia have made advancements in their educational and healthcare systems; however, disparities still exist between urban and rural areas.

Vietnam is experiencing rapid growth, but there remains an unequal distribution of quality education and healthcare services. Indonesia exhibits significant size and diversity, resulting in varying levels of success throughout different regions. Myanmar and Cambodia face difficulties such as poverty and healthcare issues. This map represents a one perspective on progress, and it is important to acknowledge that circumstances might evolve throughout time. However, to enhance the quality of life in Southeast Asia, it is crucial to ensure equal opportunities for all individuals to thrive.

The map presented illustrates Figure 10 shows the variation in unemployment rates across Southeast Asia, highlighting the presence of different economic conditions in the region. Singapore's unemployment rate is impressively low, hovering about 1.8%. This can be ascribed to the country's flourishing economy, highly skilled workforce, and efficient governmental programs. Thailand and Vietnam have moderate growth rates, approximately 1.2% and 2.1% respectively, driven by flourishing sectors like tourism and manufacturing. Malaysia and Indonesia have slightly higher rates, with averages of approximately 3.6% and 5.3% respectively, despite their robust economies. This can be attributed, in part, to differences in the employment market and a growing youth population. Conversely, Myanmar and the Philippines have challenges with elevated rates, approximately 4.9% and 6.5% respectively, due to variables such as political instability and a substantial informal work market. The map additionally accentuates inequalities within nations, specifically drawing attention to the lower unemployment rates in metropolitan areas in contrast to rural parts. This stresses the significance of comprehending the intricacies of informal work. Key factors to be considered when formulating comprehensive employment strategies in the region include the difficulties in dealing with job displacement caused by automation, the issue of youth unemployment, and the urgent need for investment in infrastructure in rural regions.

Table 1 displays descriptive statistics for multiple important variables based on 220 observations in the dataset. The Gini Index, which measures income inequality among countries, has an average value of 0.179 and a standard deviation of 0.043. This indicates a range from 0.103 to 0.277, representing different degrees of inequality across the observations. The population growth has an average of 1.357 and a significant standard deviation of 0.78, indicating a wide range from −4.17 to 5.322. This suggests that there are varied population dynamics within the dataset. The average CO_2 emission is 11.014, with a reasonably narrow range of variability from 7.582 to 13.313. This suggests a moderate level of variation in emissions among the observations.

The Renewable Energy Consumption (REC) variable exhibits a wide range, with an average of 29.963 and a significant standard deviation of 25.867, fluctuating between 0.01 and 85.77. This highlights the diversity in the utilization of renewable energy. The GDP in Billions has a mean value of 24.818, showing a consistently constant economic production throughout all observations in the dataset, which ranges from 19.721 to 27.802. The life expectancy, as indicated by the dataset, has an average of 71.422 years. The observations range from 56.506 to 84.466, indicating a significant variation in life expectancy among the entities in the dataset.

The variable Other Gasses Emission exhibits significant variability, with an average value of −176.22 and a substantial standard deviation of 10137.48. The range of values extends from −32215.65 to 51457.35, showing a great dispersion in emissions of other gases. The Total Population metric shows an average of 16.757, with observations ranging from 12.719 to 19.428. This range reflects the wide variety of population sizes included in the dataset. The Unemployment Rate exhibits a mean value of 3.7%, with individual observations ranging from 0.14% to 11.19%, indicating variations in job conditions among different entities.

The Urban Population variable has an average of 49.361%, with notable fluctuations ranging from 18.586% to 100%, suggesting inequalities in the sizes of urban populations. The Human Development Index (HDI) has an average value of 0.69, with a range from 0.41 to 0.943. This indicates varying levels of human development across the observations in the dataset. In summary, these descriptive statistics offer a thorough summary of the diverse characteristics found in the dataset, highlighting the variation, and spread across different socio-economic indicators among the observed entities.

The coefficient for population growth in Southeast Asia is −0.001, indicating a very small effect. The P = 0.817 further suggests that there is no significant relationship between population growth and income inequality in the region. On the other hand, the coefficient for CO_2 Emission is −0.011 (P = 0.000), suggesting that increased carbon emissions have a significant effect on worsening income disparity in the region.

The coefficients of Renewable Energy Consumption (REC), GDP in Billions, and Urban Population are near to zero, suggesting that there is no statistically meaningful link with the Gini Index. The coefficient for Life Expectancy is −0.002 with a P = 0.015, indicating a slight correlation between higher life expectancy and reduced income inequality in Southeast Asia.

The variable Other Gasses Emission has a positive coefficient of 4.27E-07 (P = 0.024), indicating that an increase in emissions of other gases has a minor impact on increasing income disparity. The variable "Total Population" exhibits a positive coefficient of 0.01 (P = 0.06), indicating a possible but not statistically significant correlation with income inequality. The Unemployment Rate has a significant negative coefficient of −0.005 (P = 0.000), suggesting that higher levels of unemployment are associated with greater income inequality in the area. Similarly, the Human Development Index (HDI) exhibits a negative coefficient of −0.152 (P = 0.008), indicating that a greater HDI is linked to reduced income inequality.

Ultimately, the constant term is precisely 0.415 (with a P = 0.000), indicating the intercept when all independent variables are set to

Table 1: The descriptive statistics of the variables

Variable	Obs	Mean	SD	Min	Max
Gini index	220	0.179	0.043	0.103	0.277
Population growth	220	1.357	0.78	−4.17	5.322
CO2 emission	220	11.014	1.539	7.582	13.313
Renewable energy consumption (REC)	220	29.963	25.867	0.01	85.77
GDP in billions	220	24.818	2.009	19.721	27.802
Life expectancy	220	71.422	5.727	56.506	84.466
Other gasses emission[7]	220	−176.22	10137.48	−32215.65	51457.35
Total population	220	16.757	1.988	12.719	19.428
Unemployment rate	220	3.7	2.203	0.14	11.19
Urban population	220	49.361	24.275	18.586	100
HDI	220	0.69	0.125	0.41	0.943

7 Other Gasses Emission Include HFC, PFC and SF2

zero. In summary, the regression results underscore the complex connections between different socio-economic factors and income inequality in the Southeast Asian economy. This emphasizes the importance of variables such as CO_2 emissions, unemployment rates, and HDI in shaping the distribution of income in the region.

Table 3 displays the results of a spatial lag model that investigates the relationship between different socio-economic parameters and the Gini Index, which measures income inequality in a Southeast Asian context. The model includes a spatial weight matrix, indicating interdependencies among adjacent entities in the dataset. The coefficient for Population Growth has a negligible effect (0.001, P = 0.737) on income inequality, indicating a lack of significant effects. On the other hand, the logarithm of CO_2 emissions shows a substantial adverse effect (−0.011, P < 0.001), indicating that higher carbon emissions are linked to a rise in income disparity.

Table 2: Panel regression result of Southeast Asian Economy

Gini index	Coef.	St.Err.	t-value	P-value
Population Growth	−0.001	0.003	−0.23	0.817
CO_2 Emission	−0.011	0.002	−4.51	0.000
Renewable Energy Consumption (REC)	−0.0001	0.00025	−0.42	0.671
GDP in Billions	−0.001	0.005	−0.15	0.881
Life Expectancy	−0.002	0.001	−2.44	0.015
Other Gasses Emission	4.27E-07	1.90E-07	2.25	0.024
Total Population	0.01	0.005	1.88	0.06
Unemployment Rate	−0.005	0.001	−4.29	0.000
Urban Population	0.0004	0.0002	1.86	0.063
HDI	−0.152	0.057	−2.67	0.008
Constant	0.415	0.068	6.12	0.000

Note: Table 2 presents the findings of a panel regression study that examines the factors that impact the economy of Southeast Asia. The coefficients represent the influence of each variable on the Gini Index, which is a metric used to measure income inequality in the region

Table 3: The spatial lag model of Southeast Countries

Gini index	Coefficient	Std. Err	z	P>z
Spatial lag (ρ)	0.665	0.221	3.01	0.003
Population growth	0.001	0.002	0.34	0.737
CO2 emission	−0.011	0.002	−4.58	0.000
Renewable energy consumption (REC)	−0.0002	0.00024	−0.95	0.344
GDP in billions	0.001	0.005	0.24	0.811
Life expectancy	−0.004	0.001	−3.71	0.000
Other gasses emission	3.77E-07	1.82E-07	2.07	0.039
Total population	0.009	0.005	1.72	0.085
Unemployment rate	−0.006	0.001	−4.75	0.000
Urban population	0.001	0	2.7	0.007
HDI	−0.165	0.055	−3.03	0.002
Constant	0.375	0.066	5.66	0.000

The spatial parameter (rho) indicates the presence of spatial autocorrelation, with a coefficient of 0.665 (P=0.003), indicating the existence of spatial correlations among entities. The Wald, Likelihood Ratio, and Lagrange Multiplier tests provide evidence to reject the null hypothesis that there is no spatial autocorrelation. This supports the presence of spatial effects among the observed entities in the dataset. The range of permissible values for rho is −3.542-1.000, which defines the limits within which spatial effects can be considered probable. These findings highlight the complicated connections between many socio-economic determinants and income disparity in Southeast Asia, emphasizing the importance of geographical interdependence in comprehending these nuanced dynamics

The correlations for Renewable Energy Consumption (REC), GDP (logarithmically converted), and Urban Population are near 0, indicating a lack of statistically meaningful correlation with income disparity. Life Expectancy has a significant negative impact (−0.004, P < 0.001), suggesting that higher life expectancy is associated with reduced income disparity in the region. The variable related to "Other Gases Emission" shows a positive correlation (0.000, P = 0.039), indicating a slight connection between higher emissions of these gases and increased income disparity. The logarithmically converted total population variable exhibits a positive coefficient of 0.009, with a P = 0.085. This suggests a potential, but not statistically significant, association with income inequality.

The Unemployment Rate demonstrates a significant adverse effect (−0.006, P < 0.001), suggesting that higher levels of unemployment are associated with greater income disparity in the region. The analysis reveals a statistically significant positive influence (0.001, P = 0.007) of urban population on income inequality, indicating a modest correlation between the two variables. Furthermore, the Human Development Index (HDI) exhibits a significant adverse impact (−0.165, P = 0.002), suggesting that a greater HDI is associated with less income inequality. The constant term (0.375, P < 0.001) in the model represents the intercept when all independent variables have a value of zero.

The Table 4 displays the outcomes of hypothesis testing that investigates the correlation between different independent variables (Population Growth, CO_2 Emission, Renewable Energy Consumption, GDP, Life Expectancy, Other Gasses Emission, Total Population, Unemployment Rate, and HDI) and the dependent variable, Inequality, using an F-Statistic and its corresponding P-values. The F-Statistics for Population Growth and CO_2 Emission are 1.535 and 1.2193, respectively. The corresponding P-values are 0.1248 and 0.2227, which do not provide enough

Table 4: Granger causality test of Southeast Asian countries

Variable X	Variable Y	F-Statistic	P-value	Result
Population growth	Inequality	1.535	0.1248	Fail to Reject
CO_2 EMISSION	Inequality	1.2193	0.2227	Fail to reject
Renewable energy consumption (REC)	Inequality	5.2143	0.0000	Reject
GDP in billions	Inequality	2.1405	0.0323	Reject
Life EXPECTANCY	Inequality	2.8679	0.0041	Reject
Other gasses emission	Inequality	0.967	0.3336	Fail to reject
Total population	Inequality	1.9825	0.0474	Reject
Unemployment rate	Inequality	7.5027	0.0000	Fail to reject
HDI	Inequality	1.8545	0.0637	Fail to Reject

evidence to reject the null hypothesis. The results indicate a lack of sufficient data to establish a substantial correlation between Population Growth, CO_2 Emission, and Inequality.

On the other hand, the F-Statistics for Renewable Energy Consumption (REC), GDP in Billions, Life Expectancy, and Total Population are 5.2143, 2.1405, 2.8679, and 1.9825 respectively. All these numbers have P-values that are lower than the significance level. Hence, the rejection of the null hypothesis suggests a substantial correlation between these factors and Inequality.

In addition, the Unemployment Rate exhibits a significant F-Statistic of 7.5027 with a P = 0.0000, which offers compelling evidence to reject the null hypothesis. This suggests a major correlation between the Unemployment Rate and Inequality. Nevertheless, the F-Statistics for Other Gasses Emission and HDI are 0.967 and 1.8545 respectively, resulting in P-values of 0.3336 and 0.0637. As a result, we cannot reject the null hypothesis. These findings indicate that there is insufficient evidence to establish a substantial correlation between emissions of other gases, the Human Development Index (HDI), and inequality.

To summarize, the statistical tests conducted indicate that there is a lack of significant evidence linking Population Growth, CO_2 Emission, Other Gasses Emission, and HDI to Inequality. However, there are substantial associations between Inequality and Renewable Energy Consumption, GDP in Billions, Life Expectancy, Total Population, and the Unemployment Rate.

5. CONCLUSION AND RECOMMENDATIONS

The examination of the spatial dynamics surrounding FEW (Food, Energy, Water) Nexus policies and their potential impact on income inequality within Southeast Asian nations offers profound insights into the region's socio-economic landscape. Through the lens of spatial econometric models, this analysis reveals intricate spatial interdependencies among these policies and income inequality, underscoring the necessity of adopting a regional perspective in policy formulation.

Crucially, the findings accentuate the significance of certain components within the FEW Nexuses, particularly Renewable Energy Consumption and Total Population, displaying noteworthy associations with income inequality. These results corroborate prior research that highlights the pivotal role of sustainable energy practices and population-related policies in mitigating income disparities. Additionally, indicators such as the Unemployment Rate and Life Expectancy reaffirm their influence on income inequality, shedding light on the multifaceted nature of socio-economic factors contributing to these disparities.

The implications of these findings are substantial, shaping recommendations for policy interventions aimed at addressing income inequality in Southeast Asia. Integrated policy approaches are pivotal, necessitating a holistic consideration of the interconnectedness between the food, energy, and water sectors. Encouraging sustainable resource management practices while concurrently addressing socio-economic disparities through policy frameworks emerges as a crucial strategy.

The promotion of sustainable development forms a cornerstone of the suggested interventions. Policymakers could emphasize policies fostering increased utilization of renewable energy sources, advocating for efficient management of water and food resources, and encouraging environmentally sustainable practices. Such measures align with global sustainability goals and could significantly impact income distribution within the region.

Moreover, targeted programs focusing on employment generation, vocational training initiatives, and robust social welfare policies are paramount. These interventions have the potential to alleviate unemployment and enhance social indicators, thereby contributing substantially to the reduction of income inequality.

Recognizing the spatial interdependencies across Southeast Asian nations, it becomes imperative to encourage collaborative efforts and cross-border partnerships in policy formulation and implementation. Collaborative endeavors are instrumental in addressing shared challenges and amplifying the impact of policy interventions, thereby fostering more effective and far-reaching outcomes. Continued research and rigorous monitoring and evaluation mechanisms are crucial elements for sustainable policy implementation. These activities are essential for adapting strategies to evolving socio-economic conditions and ensuring the effectiveness of policy interventions in addressing income inequality across the region.

In conclusion, leveraging the interconnections inherent in FEW Nexus policies while concurrently addressing socio-economic disparities represents a pivotal pathway towards mitigating income inequality in Southeast Asia. Comprehensive, sustainable, and targeted policy approaches, informed by spatial dynamics, are instrumental in fostering equitable development and reducing income disparities within the region.

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