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The Evaluation and Measurement of Green Economic Efficiency for Less Developed Countries

Muhammad Farqan Maqsood[1] Abre-Rehmat Qurat-ul-Ann[2]

[1] PhD Scholar, Department of Economics, University of Gujrat, Gujrat, Punjab, Pakistan.

[2] Assistant Professor, Department of Economics, University of Gujrat, Gujrat, Punjab, Pakistan.

Corresponding Author: Muhammad Farqan Maqsood, **Email:** furqan517@gmail.com

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ABSTRACT

Environmental degradation and climate change have redirected the conventional development models towards green development. This shift is mandatory while achieving 1.5ºC target set under the Paris Agreement. Green economic efficiency emerged as an important tool to assess and evaluate the level of sustainability as it simultaneously considers desirable and undesirable output levels with resource input efficiency. The existing literature is mainly focused on developed countries with limited evidence from developing countries that are vulnerable to climate risk and in pressing need of efficient utilization of resources. Using a Slack-Based Measure Data Envelopment Analysis, this study measures green economic efficiency for 74 less developed countries for the period of 1996 to 2022. The study incorporates gross domestic product as a desirable output and CO_2 emissions as undesirable output. The results indicate a substantial regional heterogeneity with a positive trend for the overall sample. Country-specific analysis highlight that Iran (0.80), India (0.63), Mongolia (0.62), Bolivia (0.73), Ukraine (0.89), Angola (0.79), Nigeria (0.86) and Algeria (0.85) show relatively higher levels of average GEE among countries. Regional heterogeneity requires region-specific policies with a focus on renewable energy utilization, resource efficiency improvement, gradual transition of technologies and shifting of financial resources towards green products. The results suggest a three-tier policy for rapid transition encompassing smart financial incentives, improvement in governance quality and implementation of carbon audits, and embracing technological innovations with provision of market-oriented data-driven solutions.

1. Introduction

Economic growth is the ultimate objective of any economic policy, however, dependence on fossil fuels has generated serious environmental concerns. Massive industrialization and excessive consumption of non-renewable energy have triggered environmental challenges, including climate change. Climate change is the most critical challenge of the century, reshaping

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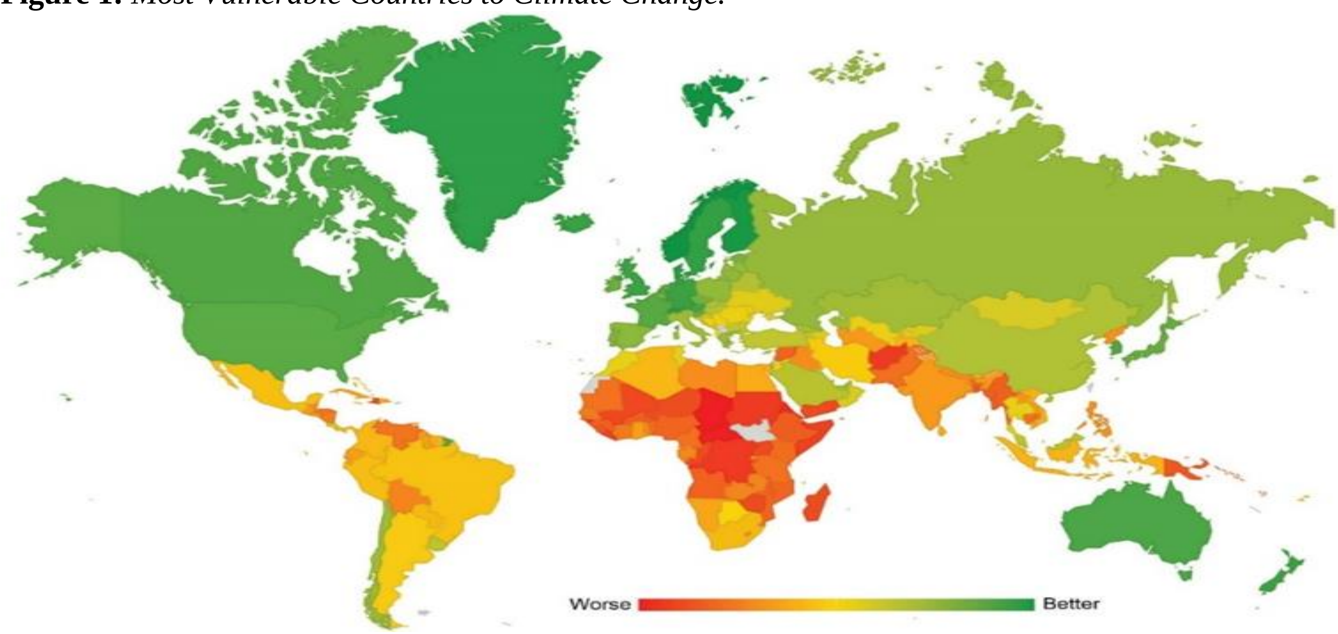
economic priorities and development strategies. Traditional growth models have become obsolete with the emergence of environmental issues. The concepts of green growth and green development emerged in response to environmental degradation. Green development is defined as achieving economic prosperity while minimizing environmental degradation (Zhao et al., 2018). Policymakers and researchers have shifted their focus from the measurement of economic growth to evaluating efficiencies while maximizing desirable output with the minimization of undesirable greenhouse gases.

The concept of Green Economic Efficiency (GEE) has become an important measuring rod for assessing the quality and quantity of economic growth. This concept incorporates economic growth, resource input utilization and environmental degradation. Conventional productivity measures consider the maximization of output with given resources, whereas GEE minimizes environmental degradation along with the maximization of output (Sun et al., 2024). Under green growth, environmental standards are maintained through cleaner production, greener technologies, renewable energy and efficient utilization of resources.

Understanding of GEE is particularly important to realize with reference to Sustainable Development Goals (SDGs) 7, 8 and 12which are access to affordable and clean energy, decent work and economic growth and responsible consumption and production, respectively. The entire world has implemented climate pledges under the Paris Agreement to achieve these set goals. (UNDP, 2022). Attainment of green economic efficiency plays a key goal to achieve sustainable development and inclusive growth.

Understanding of GEE for LDCs is important to counter climate shocks and continue the process of development. The less developed countries are highly vulnerable to climate shocks (see Figure 1). Moreover, poor economic conditions coupled with inadequate adaptive capacity required a thorough understanding to redirect resources toward climate-resilient infrastructure and consistency in economic development.

Figure 1: *Most Vulnerable Countries to Climate Change.*



Source: *Notre Dame Global Adaptation Initiative measures overall vulnerability to climate change while considering exposure, sensitivity, and ability to adapt. https://gain.nd.edu/our-work/country-index/*

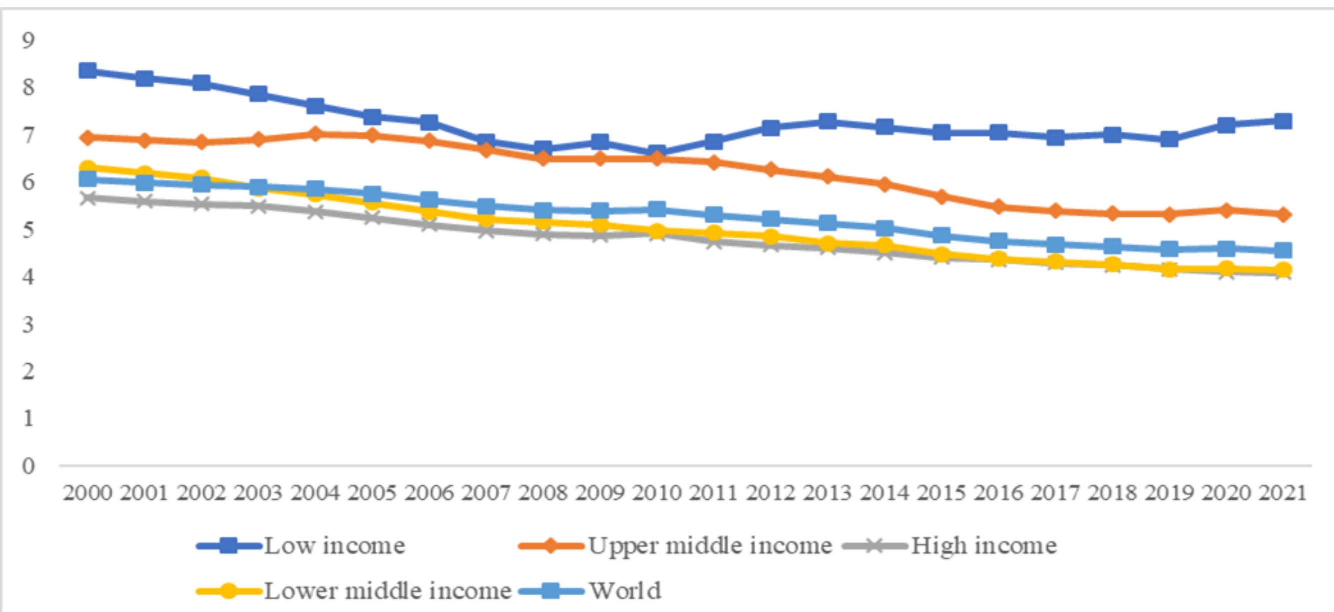
The red color in Figure 1 shows the most vulnerable countries to climate change as per Notre Dame Global Adaptation Initiative (ND-GAIN) index. Majority of the climate vulnerable countries are in Africa and Asia which are also economically less developed. These less developed countries only contribute less than 4 percent of global greenhouse gas emissions (UNDP, 2026).

LDCs deal with a shortage of resources to continue the process of development. Thus, these aim for the efficient utilization of existing resources with the minimization of environmental degradation but continuous degradation of environment has imposed further controls over development trajectories. Achieving efficiency while minimizing undesirable outputs like greenhouse gases is considered a challenge (Zhao et al., 2020; Li et al., 2013; Yuan et al., 2020). GEE is defined as the maximization of desirable output with minimum environmental impact (Y. Chen et al., 2023a). The literature has approached GEE in different perspectives, for instance, Camioto et al. (2016) measured total factor productivity while treating CO2 emissions as an undesirable output. Wang et al. (2019) reflected GEE as a measure of social welfare with economic and environmental dimensions while Yi and Zhang (2018) emphasized quantity and quality of development.

GEE is negatively associated with carbon-intensity level, low carbon usage results in high GEE and high carbon intensity results in low GEE (Y. Chen et al., 2023a). It assesses the performance level of an economy in terms of how well it is managing environmental issues along with the maximization of output. Path dependencies and structural rigidities shape the smoothness of the transition towards low-carbon emissions (Zhao et al., 2024). Techno-institutional rigidities limit the adoption and innovation of greener technologies, whereas a smoother transition reduces environmental degradation (Liu et al., 2022). Thus, the measurement of GEE is important to define the role of techno-institutional rigidities in the transition process (Y. Chen et al., 2023a).

GEE can be assessed through carbon and energy intensities. Energy intensity measures how much energy is used to produce a specific level of output and carbon intensity measures how much carbon is emitted to produce a specific level of output. Figures 2 and 3, respectively, present the global energy intensity and carbon intensity levels across different income groups.

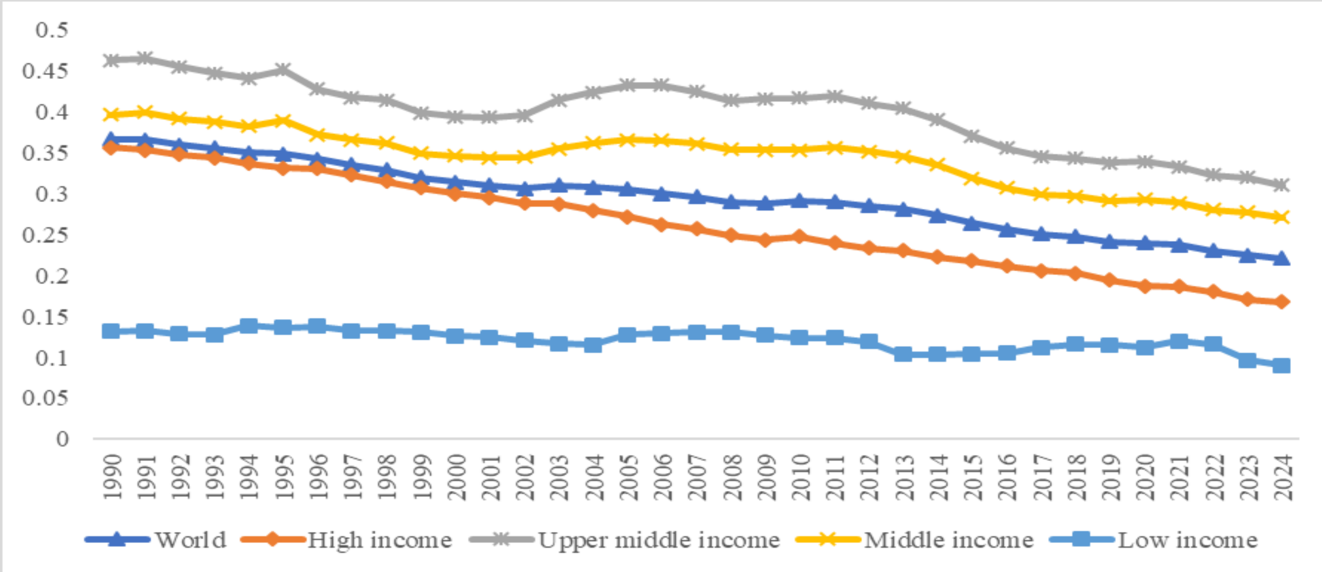
Figure 2: *Energy Intensity, Megajoules of Primary Energy Consumed Per 1 US dollar of GDP (measured in 2021 PPP terms).*



Data Source: *World Bank, World Development Indicators (2024)*

Figure 2 illustrates a consistent decrease in overall world energy intensity level and across different income groups, indicating improvement in efficiency over time. While low-income countries present structural inefficiency through a rising trend of energy intensity level. Alternatively, Figure 3 illustrates carbon intensities over time, with a constant decline in carbon emitted per unit of output. This decline is the outcome of a global shift in efforts toward renewable energy adoption. GEE is an opportunity and a challenge within a path-dependent framework, whereas fossil fuel infrastructure tends to suppress efficiency and increase environmental costs.

Figure 3: *Carbon intensity of GDP (kg CO2e per 2021 PPP $ of GDP)*



Data Source: *World Bank, World Development Indicators (2024)*

Ongoing shift toward green growth necessitates a thorough evaluation and measurement of green economic efficiency. Thus, the objectives of this study are to evaluate and measure green economic efficiency for less developed countries. The rest of the paper is structured as follows. Section 2 elaborates the literature for the measurement of GEE. Section 3 provides methodology of measurement of GEE. Section 4 discusses results obtained from SBM and Section 5 provides the conclusion with appropriate policy recommendations.

2. Literature Review

Literature suggests variety of methods used for measurement of green economic efficiency. Li et al. (2013) and Bian et al. (2016) used Slack-based measure (SBM), Chen et al. (2017), Zhao et al. (2020) and Tan et al. (2023) employed super-SBM, and Chen et al. (2023b) measured green economic efficiency (GEE) with super-SBM with Global Meta frontier.

Wagn et al. (2016) and Liu et al. (2022) used non-radial direction distance function and Sun et al. (2024) and Zhao et a. (2018) developed two and three stage DEA, respectively.

Likewise, different studies have given different names to green economic efficiency. The most common are total-factor efficiency (P. Zhang et al., 2020), total-factor carbon emission efficiency (Q. Wang et al., 2016; Lv et al., 2021), total-factor energy efficiency (W. Zhao et al., 2018; Tang & He, 2021), eco-efficiency (Y. Chen et al., 2023a, 2023b), environmental efficiency (Q. Wang et al., 2022b; Twum et al., 2021), circular economy performance (S. Wang et al., 2021) and green economic efficiency (Y. Chen et al., 2023; P. Zhao et al., 2020, 2022; Zhuo & Deng, 2020; Liu et al., 2022; Q. Wang et al., 2022a; S. Wang et al., 2022c).

The basic difference among these measures of green economic efficiency originates from consideration of different types of undesired outputs but the measurement method is similar as the starting point is neoclassical economic growth theory with desired and undesired outputs. This study uses the term green economic efficiency as it is widely used across different studies.

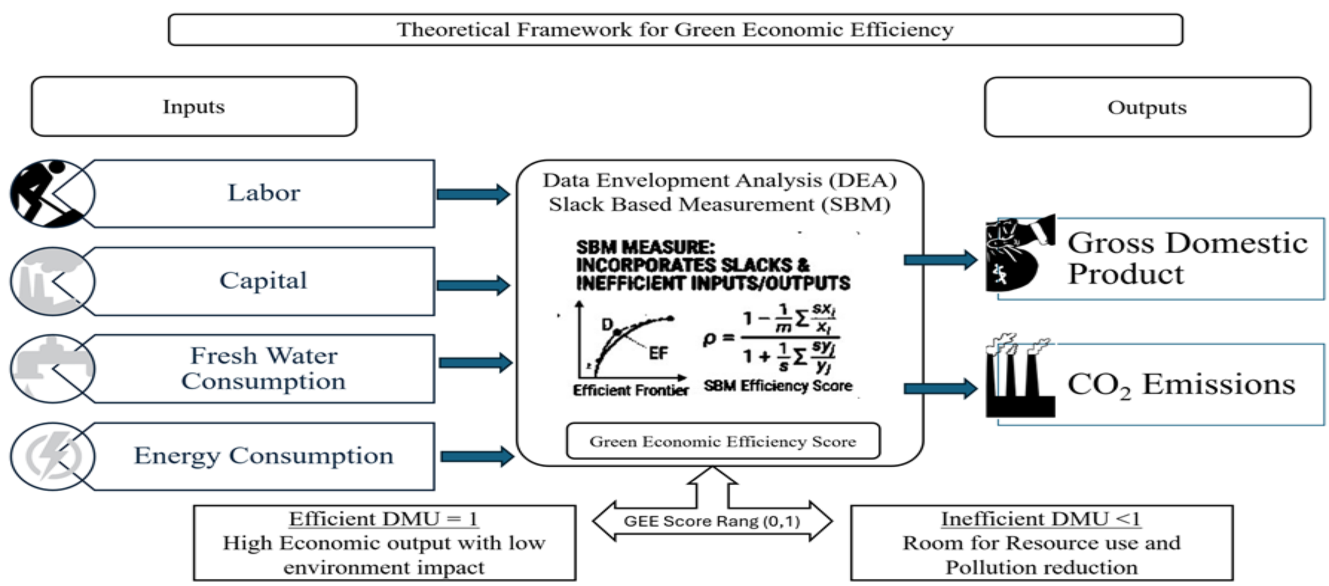
The assessment of green economic efficiency can be done through multiple options, such as single and multiple variables. As a single factor, energy intensity is utilized as a measuring rod to gauge the level of green economic efficiency. But this method does not consider environmental cost and the possibility of substitution between energy and other inputs. These drawbacks limit the applicability of single factors as a good measure of green economic efficiency. Multiple factors, such as SBM, can also be considered for the green economic efficiency. This method integrates both desirable and undesirable outputs, due to which it is preferred over other measures. Data Envelopment Analysis (DEA) (Farrell, 1957) and

Stochastic Frontier Analysis (Kumbhakar and Lovell, 2000) are common techniques for the measurement of GEE. The literature revealed that DEA has been widely used for the measurement of GEE. The DEA method accommodates country-specific structural challenges and the SBM-DEA is particularly important to consider desirable and undesirable outputs (Tone, 2001;2003). It has become an important tool to simultaneously maximize gross domestic product and minimize CO2 emissions.

While using slacks-based model (SBM), data envelopment analysis (DEA), Barberio Mariano et al. (2016) measured GEE for G7 and BRICS countries and found G7 more efficient than BRICS. Salman et al. (2022) measured environmental efficiency for 162 countries using a dataset from 1990 to 2020. Environmental efficiency showed declining trend for less developed countries but it improved for developed countries. Similarly, S. Wang et al. (2022c) measured green economic development for 40 resource rich countries of Asia, Africa and Latin America using non-radial distance function (NDF) from 1990 to 2012. Three stage DEA model has been used to measure GEE for 35 Belt and Road Initiative partner's countries (C. Zhao et al., 2018). Twum et al. (2021) also measured GEE for Asia-Pacific countries through super efficiency DEA model for the period of 1990 to 2018. Results indicated that East Asia has the highest level of GEE whereas South Asia has the lowest level of GEE. Q. Wang et al. (2022b) also employed DEA model to estimate green economic efficiency for developed and less developed countries to estimate the potential impact of protectionism policy on GEE. Ohene-Asare et al. (2020) also employed slack-based method to measure GEE for 46 African countries. However, Lv et al. (2021), P. Zhao et al. (2020), Liu et al. (2022), Tang and He (2021) and S. Wang et al. (2022c) measured GEE for China by using Shephard distance function, spatial Durbin model, DEA method, Luenberger-Hicks-Moorsteen (LHM) indicator and Epsilon-Based DEA method respectively.

Green economic efficiency is quantified through three elements, including inputs, desirable output and undesirable output. Figure 4 provides detailed framework of measurement of GEE. Following the work of Y. Chen et al. (2023), P. Zhao et al. (2020), (2022), Zhuo and Deng (2020), Liu et al. (2022), Q. Wang et al. (2022a) and S. Wang et al. (2022c), this study employs SBM for the measurement of green economic efficiency. DEA is a non-parametric linear programming approach to measure efficiency. It does not require a predefined functional form to calculate efficiency. Moreover, it considers multiple inputs and outputs at the same time. Slack-based measures of efficiency incorporate slacks of inputs and outputs into the objective function to calculate efficiency for decision making units (DMUs).

Figure 4: *Measurement Framework of Green Economic Efficiency*



Source: *Authors' own work*

To measure the green economic efficiency, the variables from input side are labor force, capital formation, energy consumption and water consumption. Whereas, from desirable output, real GDP is used and from the undesirable output side, CO2 is used to assess the green economic efficiency of LDCs (S. Wang et al., 2022c; C. Zhao et al., 2018; Twum et al., 2021; Barberio Mariano et al., 2016; Salman et al., 2022; Q. Wang et al., 2022b).

3. Research Methodology

This study has utilized a sample of 74 less developed countries whose annual per capita income is less than \$4466 dollars. 6 countries were dropped due to the non-availability of data. The study uses the SBM-DEA method for the measurement of GEE. DEA method was proposed by Charnes et al. (1978) neglecting slack variables. Though it is widely used in literature, it does not consider undesirable output. Tone (2001) introduced non-radial, non-angle slack based measurement model to incorporate unexpected output. SBM captures slacks for all inputs and output even for non-proportionally changing inputs and outputs. This measurement method is widely used for measurement of green economic efficiency, environmental efficiency, sustainability and energy efficiency.

Following Li et al. (2021), Zhao P. et al. (2020), Camioto et al. (2016), Twum et al. (2021), Ohene-Asare et al. (2020) and Zhuo & Deng (2020) this study uses SBM model to calculate green economic efficiency. Each country i here is considered as a single Decision-Making Unit (DMU). Suppose country i in period t uses m inputs then the input vector is given in equation (1)

$$X_{it} = [x_{1it}, x_{2it} \ldots\ldots, x_{mit}] \epsilon R_m^+ \quad (1)$$

To produce n desired output in period t in country *i*, the vector of desired output is in equation (2).

$$Y_{it}^d = [y_{1it}^d, y_{2it}^d \ldots\ldots, y_{nit}^d] \epsilon R_n^+ \quad (2)$$

g undesired output vector in period t, country *i* is given in equation (3),

$$Y_{it}^{ud} = [y_{1it}^{ud}, y_{2it}^{ud} \ldots\ldots, y_{git}^{ud}] \epsilon R_g^+ \quad (3)$$

If the weight of all the observed values of country *i* in period t is λit then equation (4) is production possibility set.

$$P_{it} = \left\{ \begin{matrix} X_{it} Y_{it}^d Y_{it}^{ud} \middle| x_{jit} \geq \sum_{i=1}^{p} \lambda_{it}\, x_{jit}, \forall j \\ y_{kit}^d \leq \sum_{i=1}^{p} \lambda_{it}\, y_{kit}^d, \forall k \\ y_{rit}^{ud} \leq \sum_{i=1}^{p} \lambda_{it}\, y_{rit}^{ud}, \ \forall r, \lambda_{it} \geq 0, \forall r \end{matrix} \right\}$$

(4)

In equation (4 $\sum_{i=1}^{p} \lambda_{it}$ is a nonnegative intensity vector, that indicates the constant returns to scale. If it is equal to 1 it would indicate variable returns to scale. Therefore, the SBM model for green economic efficiency in country *i* at period t would be as in equation (5).

$$GEE = min \frac{1 - \frac{1}{m}\sum_{j=1}^{m} \frac{s_{jt}^-}{x_{jt0}}}{1 + \frac{1}{n+g}\left[\sum_{k=1}^{n} \frac{s_{kt}^n}{y_{kt0}^n} + \sum_{r=1}^{g} \frac{s_{rt}^g}{y_{rt0}^g}\right]} \quad (5)$$

$$subject\ to \begin{cases} x_{jt0} = \sum_{i=1}^{p} \lambda_{it} x_{jit} + s_{jt}^- \\ y_{kt0}^n = \sum_{i=1}^{p} \lambda_{it} y_{kit}^n - s_{kt}^n \\ y_{rt0}^g = \sum_{i=1}^{p} \lambda_{it} y_{rit}^g + s_{rt}^g \\ s_{jt}^- > 0, s_{kt}^n > 0, s_{rt}^g > 0, \lambda_{it} > 0 \end{cases}$$

(6)

Here, s is slack variable of input and output, GEE is green economic efficiency of a country, and the value of GEE is between 0 and 1, where 1 indicates the highest green economic efficiency and 0 indicates lowest green economic efficiency. Similarly, in equation (5) sn is desirable output loss, s- is excess inputs and sg expresses undesirable output. The 0 subscript indicates the countries that are having their efficiency values estimated. If GEE = 1, then s- = sn = sg = 0, or any value of GEE < 1 it is inefficient hence input-output needs to be improved. Table 1 presents the input-output variables in super-SBM with definition.

After the adoption of the United Nations Framework Convention on Climate Change in 1992 the focus has increased towards climate related issues and the reporting mechanism. Thus, several time series variables related to environment and climate start from 1996. This study is based on panel data starting from 1996 to 2022 across 74 less developed countries. The study has retrieved the data from World development indicators (WDI).

Table 1: *Input-Output Variables for SBM Model*

Category	Variable	Definition
Input	Labor Force	Total labor force
	Capital	Gross Fixed Capital Formation in billions of dollars
	Energy Consumption	Fossil fuel energy consumption as a % of total energy consumption
	Water Consumption	Total freshwater withdrawals for agriculture domestics and industry in billion cubic meters
Desirable output	Real GDP	GDP adjusted with prices in billions of dollars
Undesirable output	CO_2	CO_2 emissions

Source: *Authors' own work*

4. Results and Discussion

This section is dedicated to present the results of the measurement of GEE. Table 2 displays descriptive summary statistics. The statistics indicate a substantial variation in GEE across different regions. Middle East and North Africa are the regions with the highest mean value of 0.57 followed by Latin America and the Caribbean with a mean value of 0.54.

Table 2: *Descriptive Statistics of Measurement of Green Economic Efficiency.*

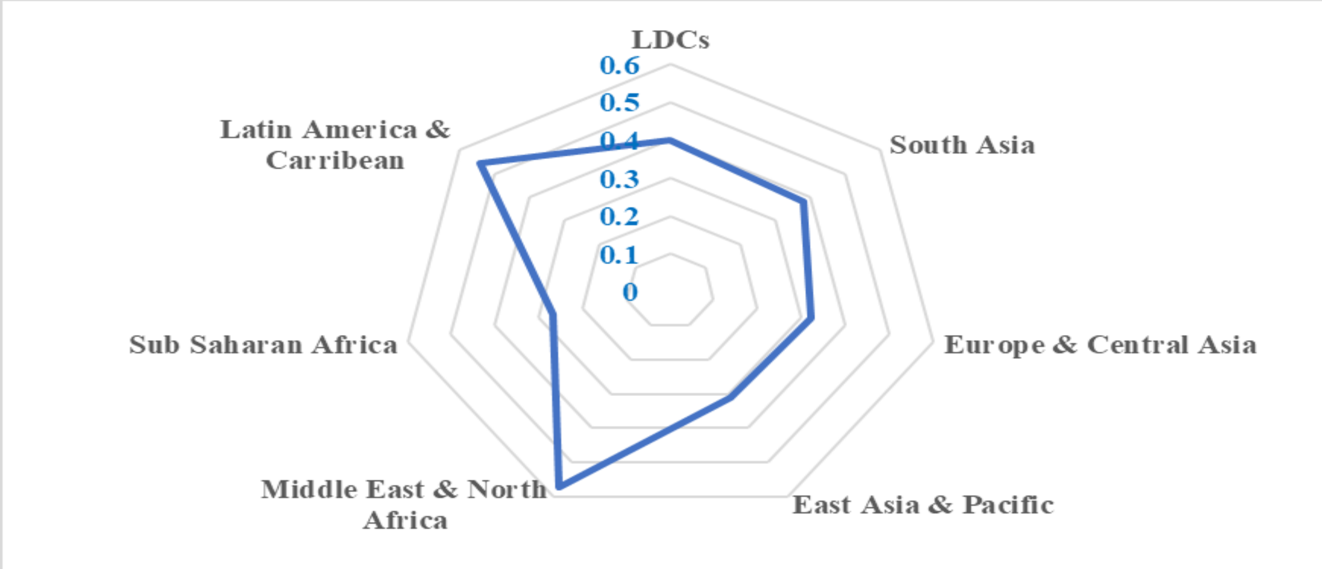
Region	Mean	Median	Min	Max	Std. Dev
South Asia	0.3809	0.2687	0.1715	0.7302	0.2062
Europe & Central Asia	0.3208	0.3244	0.2514	0.3845	0.0368
East Asia & Pacific	0.3092	0.2761	0.1638	0.5779	0.1256
Middle East & North Africa	0.5734	0.5700	0.3746	0.7358	0.1227
Sub-Saharan Africa	0.2681	0.2430	0.2070	0.3748	0.0546
Latin America & Caribbean	0.5413	0.5445	0.3758	0.6995	0.1076

Source: *Authors' own work.*

These two regions show relatively better efficiency with minimum environmental degradation. Sub-Saharan Africa has the lowest mean value of GEE (0.2681) while East Asia & Pacific shows a relatively better position than Sub-Saharan Africa, with a value of 0.3092. Sub-Saharan Africa is the poorest region among all, with greater structural problems, thus it rightly indicates the lowest value of GEE for this region. South Asia (0.3809) shows slightly better numbers than Europe & Central Asia (0.3208) and East Asia & Pacific (0.3092) but it is far behind Middle East and North Africa.

Overall, the averages of GEE for different regions suggest heterogeneity among LDCs. These differences mainly come from different economic structures, level of development, resource concentration and environmental priorities. For regional heterogeneity with respect to GEE is given in figure 5. Differences among regions with respect to GEE indicate differences in institutional quality, economic structure, energy and technology structures. Regions with greater implementation of green strategies are likely to achieve higher GEE.

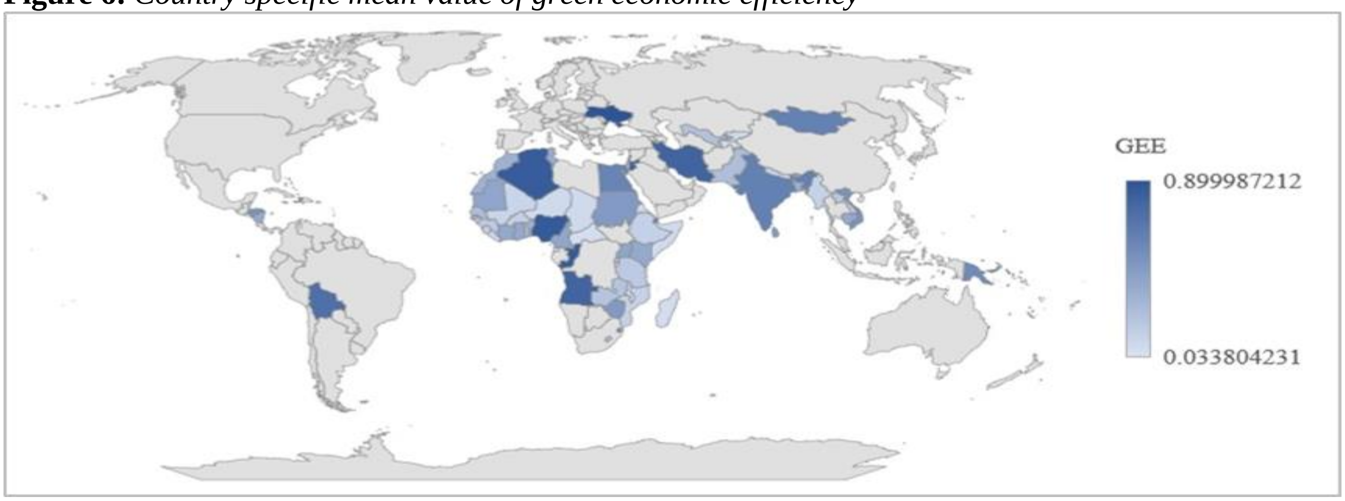
Figure 5: *Mean Value of GEE for Different Regions and Overall LDCs*



Source: *Authors' own work.*

Figure 6 illustrates the spatial distribution of average GEE for LDCs. Darker shades depict higher GEE while lighter shades indicate low levels of GEE. The spatial distribution of GEE indicates that the process of transition is uneven among LDCs. Iran (0.80), India (0.63), Mongolia (0.62), Bolivia (0.73), Ukraine (0.89), Angola (0.79), Nigeria (0.86) and Algeria (0.85) demonstrate relatively higher level of average GEE within 1996 to 2022. On the other hand, Sub-Saharan African countries demonstrate a very low level of average GEE as the lighter blue shade indicates in figure 6.

Figure 6: *Country specific mean value of green economic efficiency*

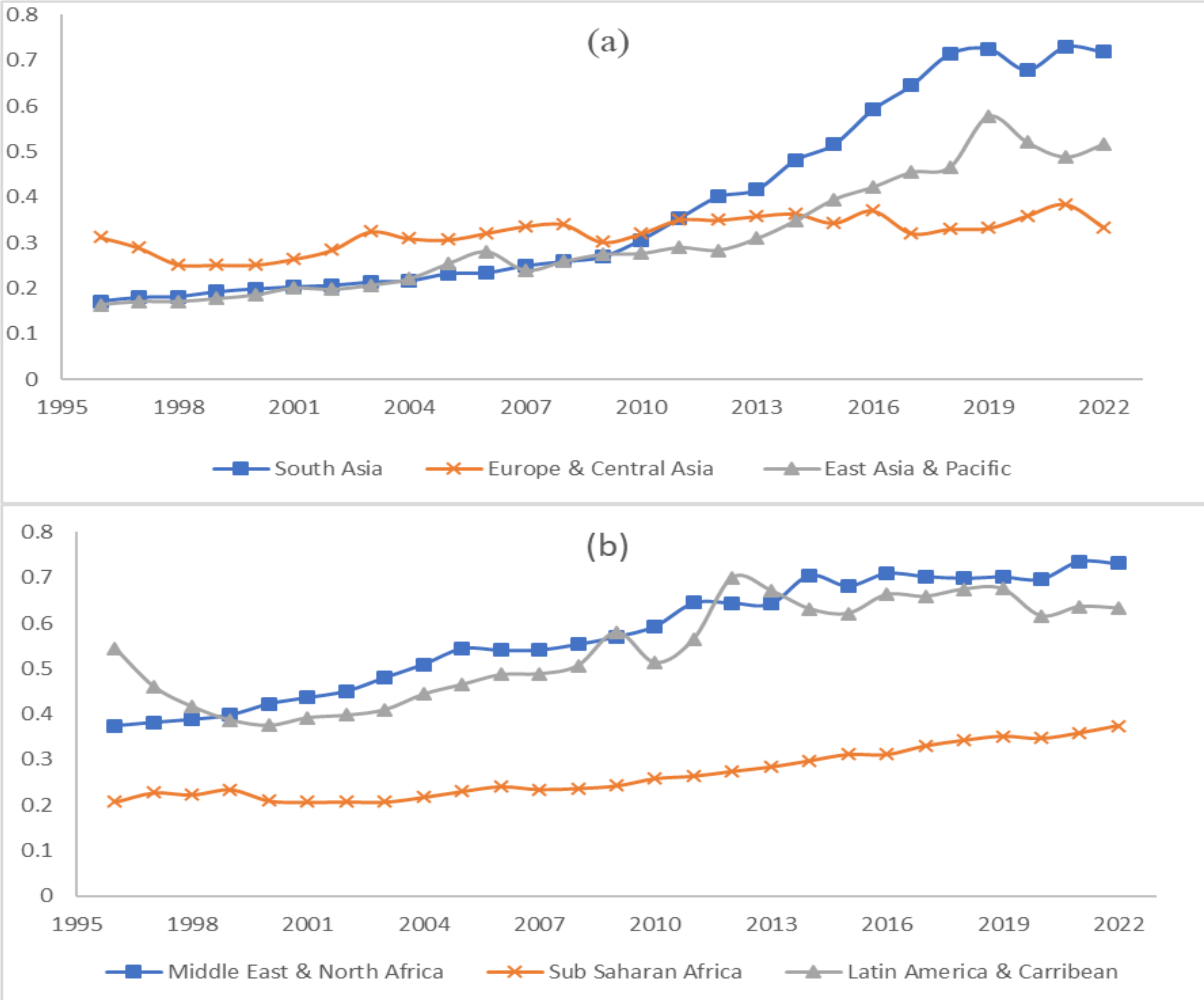


Source: *Authors' own work.*

These variations among average GEE for different countries represent the existence of variation in energy and technology infrastructure, good governance, and priorities towards green development.

Figure 7 illustrates the regional trends of all six regions in panel (a) and (b). All the regions of LDCs depict a positive trend over time with variation in growth. The trends of South Asia, East Asia & Pacific and Europe & Central Asia are given in part (a) of figure 7. In these three regions, the evolution of GEE is quite divergent over time. South Asia shows a steady rise from the late 1990s, but witnesses a sharp acceleration after year 2010, reaching the highest GEE in year 2022. This pattern indicates a delayed but sharp progress which can be a result of structural shift in the economy, adoption of efficient technologies, and scale effects in large economies of the region like India and Pakistan.

Figure 7: *Trends of Regional Green Economic Efficiency*



Source: *Authors' own work.*

In contrast, Europe & Central Asia remain relatively consistent and have a relatively consistent trend. The consistency of green economic efficiency in this region refers to the earlier maturation of economy, where minor fluctuations are evident instead of major ups and downs. These minor fluctuations are an indicator of improvement in efficiency rather than any radical change. East Asia & Pacific region also follow a smooth trend until 2010s, then a sharp increase is observed in GEE (See Figure 7, panel a). This trend suggests rapid efficiency gains.

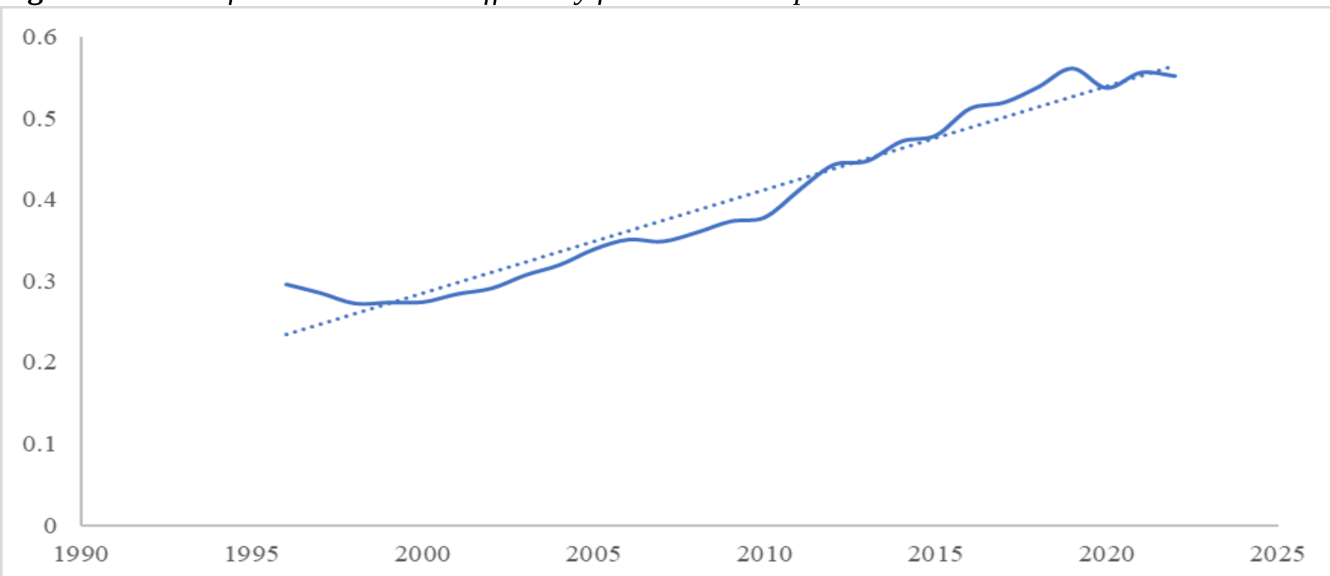
Panel (b) of figure 7 depicts the time trends for Latin America & Caribbean (LAC), Middle East & North Africa (MENA), and Sub-Saharan Africa. MENA and LAC start from a higher level relative to Sub-Saharan Africa. MENA shows a steady upward trend with minor fluctuations after 2010s. In spite of short-term oscillations, long-term consolidation explains a sustained increasing pattern.

Latin America and the Caribbean is the region with the highest volatility with respect to GEE. There are sharp upward trends followed by declines. Despite these ups and downs, Latin America and Caribbean maintain a high level of GEE. Sub-Saharan Africa has the lowest level of GEE over the entire period of study with a positive trend. This slight upward trend depicts the gradual transition towards cleaner and efficient production.

Figure 7 (panel an and b) reveal a non-linear and region-specific improvement in GEE. Distinct late fluctuations are an indication of transitional dynamics and adjustment processes.

Figure 8 presents the time trend for the overall sample of LDCs. There is a positive trend of GEE for LDCs over a given period of time. The positive GEE trend suggests a gradual progress shift toward low undesired output and high desired output. Despite facing developmental challenges and low level of industrial development, these regions are moving towards the adoption of cleaner energy and gradually improving resource efficiency. While interpreting the positive trend in GEE, a careful understanding is required because this trend does not indicate that sustainable development has been achieved by LDCs; rather, it indicates the efficient utilization of given resources with minimal environmental impact.

Figure 8: *Trend of Green Economic Efficiency for Less Developed Countries*



Source: *Authors' own work.*

5. Conclusion and Policy Recommendations

The findings conclude that the measurement of green economic efficiency revealed a positive trend over time with substantial regional heterogeneity among less developed countries. All the regions follow an increasing trend with variable speed. Especially the green economic efficiency numbers in South Asia and East Asia & Pacific regions take a sharp jump after 2010, but the Middle East & North Africa is consistent over the study period. Latin America & the Caribbean is the region with the maximum number of ups and downs in green economic efficiency levels. Europe & Central Asia are slow-moving with a moderate level of green economic efficiency. Sub-Saharan Africa is the only region that maintains the highest distance from the efficient frontier with consistency over time. These differences are structural in nature and indicate variation in the adoption of clean technologies and the movement towards DE carbonization. Further, it is concluded that GEE is a precondition for achieving sustainable growth for LDCs. These countries have just started the process of economic development and timely management of environmental degradation along with improvement in efficiency will lead to sustainable development.

Findings suggest that an integrated policy is required to improve green economic efficiency. Each stakeholder has to play the role for the improvement of GEE across LDCs. Therefore, governments of developing economies should focus on the renewable energy transition through dealing with carbon-emitting technologies in form of incentive-based regulations and subsidies on the provision of solar energy, sustainable houses and electric vehicles. Green tax incentives such as duty-free import of green technologies and green credit could help to meet sustainable development goals. It is also useful to support and encourage technological development and transformation to enhance productive and clean efficiency. International donors and policymakers should divert resources towards cleaner investments in these countries. Country and regional heterogeneity demand a specific policy for each region and country, given the structural nature of the issue. The successful and effective practices in some regions must be tailored and replicated in the other regions. Collaborative efforts are necessary to attain inclusive growth with minimum desirable output globally.

This study extended the literature by measuring GEE for LDCs and also provides several future research agendas. Identification of determinants of GEE is the first step. In this regard, institutional quality, renewable energy, financial development, and innovation can be incorporated. Additionally, the application of other efficiency measurement methods can be more insightful to understand GEE. Similarly, relative position of LDCs with respect to developed countries can provide rich insight into GEE.

Conflict of Interest

The authors showed no conflict of interest.

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