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Assessing sustainable development goals attainment through energy-environmental efficiency: The case of Latin American and Caribbean countries

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A R T I C L E I N F O

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A B S T R A C T

This study evaluates the attainment of sustainable development goals (SDGs) using energy-environmental efficiency as a principal driver. Hicks-Moorsteen Index, based on optimal targets, is utilized to estimate the performance of Latin America and the Caribbean (LAC) countries towards SDGs. Performance is decomposed into catch-up efficiency and technological progress. Results show that, compared to 2012, only 15% of the countries evaluated exhibit improved catch-up efficiency in 2020, while 74% of the countries evaluated showed technological progress in 2020 compared to 2012. Improvement in SDGs attainment in LAC results from technological advancement and not catch-up efficiency. Gross catch-up inefficiency appears to obstruct SDGs attainment. The regression elaborates the indirect extrinsic socio-economic dimension of the SDGs accomplishment. Specifically, the results of the fully modified ordinary least squares and generalized method of moments for the examined years support the desired prospects for green productivity among the cross-section of LAC. Moreover, in each of the upper years, the result suggests that environmental performance and renewable energy-induced economic progress are vital for the examined countries' sustainable green productivity. Notably, the result predicts a slow but progressive path toward achieving the SDGs, suggesting more intentional and inclusive effort by the respective economies.

Introduction

The sustainable development goals (SDGs), also known as global goals, were initiated at the United Nations (UN) Conference on Sustainable Development in Rio de Janeiro in 2012 [1]. All UN member states adopted it in 2015. The SDGs replace the Millennium Development Goals, which started a globally sustainable and global development effort in 2000. SDGs are bold but necessary steps towards prosperity for people and the planet. It consists of 17 goals urging swift actions into pressing issues ranging from inequality to economic growth while tackling climate change and preserving oceans and forests by 2030 [2]. The 2030 agenda ensures sustainability for all, and it focuses on managing the significant challenges faced globally. The 17 SDGs consist of 169 targets creating an integrated system that recognizes that action in one area affects others. Development must balance social, economic, and environmental dimensions of sustainability with impact across all societies and sectors. Countries have committed resources to fast-track efforts and progress towards its attainment.

The primary goal of this study is to develop an integrated model to analyze and track SDGs progress with energy and environment as key indicators. Given the integrated nature of SDGs, the improvement in one sector impacts others. To fast-track attainment of the SDGs, it is vital to identify how progress in key indicators influences the accomplishment of others. The study examines the interconnections between the SDGs, analyzes key indicators' performance, and draws practical policy recommendations for performance improvement. The objective is to highlight the relationship between energy-environmental efficiency and other socio-economic aspects of SDGs. The term energy-environmental efficiency refers to the ability of a system to utilize the appropriate amount of energy from the environment with a minimal adverse effect

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on the environment. The environment is the recipient of human activities toward development. The direct outputs of the energy-environmental relationship encompass the SDGs. To ensure a sustainable practice, the energy source and product of human development must be sustainable.

Energy is the principal driver of economic and social development and a significant link to improved quality of life. However, it is among the leading cause of CO_2 emission and thus environmental degradation [3]. The United States (US) energy information administration stated that Fossil fuel combustion for energy accounted for 74% of total US GHG emissions. According to the International Energy Agency (IEA), the power sector accounted for nearly two-thirds of global emissions growth, with over 40% of energy-related CO2 emissions from burning fossil fuels for electricity generation. A significant amount of global energy production and consumption are made in not sustainable ways. Climate change and environmental degradation are worldwide challenges with serious economic, social, and ecological consequences [4]. The integrated form of SDGs assesses its overall attainment level complex. However, energy is an essential requirement for attaining almost all SDGs for its role in poverty eradication, advancement in education and healthcare, industrialization, and water supply [5]. Energy efficiency, renewable energy, energy access, and other energy-related issues are imperative in facilitating relevant development processes.

The paper focuses on Latin America and the Caribbean (LAC) countries as a case study. LAC is a region in transition to provide a sustainable future with great potential to attain the SDGs. The renewable energy portfolio of the area and the society makes a great study to analyze the viability of SDGs attainment. In developed and developing countries, energy consumption is considered an indicator of economic progress and industrialization. However, the rising demand for nonrenewable energy is causing a negative impact [6]. There is an upsurge and promotion of economic growth in developing countries, causing them to consume more energy, predominantly nonrenewable energy with harmful environmental effects. The transition nature of LAC can validate the notion that clean energy-environmental efficiency co-exists with economic and social development. Given the interconnection between the SDGs and the principal role energy and environment plays in their attainment, it is imperative to analyze the energy-environmental performance of SDGs. If countries' energy-environmental performance with their direct impact are efficient, examining how much this affects the country's intrinsic socio-economic dynamic will provide informative improvement strategies. Therefore, this study aims to establish the interconnection between the SDGs, assess the complex interconnection through efficiency and productivity analysis, and provide practical policy recommendations to boost the achievement of the SDGs. The following questions will be answered in achieving this goal: *What are the connections (direct and indirect) between the critical primary resources and SDGs? What is the performance level of a transition region (LAC) with great potential to achieve SDGs? How are they changing, and at what level? What is the intrinsic socio-economic impact on efficiency level?* The study should contribute to overcoming the four vicious development traps limiting the capacity of LAC countries' development: the productivity trap, the social vulnerability trap, the institutional trap, and the environmental trap [7].

LAC covers a vast region from Bahamas and Mexico to Argentina and Chile, with a population of about 675 million people covering around 22 million square kilometers [8]. When discussing sustainable development in LAC, we must talk about the estimated 86million people that will be added to the population in 2030 that will inherit the consequences of human activities. According to SDG funds, disparities between LAC countries towards SDG progress will likely occur if current trajectories continue [9]. Compliance with policies and synergy across LAC is imperative for the entire region to achieve a universal SDG attainment. LAC has made strides in SDG progress. A sustainable production and consumption pattern is necessary for a successful transition for general development. Energy is crucial for any development process. It is a sector with ample potential to incorporate renewable energy alternatives and minimize the environmental impact of energy consumption. In addition, sustainable technologies across all industries also play a significant in energy conservation and energy efficiency.

In over two decades, electricity coverage in the region went from 50% to 90%. However, 22 million people still do not have access to electricity [10]. 80million people still depend on biomass fuels using firewood and charcoal for cooking, which has been associated with respiratory diseases predominant in women and girls due to the high time they spend close to the fire [11]. Other socio-economic aspects of SDGs, such as poverty, have reduced from 43% in 2002 to 30.6% in 2016. However, the World Bank highlighted that 39% of LAC practically remain vulnerable to relapse into poverty [11,12]. Therefore, sustainable, practical policies need to be implemented to prevent progressive deterioration. Assessing progress in SDGs requires a strategic and holistic approach. Energy and environment are integrated into all SDGs and play a central role in countries and regional ability to meet the SDGs [13].

As a developing region, LAC is committed to achieving the SDGs by focusing on integral critical factors in SDGs attainment. Energy-environmental SDG efficiency is defined as attaining economic growth and environmental performance with decent work, capital, and responsible energy production and consumption. The development must consider social, ecological, and economic factors to be sustainable. It is a developments strategy that meets the present generation's needs without compromising the ability of future generations to meet their own needs [13]. A precondition for poverty reduction and sustainable development is access to clean and modern energy [14]. Energy contributes to work productivity and a rise in income [15]. Small and medium-sized businesses regarded as the engine of economic growth will foster production with new opportunities to generate income, thus, reducing poverty [16]. The industrialization has been closely related to a significant increase in energy consumption, primarily fossil fuels established to have a devastating impact on the environment [17,18]. Developing, newly industrialized, and transition countries such as LAC trying to catch up in economic and social terms tend to exploit the conventional energy technologies, thus contributing to environmental degradation. Promoting renewable energy production and exploring energy-saving technologies will significantly enhance energy efficiency and environmental sustainability.

SDG7 outlines the 2030 energy targets, including universal access to affordable, reliable, and modern energy services, increasing renewable energy share in the global energy mix, improving energy efficiency, promoting investment, and expanding infrastructure technology to supply sustainable energy services [19]. The LAC region is a worldwide leader in renewable energy, with renewable energy accounting for about 28% of its total energy consumption, compared to the global average of 18% [20]. Many countries set ambitious goals for the energy sector following the SDG targets. Rigorous policies focusing on more thoughtful and sustainable electricity as a roadmap for achieving the SDGs are lacking in LAC.

A holistic SDG performance analysis is developed for indicators with a direct connection, supported by regression analysis in the second stage to establish a relationship for the indirect indicators, address LAC's possible development traps, and recommend a concrete improvement strategy. The mathematical models used originate from the Data Envelopment Analysis method (DEA) [21,22], which estimates the efficiency of systems generically called decision-making units (DMUs). The holistic goals of SGDs and the interconnection between the multiple inputs and outputs required for energy-environmental analysis make DEA the preferred method to evaluate efficiency due to its ability to adequately evaluate multiple inputs and outputs systems, analyze progress overtime, and propose progress over time evidence-based technical improvement strategies. The discriminatory power of the DEA model makes it easier to differentiate between underperforming countries. Improvement strategies could also be drawn from efficiency

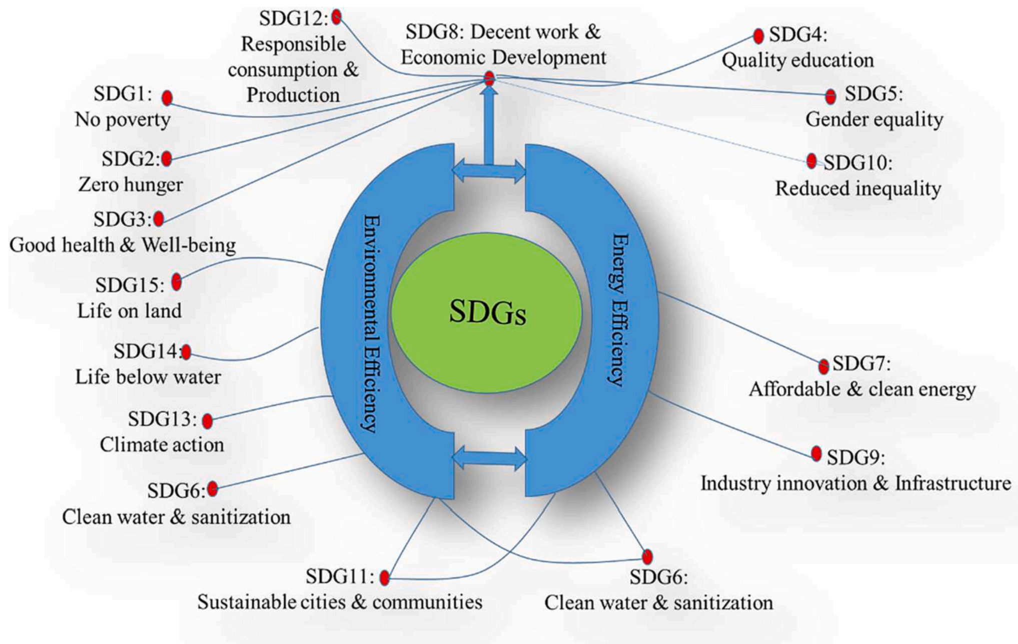

Fig. 1. Conceptual framework (Relational map).

score decomposition. DEA assumes a system uses a vector of ***X*** to produce a vector output ***Y***. It weighs the output factors against input factors to measure the closeness of every DMU to a fully efficient state. Using the linear programming technique, it weighs the inputs and outputs of each DMU against all other DMUs in the group and generates an efficiency index [23,24]. One can find applications of DEA in sustainability analysis, for instance, in Ibrahim and Alola [4], Lombardi et al. [24], Tsaples and Papathanasiou [25], Chachuli et al. [26], Chodakowska and Nazarko [27], to name a few.

The paper's organization is as follows. Section 2 discusses the conceptual framework with a Literature review. Section 3 presents the data and applied methodologies, while section 4 discusses the obtained results and outlines policy recommendations. Finally, Section 5 contains conclusive remarks for future research.

Literature review

The relationship between energy-environmental efficiency and SDGs is documented. Several studies present research linking energy efficiency to clean and affordable energy (SDG7) [28,29] and energy efficiency to economic development SDG8 [30]. Studies also show that economic development decreases poverty (SDG1), eliminates hunger (SDG2), improves gender equality (SDG5), reduces inequality (SDG10), and improves the overall quality of life [31]. Additionally, environmental efficiency is directly related to life below water (SDG14) [32], life on land (SDG15) [33], clean water and sanitation (SDG6) [34], and better climate action (SDG13) [35]. Fig. 1 illustrates a relational map of the study's conceptual framework, showing the relationship between energy-environmental efficiency with economic development and SDGs. The present study adopted the framework to track SDG attainment progress using energy-environmental efficiency as the principal driver.

Several studies have analyzed efficiency at the national and regional levels to track SDG attainment progress. The ability of EU countries to achieve their 2020 objective strategy was performed by [34]. The indicators utilized were electricity production from renewable energy sources, fossil fuel energy, alternative energy, unemployment, and Gross Domestic Product (GDP) per capita. Iftikhar et al. [36] focused on significant economies' energy and CO_2 emission efficiency to assess sustainability, using labor, capital, energy, GDP, and CO_2 as indicators. Grochová et al. [37] analyzed how the EU reaches its CO_2 emission targets using labor, capital, energy, GDP, and CO_2 as variables. Bekun et al. [38] illustrate that renewable energy consumption improves environmental quality. Further analysis indicates distortion of ecological sustainability as a result of nonrenewable energy consumption.

Analyzing the efficiency of SDGs achievement holistically is a complex task, and few studies have estimated the efficiency of individual SDGs at mostly the national level. Friess et al. [32] evaluated the efficiency of the Spanish clean water and sanitation sector. German watch, a non-governmental organization, tracks countries' progress toward climate change mitigation using emission levels, renewable energy development, and energy efficiency as indicators [39]. Van de Ven [40] analyzed multiple sustainable development goals in eastern Africa, focusing on household energy needs. Their study proposed an optimized portfolio of energy technology subsidies consistent with global green climate funds. Allen et al. [41] assessed SDGs' national progress and priorities for Australia using an expert-driven and consultative process. Their results show mixed performance on SDGs for Australia. The effect of economic activities on environmental sustainability was tested using the environmental Kuznets curve hypothesis. Energy intensity was used to show the actual outputs tradeoffs for ecological sustainability in the EU [42]. In the context of DEA, Zhao et al. [43] examine the efficiency of sustainable development systems by considering economic, environmental, and social dimensions. A comprehensive review of DEA and the concept of sustainability is available in the study of Tsaples and Papathanasiou [25].

There is indivisibility between energy-environmental efficiency and SDGs, and it is incomplete only to assess individual SDGs performance while there is ample evidence of interconnection. While the direct connection is quickly set, the indirect contact can also be outlined. To fill the gap in the literature, this study established an integrated system using the interconnections between the SDGs and employed a two-stage empirical analysis of efficiency and productivity with socio-economic relation to SDGs attainment. To ensure a robust analysis, the study follows the "indicator-indicated fact" relation [44] in selecting relevant and clear indicators. Informative policy conclusions with empirical evidence can, thus, be drawn to overcome the four vicious development traps (productivity, social vulnerability, institutional, and environmental traps) limiting the capacity of LAC countries to achieve sustainable development.

Material and methods

Data and sources

The data set used for the analysis is consistent with the EUROSTAT SDGs indicators set [45] and previous studies that have evaluated individual SDGs performance at some capacity [27,29].

Data used for the analysis resulted from two publicly available sources: Yale Center for Environmental Law and Policy [46] and World Bank [47]. The DEA inputs/outputs data description are as follows:

Input

- Labor (Total labor): labor is an essential component of sustainability and crucial for fighting poverty [48]. SDGs 1, 2, 8, and 12 can be directly linked to Labor. The labor force comprises people ages 15 or older who supply labor to produce goods and services during a specified period. It includes currently employed people and those unemployed but seeking work and first-time job-seekers. This input supports SDG5 and SDG10. Studies such as [49,50] used total labor as a critical input for assessing environmental and economic sustainability.
- Capital (Gross fixed capital formation): capital plays a significant role in development, especially for developing countries. For development to be realized, resources in various forms must be made available. Gross fixed capital formation used as input includes land improvements, plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. These are all infrastructural that improve economic development (SDG8). For instance, Abbas et al. [51] analyzed the role of fixed capital formation as a critical input in energy growth and environmental sustainability. Similarly, [52] utilized gross fixed capital formation for eco-efficiency analysis.
- Total final energy consumption (TFEC): This indicator is derived from energy balance statistics and is equivalent to total final consumption, excluding non-energy use. Since energy efficiency is a vital component of the analysis, the use of total energy consumption as an input in the system is pertinent. Several studies with energy efficiency as its theme have used it as a vital input indicator to assess efficiency and sustainability in DEA models [50,53].

Output

- Renewable electricity generation (GWh): Electric output of power plants using renewable resources, including wind, solar photovoltaic, solar thermal, hydro, marine, geothermal, solid biofuels, renewable municipal waste, liquid biofuels. As countries try to achieve a clean economy, renewable electricity generation is an essential component. It directly supports SDG7 and SDG11. Studies such as Bekun [54] and Baloch et al. [55] show strong evidence of the role of renewables in environmental and economic sustainability. It has been used as an output representation for clean energy implementation [53].
- Gross Domestic Product (GDP): GDP is an important economic indicator to measure the country's economic development. It is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Some studies have used it as the economic dimension of their analysis [52,56]. There is strong evidence of dynamic interconnection between financial development, energy innovation, and environmental quality [55]. Therefore, to account for the linkage of the interconnection and represent financial development, GDP is used in this study.
- Environmental Performance Index (EPI) is a composite indicator that encompasses clean water and sanitation (SDG6), climate action (SDG13), life below water (SDG14), life on land (SDG15) with twenty-five indicators on the two objectives above and six policy categories: climate change, productive natural resources, biodiversity and habitat, water, air pollution, and environmental health. The indicators are linked to a long-term public health or ecosystem sustainability target. EPI is a data-driven summary of the state of sustainability of a country. EPI is developed using 32 performance indicators across eleven issue categories under two major issues-Environmental health and ecosystem vitality. The EPI offers a powerful policy tool to support efforts to meet the targets of the UN SDGs and move society toward a sustainable future. The EPI score indicates which country best addresses every nation's environmental challenge while conducting its economic and infrastructural developments. This indicator helps understand environmental progress and refine policy recommendations [46]. Studies such as [57,58] have comprehensively used EPI to represent the ecological dimension of sustainability. Furthermore, environmental sustainability is a major factor in attaining economic sustainability and better living conditions [54].

Computing the Malmquist Index using log-convex frontiers

This subsection describes the Hicks-Moorsteen Index (HMI) computation based on optimal targets rather than radial distance functions. Such index results from the advances made by Ferreira and Marques [59], after Portela and Thanassoulis [60] have introduced the concept of Geometric Distance Function (GDF), which relates those optimal targets to the observed values. The GDF may account for all inefficiency sources provided that targets result from combining the sample's observations. Furthermore, the advantage of utilizing HMI, which is rooted from data envelopment analysis, supports the SDGs model's structure to attain all goals simultaneously. DEA evaluated the efficiency of systems with multiple inputs and outputs. The model considers any factor used to characterize the production using an optimization framework. DEA optimizes the efficiency score via linear programming, assigning the best possible weighting scheme to each entity under evaluation.

Let a system j, generically called DMU, use a set of m inputs, $x^j = \left(x_1^j, \cdots, x_i^j, \cdots, x_m^j\right)$ to produce s distinct outputs, $y^j = \left(y_1^j, \cdots, y_r^j, \cdots, y_s^j\right)$. We assume that all entries of these two arrays are positive. Overall, n DMUs are composing the system and the Production Possibility Set (PPS):

$$PPS = \left\{(x,y) \in \mathbb{R}_+^{m+s} : x \text{can produce} y\right\}. \tag{1}$$

There is a frontier associated with this PPS, and it contains the most efficient DMUs. Inefficient DMUs fall apart from that frontier, and their inefficiency level is directly related to the distance to the boundary. This frontier can establish a set of optimal targets for both inputs and outputs, denoted by $\widehat{x}^j = \left(\widehat{x}_1^j, \cdots, \widehat{x}_i^j, \cdots, \widehat{x}_m^j\right)$ and $\widehat{y}^j = \left(\widehat{y}_1^j, \cdots, \widehat{y}_r^j, \cdots, \widehat{y}_s^j\right)$. We impose that, for being efficient, the DMU j must obey the condition $\widehat{x}^j \equiv x^j$ and $\widehat{y}^j \equiv y^j$. Indeed, back to the definition of GDF for DMU j, we have:

$$GDF(j) = \left(\prod_{i=1}^{m} \frac{\widehat{x}_i^j}{x_i^j}\right)^{\frac{1}{m}} \Bigg/ \left(\prod_{r=1}^{s} \frac{\widehat{y}_r^j}{y_r^j}\right)^{\frac{1}{s}}. \tag{2}$$

Therefore, if the condition $\widehat{x}^j \equiv x^j$ and $\widehat{y}^j \equiv y^j$ holds, $GDF(j) = 1$, and the DMU j is efficient regarding the frontier. Otherwise, it is inefficient and must verify $GDF(j) < 1$. It is straightforward to conclude that $\widehat{x}_i^j \leq x_i^j$ for any $i = 1,\ldots,m$, and $\widehat{y}_r^j \geq y_r^j$ for any $r = 1,\ldots,s$. These two relationships imply that, for being inefficient, it is sufficient that $\widehat{x}_i^j < x_i^j$ or $\widehat{y}_r^j > y_r^j$ for some inputs or outputs. The larger the value of GDF, the higher the technical efficiency regarding the PPS; i.e., if $GDF(j) > GDF(k)$, the DMU k is less efficient than the DMU j concerning the frontier associated with the PPS.

It is now clear that the computation of efficiency scores, including the GDF, presupposes estimating appropriate values for the targets. After some decision-making processes, we can impose these targets directly, which may be objectionable, given the subjective nature underlying these processes. Instead, we impose that these targets are data-driven, resulting from the combination of the benchmarks' observations:

$$\widehat{x}_i^j = \langle \lambda^j | x_i \rangle, i = 1, \cdots, m, \tag{3}$$

and

$$\widehat{y}_r^j = \langle \lambda^j | y_r \rangle, r = 1, \cdots, s, \tag{4}$$

where $\langle a|b \rangle$ represents a weighted power mean of vector b of some order, q, i.e., $\langle a|b \rangle = \left(\sum_p a_p b_p^q\right)^{\frac{1}{q}}$ with $\sum_p a_p = 1$. If $q \rightarrow 0$, we reach the so-called geometric mean, such that $\langle a|b \rangle = \prod_{p=1}^n b_p^{a_p}$. It is easier to handle with sums instead of products, thus $\log\langle a|b \rangle = \log\prod_{p=1}^n b_p^{a_p} = \sum_{p=1}^n a_p \log b_p$. Bearing this in mind, Equations (3) and (4) become, respectively:

$$\widehat{x}_i^j = \exp\sum_{p=1}^n \lambda_p^j \log x_i^p, i = 1, \cdots, m, \tag{5}$$

and

$$\widehat{y}_r^j = \exp\sum_{p=1}^n \lambda_p^j \log y_r^p, r = 1, \cdots, s. \tag{6}$$

Based on these equations, targets result from the contribution of all n observations (DMUs) being part of the PPS. However, it is safe to assume that inefficient DMUs should not contribute to these targets. We do not know *a priori* which are the (in)efficient DMUs, but we must ensure that coefficients λ^j must be zero for any inefficient DMU p. The following linear program model takes that into account [61]. If ε is a non-Archimedean quantity, we have:

$$\max \beta^j + \varepsilon\sum_{i=1}^m s_i^{j-} + \varepsilon\sum_{r=1}^s s_r^{j+} \mathit{subjectto}: \sum_p \lambda_p^j \log x_i^p + d_i^j\beta^j + s_i^{j-} = \log x_i^j; i = 1, \cdots, m, \sum_p \lambda_p^j \log y_r^p - d_r^j\beta^j - s_r^{j+} = \log y_r^j; r = 1, \cdots, s, \lambda_p^j \geq 0, p = 1, \cdots, n, s_i^{j-}, s_r^{j+} \geq 0; i = 1, \cdots, m; r = 1, \cdots, s. \tag{7}$$

In Equation (7), β^j is the distance of DMU j to the frontier following the path defined by a directional vector $d^j = (d_i^j, d_r^j)$, which is typically equal to the observation: $d_i^j = \log x_i^j, d_r^j = \log y_r^j$ [58]. A zero-distance means that the DMU is technically efficient regarding the frontier of its PPS [57]. This model is directional, meaning that the contraction/expansion of variables is radial, but it also allows for non-radial inefficiency sources: the slacks, s_i^{j-} and s_r^{j+}. If existent, these inefficiency sources must be accounted for [62]. Besides, dealing simultaneously with radial and non-radial inefficiencies is something that the GDF can easily handle, as Equation (2) defines. Indeed, we can determine the targets that are used in the GDF by joining Equations (5–7):

$$\begin{cases} \widehat{x}_i^j = \exp\left(-d_i^j\beta^j - s_i^{j-} + \log x_i^j\right), i = 1, \cdots, m, \\ \widehat{y}_r^j = \exp\left(d_r^j\beta^j + s_r^{j+} + \log y_r^j\right), r = 1, \cdots, s. \end{cases} \tag{8}$$

In many cases, as happens with our case study, the n DMUs are observed in several moments, t, t + 1, t + 2, … It implies the existence of different PPS and, accordingly, distinct frontiers, one for each PPS and each moment [59]. The gap between the boundaries of two consecutive moments determines the productivity change, PC. It depends on the benchmarks' capacity in one moment consuming fewer resources or producing more outputs than the benchmarks in the previous moment. In that case, the productivity change is positive (PC > 1), and the technology watched the progress. In opposition, the difference is negative (PC < 1), and the technology declined.

Another interesting aspect of performance evolution is efficiency change. Unlike the productivity change that compares two frontiers, thus being a dynamic measure of performance, efficiency regards a single frontier, being a static measure of performance. This way, the efficiency change, EC, of a DMU is simply the ratio of two efficiency scores obtained concerning two distinct frontiers. Therefore, if EC > 1, there was an improvement in technical efficiency of resource use and output production, whereas EC < 1 means an efficiency decay between two moments, and DMUs become less efficient on resource usage/outputs production. Other components of performance evolution may also exist, e.g., the returns to scale change. However, this change is naturally unitary if the PPS exhibits constant returns to scale.

The HMI is broadly used in performance evolution assessment [63–65] as a true total factor productivity (TFP) index in the case of variable returns to scale. If that condition is satisfied, the HMI can be decomposed into the two components, EC and PC, detailed above [59]. Let us consider two moments, t and t + 1, for which there are two distinct PPSs (and frontiers):

$$PPS^t = \left\{(x_t, y_t) \in \mathbb{R}_+^{m+s} : x_t \text{ can produce } y_t \text{ at time } t\right\}, PPS^{t+1} = \left\{(x_{t+1}, y_{t+1}) \in \mathbb{R}_+^{m+s} : x_{t+1} \text{ can produce } y_{t+1} \text{ at time } t+1\right\}. \tag{9}$$

Since there are two frontiers for those two moments, then there are two pairs of targets per observation in each instant: $(\widehat{x}_t^{j,\tau}, \widehat{y}_t^{j,\tau})$ is the pair of DMU targets observed in the moment t concerning the frontier of τ (τ = t, t + 1).

The efficiency change associated with the DMU j and instants t and t + 1 is EC(j,t,t + 1):

$$EC(j,t,t+1) = GDF_{t+1}(j)/GDF_t(j), \tag{10}$$

where GDFτ (j) is the technical efficiency of DMU j observed at the moment τ concerning the frontier of τ (τ = t, t + 1). If $GDF_{t+1}(j) > GDF_t(j)$, we have $EC(j,t,t+1) > 1$ and the DMU j improved its technical efficiency from t to t + 1.

As explained before, the PC component of the HMI represents the gap between the two frontiers. Such a gap results from technological progress/decline, which, in turn, can be due to more/less inefficient resource use or output production. Therefore, the productivity change associated with DMU j and instants t and t + 1 is PC(j,t,t + 1) and can be multiplicatively decomposed into two terms:

$$PC(j,t,t+1) = \Delta X(j,t,t+1) \cdot \Delta Y(j,t,t+1), \tag{11}$$

where:

$$\Delta X(j,t,t+1) = \left(\prod_{i=1}^m \frac{\widehat{x}_{i,t}^{j,t} \cdot \widehat{x}_{i,t+1}^{j,t}}{\widehat{x}_{i,t}^{j,t+1} \cdot \widehat{x}_{i,t+1}^{j,t+1}}\right)^{\frac{1}{2m}} \tag{12}$$

and

$$\Delta Y(j,t,t+1) = \left(\prod_{r=1}^s \frac{\widehat{y}_{r,t}^{j,t+1} \cdot \widehat{y}_{r,t+1}^{j,t+1}}{\widehat{y}_{r,t}^{j,t} \cdot \widehat{y}_{r,t+1}^{j,t}}\right)^{\frac{1}{2m}} \tag{13}$$

If $\Delta X(j,t,t+1) > 1$, the benchmarks in the region of DMU j improved their input consumption. Likewise, $\Delta Y(j,t,t+1) > 1$ implies enhancing output production by the benchmarks located in the same PPS region of DMU j. Therefore, $PC(j,t,t+1) > 1$ results from improvements in input consumption or output production by the benchmarks that define the frontiers.

Table 1
Descriptive statistics of efficiency indicators.

Year		Total labor (thousand persons)	Gross fixed capital (million US$)	Energy Consumption (TJ)	Renewable electricity generation (GWh)	GDP (million US $)	EPI
2012	Average	12703.77	52608.84	403.74	34905.95	244962.05	55.06
	Std. Dev.	22638.54	115145.25	810.25	98170.64	544080.47	5.76
	Min	140.79	210.48	2.59	110.90	1437.55	41.15
	Max	97597.80	488354.57	3246.74	456159.51	2340783.92	69.03
2014	Average	13023.93	53912.08	418.40	34515.12	255953.98	50.84
	Std. Dev.	23161.74	116194.60	845.37	93080.76	563302.17	9.67
	Min	151.51	276.70	2.85	90.00	1509.21	19.01
	Max	99932.83	494982.17	3444.85	432744.58	2423271.87	69.93
2016	Average	13460.98	48704.10	422.82	36960.98	255270.53	72.32
	Std. Dev.	23796.04	95707.18	823.02	100183.82	538281.20	8.05
	Min	164.05	369.65	3.09	64.20	1553.53	43.28
	Max	102508.95	374282.28	3310.70	465909.11	2260778.79	80.03
2018	Average	13983.14	49805.43	432.46	40525.03	264475.17	57.99
	Std. Dev.	24514.15	96393.56	833.25	106471.74	554007.99	7.17
	Min	173.52	326.84	3.05	98.25	1615.49	33.74
	Max	105542.23	378962.95	3370.65	495945.37	2320859.40	67.85
2020	Average	14380421.57	49084744.71	445.73	42212.98	228990738.3	45.83
	Std. Dev.	25010345.34	93662279.57	846.14	109099.74	434,246,632	7.21
	Min	183.77	345.08	3.25	44.67	1577.96	27.00
	Max	107371.78	362234.77	3440.01	508265.50	1749104.72	55.30

Regression analysis

Considering that this study is geared toward the aspects of SDGs' prospects for the LAC countries, in this part, the potential determinants of sustainable production are illustrated. To provide additional robustness to the investigation, a regression estimation, we employ the cross-sectional dataset for the three specific years: 2014, 2016, 2018, and 2020. These years are the upper bounds for the ranges 2012–2014, 2014–2016, 2016–2018, and 2018–2020, which were employed for the input–output analysis as described in the other sections.

In the extant studies, and to measure the determinants of green total factor productivity (GTFFP), the global Malmquist–Luenberger (GML) productivity index has been employed. In this case, we use the HMI to proxy for sustainable productivity vis-à-vis the pathway to SDGs (hereafter SP). The current study examines the role of environmental performance (by using the EPI) in green productivity. Additionally, while considering the potential role of economic expansion, the current study employs the interaction of GDP and renewable energy consumption (named 'clean growth'). Thus, the used econometric model takes the form:

$$SP_{it} = \lambda 0 + \lambda 1 \log Clean\ growth_{it} + \lambda 2\ EPI_{it} + \varepsilon it \quad (14)$$

Considering the stationarity and cointegration evidence, the regression approaches of the fully modified ordinary least squares (FMOLS)

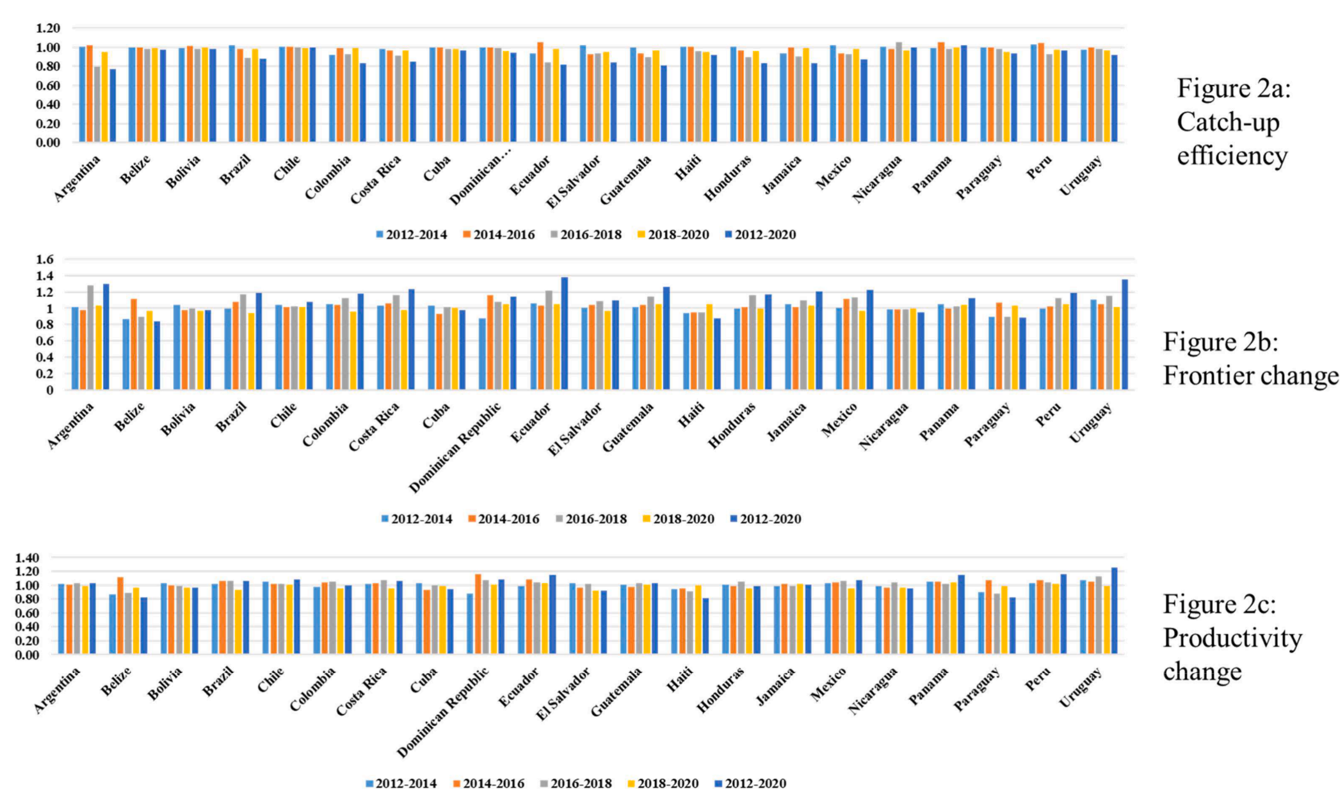

Fig. 2. Productivity index decomposition.

estimator and the generalized method of moments (GMM) are considered for their respective advantages. On the one hand, the FMOLS uses fewer assumptions, making it more robust than a similar estimator like the dynamic ordinary least squares (DOLS). It also uses semi-parametric correction for endogeneity and allows for high heterogeneity while producing long-run asymptotically unbiased estimates. On the other hand, the GMM allows country-specific effects. A more efficient estimation is realized with this procedure because it eliminates heterogeneity while employing appropriate variables as instruments to reduce the problems of omitted variables, endogeneity, and measurement errors. Considering space constraint, the step-to-step procedures of the two approaches are not covered in this study, but the information is openly available from the respective literature; see Kao and Chiang [66] and Pedroni [67] (for FMOLS) and see Baum et al. [68], Arellano and Bond [69], Arellano and Bover [70], Blundell and Bond [71] for GMM.

Results and discussions

This section presents the progress of the country's attainment of SDGs in energy-environmental efficiency as principal drivers of SDGs. This evaluation is based on the conceptual framework that energy and environmental efficiency drive the entire SDGs' progress (see Fig. 1). Based on data availability, data for 21 LAC countries were assessed for 2012, 2014, 2016, 2018, and 2020. Detailed descriptive statistics of the data and units are presented in Table 1. There has been steady growth in labor and capital in both the maximum and minimum ranges. There was a slight decrease in maximum energy consumption in 2016 and 2018 compared to 2014. However, 2020 has a slight increase in average and maximum energy consumption. Results show continuous growth in full renewable electricity generation. 2016 had the highest average renewable electricity generation and EPI. The models presented in section 3.2 estimate the relative performance of LAC countries towards SDG at different times. An index greater than one indicates an improvement in SDG performance, while less than one infers regression in performance. The index is further decomposed into efficiency change (catch-up) or productivity change.

Change in catch-up efficiency or technical efficiency is defined as disseminating best practices in activity management, resource planning, operational efficiency, and sustainability management. It could be attributed to resource utilization of the said system. This represents the diffusion of improved practices toward achieving the objectives. Fig. 2a shows the trend of catch-up efficiency of LAC countries over the evaluated period. 57% of assessed countries regressed in catch-up efficiency in 2014 and 2016. An additional 38% of the countries regressed in 2016 compared to 2014. Chile, Nicaragua, Panama, and Peru appear to have improved Catch-up efficiency in 2018 compared to 2014. Hence, only 14% of the countries evaluated showed improvement in 2018. A similar observation is made for 2020; LAC showed a decline in catch-up efficiency compared to 2020. It means that LAC countries do not focus on technical efficiency in SDGs attainment. Therefore, LAC countries need to improve operational and management requirements such as grassroots initiatives to enlighten and educate the population on individual contributions toward SDGs achievement. Furthermore, the relatively low catch-up efficiency in 2020 compared to 2012 shows that LAC countries have a lot to improve on to attain the SDGs. There needs to be a significant advancement in the system's structure to improve catch-up efficiency.

Fig. 2b shows the frontier change trend. 62% of countries evaluated showed technological progress in 2014 compared to 2012, and it improved to 71% and 76% of the countries in 2016 and 2018, respectively. However, 2020 showed a dip in frontier change, with only 57% of countries evaluated showing improvement. Overall, 71% of the assessed countries showed technological progress in 2020 compared to 2014. This infers that best practices in 2018 are more efficient than the best practices found in 2014. Belize, Bolivia, Cuba, Haiti, Nicaragua, and Paraguay are among the countries that showed an absence of technological advancement. The positive technological change can be attributed to global technological progress. It appears to have a significant impact on the overall productivity, evidenced by the gross catch-up inefficiency but positive productivity.

The overall productivity of LAC countries showed consistent improvement. However, it is imperative to note that the productivity improvement observed among LAC countries results from technological progress and not operational or technical efficiency. Fig. 2c illustrates the productivity trend. 57% of the countries evaluated showed improvement in 2020 compared to 2012. Bolivia, Cuba, Haiti, Nicaragua, and Paraguay had persistent catch-up inefficiency, which regressed their overall productivity.

Compared to the Central American and South countries evaluated, the Caribbean countries exhibit inefficient performance in all productivity decompositions. It can be attributed to the fiscal challenges facing many Caribbean countries. The commitment of international communities to support the SDGs needs to be reinforced with a particular focus on islands and landlocked developing countries. The Caribbean countries are most vulnerable to climate impact, consequently reducing the fiscal latitude needed for attaining sustainable development in such regions. Therefore, innovative financing is required to support the area. The productivity decomposition shows technological improvement as the reason for productivity improvement in SDG attainment. Hence, finance should be focused on integrating technological advancement in SDGs. Improving catch-up efficiency does not necessarily require significant finance compared to technological improvements. The focus should be directed towards strategical organizing stakeholders, operational management, and grassroots initiatives to improve catch-up

Table 2
Regression estimates (FMOLS and GMM).

2014				
	FMOLS		GMM	
	Clean-Growth	EPI	Clean-Growth	EPI
Coefficient	0.004	0.002**	0.019*	0.007**
(*p-value*)	0.286	0.021	0.001	0.028
BG SC LM Test (χ^2, p-value): (1.817, 0.130)				
Heteroskedasticity (ARC) Test (χ^2, p-value): (0.544, 0.606)				
2016				
	FMOLS		GMM	
	Clean-Growth	EPI	Clean-Growth	EPI
Coefficient	0.026*	0.003	0.024*	0.004
(*p-value*)	0.000	0.221	0.000	0.108
BG SC LM Test (χ^2, p-value): (0.355, 0.640)				
Heteroskedasticity (ARC) Test (χ^2, p-value): (0.269, 0.737)				
2018				
	FMOLS		GMM	
	Clean-Growth	EPI	Clean-Growth	EPI
Coefficient	0.018*	0.004**	0.015*	0.009*
(*p-value*)	0.004	0.030	0.002	0.002
BG SC LM Test (χ^2, p-value): (0.742, 0.492)				
Heteroskedasticity (ARC) Test (χ^2, p-value): (0.797, 0.357)				
2020				
	FMOLS		GMM	
	Clean-Growth	EPI	Clean-Growth	EPI
Coefficient	0.016*	0.003**	0.014*	0.005*
(*p-value*)	0.004	0.030	0.002	0.002
BG SC LM Test (χ^2, p-value): (0.652, 0.352)				
Heteroskedasticity (ARC) Test (χ^2, p-value): (0.565, 0.332)				

Note: Fully Modified Least Squares (FMOLS), Heteroskedasticity Test: Breusch-Pagan-Godfrey, Breusch-Godfrey Serial Correlation LM Test, and Generalized Method of Moments (GMM). The estimation is with Long-run covariance estimate/ HAC (Bartlett kernel, Newey-West fixed bandwidth = 3.0000).

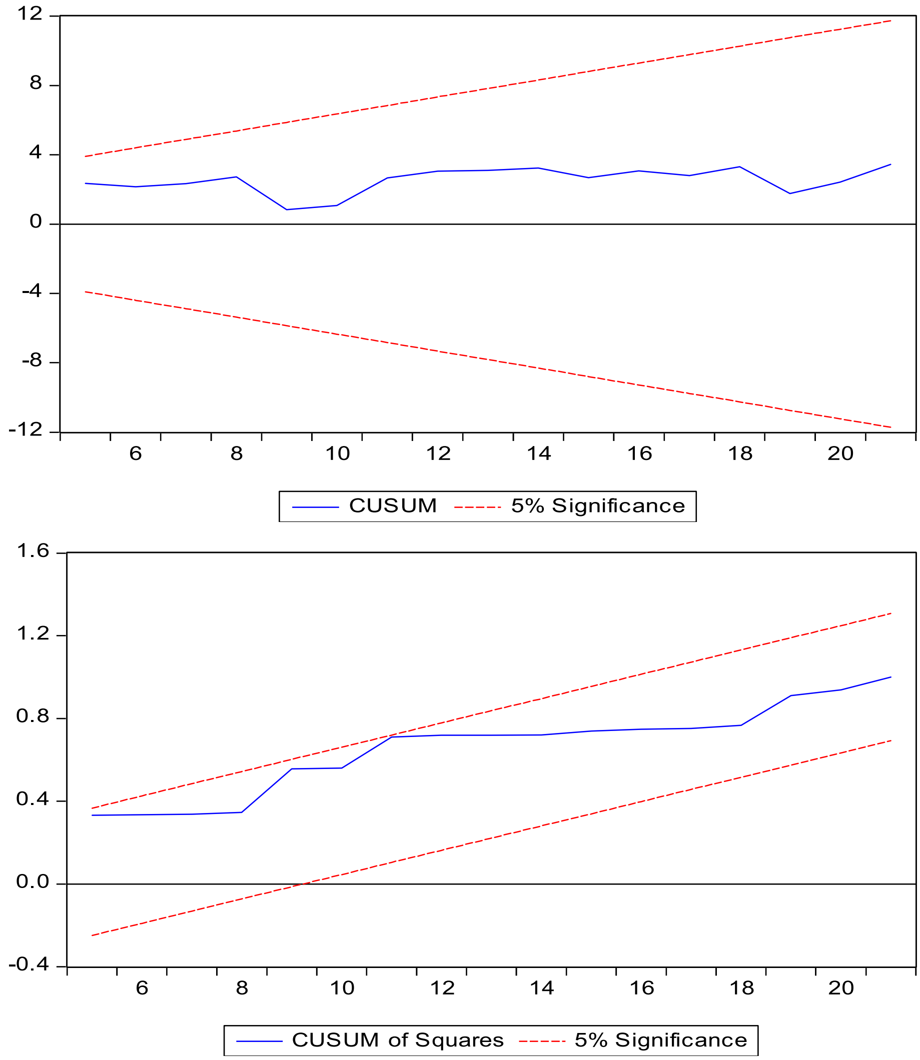

Fig. 3. 6: Stability test 3a: Stability for 2014 model (CUSUM) 3b: Stability for 2014 model (CUSUM^2).

efficiency and educate citizens on the needs and requirements of SDGs.

LAC's challenges present an unprecedented opportunity to transcend into the SDGs 2030 agenda and beyond. This study shows the premise and proves that energy and environmental efficiency are the nuclei of attaining SDG targets. They could transition directly into clean industrialization and environmentally conscious practices. Innovation in energy and ecological sustainability creates a strong foundation for improving other SDGs. Access to electricity, reliance on clean fuels and technology, renewable energy consumption, and investment in energy-efficient technology are direct measures that will enhance energy efficiency.

Above all, energy and environmental resources should be managed effectively. LAC should enhance performance by improving operational practices since productivity improvement is a result of technological improvement and not operational or catch-up efficiency; LAC must emerge from inefficient operational practices. Catch-up efficiency is

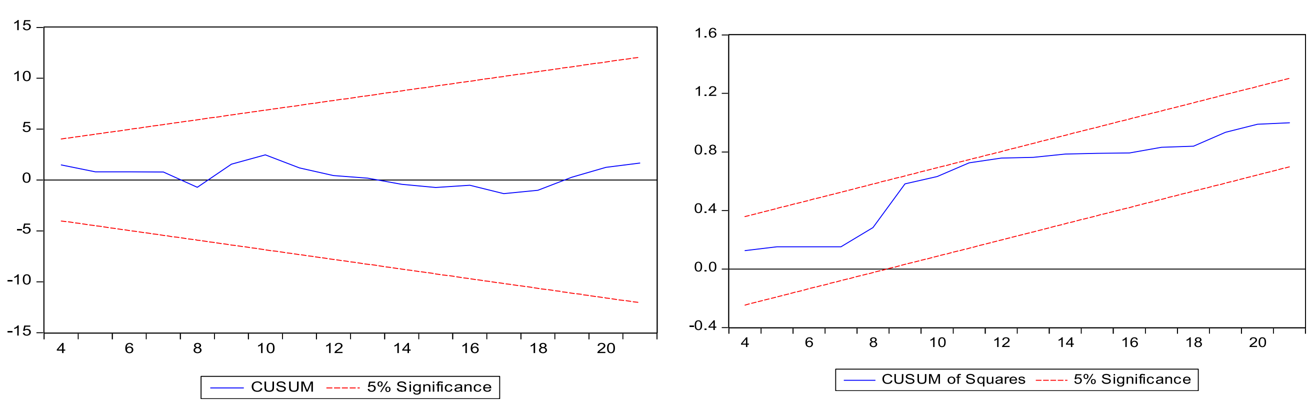

Fig. 4. A: stability for 2016 model (cusum) b: stability for 2016 model (cusum^2).

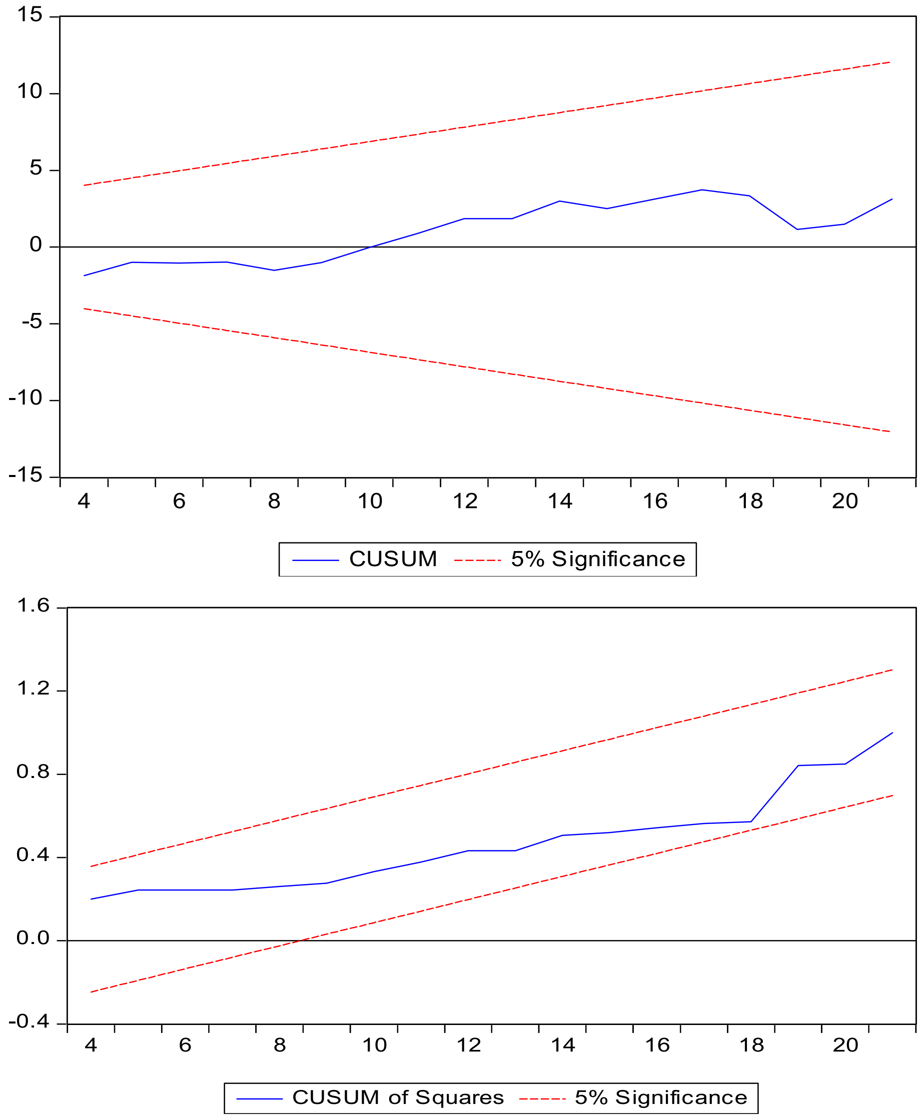

Fig. 5. A: stability for 2018 model (cusum) b: stability for 2018 model (cusum^2).

attributed to management, resource planning, and operational efficiency. Strategic initiatives must be designed with interval targets to plan resource utilization since technological progress appears to be the driving force behind the performance improvement of LAC. More efforts should be introduced towards innovation in technology and advanced research. Energy-efficient systems across multiple sectors will enhance the eco-industry initiative in place of high energy consumption and environmental degradation systems.

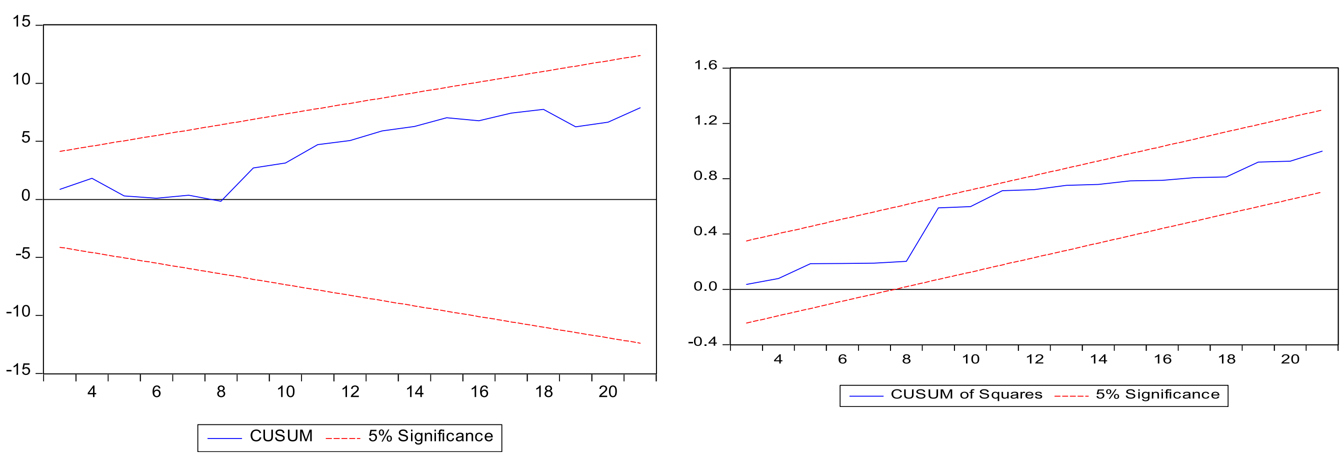

Fig. 6. A: stability for 2020 model (cusum) b: stability for 2020 model (cusum^2).

In addressing the sustainable development gap among the LAC countries, the current study employs the regression approaches in a robustness dimension. Additionally, the diagnostic result in the corresponding regression approaches is expectedly desirable. The FMOLS and GMM estimation approaches are yielded in Table 2 and Figs. 3–5.

Specifically, the result for 2014 (see Table 2) revealed that environmental performance is a significant predictor of sustainable productivity (as implied by both FMOLS and GMM estimators), while the positive influence of clean or renewable energy-induced growth is only statistically significant for the GMM estimator. The result for 2016 almost precisely reflects that of 2014, except that renewable energy-induced development and environmental performance on sustainable productivity are slightly higher. Moreover, the results of 2020 further indicate that green productivity is significantly determined by the clean energy-induced economic growth and environmental performance, as showcased in the two approaches (lower panel of Table 2). Although there is a slight dip in the impact of renewable energy-induced growth on sustainable productivity, environmental performance sustained the highest green productivity in 2018. Generally, the effect of these indicators on sustainable productivity is small, but this outcome offers an insight that LAC countries can subdue their lingering challenges. Thus, the examined economies could be on the pathway to meeting their respective SDGs aspiration by enhancing the relevant measures along with clean growth and environmental regulations. In line with Chen and Golley's [72] suggestion for the Chinese industrial sector, the LAC countries might need to consider other key and inclusive aspects of the economy to significantly drive green and sustainable productivity. Moreover, these results further validate the outcome of Iftikhar et al. [36], which highlights the role of economic activities-complexity and tax policy in energy efficiency and environmental quality.

The serial correlation and heteroskedasticity tests were carried out by providing diagnostic support for the empirical results, as indicated in each of the estimated years in Table 2. Specifically, the results show that the estimations are void of serial correlation and heteroskedasticity problems. Moreover, each of the years' estimation models presents stable inferences as depicted by the respective cumulative sum and cumulative sum of squares in Figs. 4–6.

Conclusion and policy recommendation

The synergy between energy-environmental efficiency and sustainable development is imperative for the overall wellness of humans and the environment. LAC countries have implemented policies such as scaling up renewable energy and increasing rationale to reduce greenhouse gases emission. However, not all countries in LAC are applying equal effort toward attaining the set SDGs. Since environmental degradation, economic regression, and other adverse implications of human practices are not border restricted, the region needs universal progress towards SDGs. Therefore, this study evaluates how LAC countries have progressed toward SDGs using relevant indicators and a holistic approach.

The energy-environmental efficiency-based SDGs evaluation shows disparities in SDG attainment among LAC countries. The Caribbean countries appear to progress less than their Central American and South American counterparts. Decomposition of productivity index into catch-up efficiency and technological change further highlights the root cause of inefficiency. 86% of countries evaluated regressed in catch-up efficiency, and 76% of assessed countries showed improvement in technological advancement. Investment in technology appears to provide a smokescreen for the operational and strategic inefficiency with evidence of gross catch-up inefficiency. Moreover, for the examined cross-section data, the study further revealed by employing the econometric approaches of FMOLS and GMM [67,68] that sustainable productivity is driven by clean growth and environmental performance.

In terms of the relevance of the study, the results obtained offered applicable policy directives for the examined countries. To reverse the downward trends of catch-up efficiency, the study suggests an improved strategic and operational approach through grassroots initiatives to accompany the technological advancement for LAC countries to attain the said SDGs. These could be achieved through other key and inclusive aspects of the economy to drive green and sustainable productivity significantly. Furthermore, financial support for Caribbean countries is needed to accompany their operational improvement if they progress with their regional partners towards the SDGs. In addition, considering that many of the LAC countries are pretty endowed with natural capital, sustainable productivity could be well-enhanced by exploring the respective biocapacity components, especially from the perspective of the SDG7.

However, this study is not without limitations. One obvious limitation is the restriction of the study between the time span of 2012 and 2020 and the exclusion of some countries, which is primarily due to data availability. This study only accounts for sustainable productivity at the economy's aggregate level. For future research, sector-level investigation and exploring alternation choice of the dataset to accommodate as many countries within the region as possible.

CRediT authorship contribution statement

M.D. Ibrahim: Conceptualization, Data curation, Formal analysis, Investigation, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **A.A. Alola:** Conceptualization, Formal analysis, Project administration, Software, Validation, Writing – original draft. **D.C. Ferreira:** Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Software, Supervision, Validation, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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