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A two-stage data envelopment analysis of efficiency of social-ecological systems: Inference from the sub-Saharan African countries

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ABSTRACT

Stress on ecological resources affects the sustainability of the socio-ecological system (SES). Interconnections within SES are involved. Therefore, this study considered indicators that are composite of the interconnections to estimate SES efficiency. We employed the non-parametric benchmarking order-α model, from Data Envelopment Analysis (DEA), to estimate SES efficiency and alleviate possible intricacies. We evaluated twenty-four Sub-Saharan African (SSA) nations observed from 2000 to 2014. More than half of them were inefficient. An increase in food production and environmental performance is essential for SES efficiency improvement. Quantile regression found that human development (through the lifespan, education, and standard of living) is related to the SES efficiency improvement. The SES efficiency is likely negatively associated with higher values of both female proletariat and carbon emissions. Policymakers should increase the concerted efforts of empowering human capacity and minimize the gender gap within SSA countries to become efficient and fulfill sustainable development goals.

1. Introduction

The social-ecological system integrates both people and nature, emphasizing the role of humans as "*part of*" but not "*apart from*" nature (Berkes and Folke, 1998). The "*people-in-nature*" concept highlights direct and indirect drivers of change between both the ecosystem (natural capital) and the social (human capital) systems. Socio-ecological System (SES) is the unified interaction between humans as social actors and their physical and biological environment. The environment can function and support human existence (Fabinyi et al., 2014; Bekun et al., 2019; Saint Akadiri et al., 2019a, 2019b; Usman et al., 2020).

The interactions of human beings and the environment includes unifying biophysical, social, and economic indicators. The efficiency of any SES is related to the ability of the system to withstand or absorb the advert interaction with stressors or social actors, which are predominantly anthropogenic (Kanwar, 2018). Everyday human activities include farming, education, health care, urbanization, tourism, and disforestation, among others (Ozturk and Acaravci, 2010, 2013; Asongu et al., 2020; Eluwole et al., 2020; Ibrahim and Alola, 2020). Meanwhile, the corresponding environmental reactions include climate change, drought, and erosion. To this end, sustainable development becomes paramount.

Meeting present needs, without jeopardizing the future security of the next generations, defines the term sustainable development (Piedra-Muñoz et al., 2016). These practices should be economically profitable, socially acceptable, and environmentally compatible (Solbrig, 1994). Therefore, it is vital to evaluate the efficiency of SES at the macro level, as it is relevant to ensure sustainable development, which makes possible the continuity of human survival.

Knowing the rates and directions of past trajectories in crucial processes and resources utilization, such as land, water, and energy, allow the assessment of the vulnerability of modern SES to human activities and climate change (Ibrahim et al., 2019). The vulnerability of SES enlightens that the close analysis of the SES threats (including extreme

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climate events or transformation due to continuous usage of land) calls attention to its determinants (Pandey et al., 2015). Ecological, social, and integrated SESs are likely to be threatened by non-discretionary dimensions (Berrouet et al., 2018). Nonetheless, some non-discretionary or contextual variables can also play a positive impact on SES efficiency.

Africa has the potential of being self-sufficient with its readily available arable land and other natural resources (Juma, 2015). However, practices and stress on the natural ecological resources threaten the sustainability of this region (Perry et al., 2010). The introduction of sustainable development goals (SDGs) highlights the importance of social and economic factors for achieving sustainability. The role of water, energy, and land towards global sustainability is imperative, coupled with human interaction (Ibrahim et al., 2019). Efficiency analysis of these resources utilization with social interaction supports sustainability management (Pan et al., 2020). SES efficiency should follow the premise that improvement in the ability of the social-ecological indicators reconciles the stresses and interconnectedness between sectors of the ecosystem. Furthermore, exogenous factors within the SES context highlight their role in SES efficiency.

It is imperative to emphasize that some questions and challenges may arise due to the multitude of conceptual frameworks to evaluate SES and its efficiency (Cox et al., 2020). One of those questions includes: *how to conceptually capture the efficiency of the system?* Answering this question can serve as a tool for targeting the implementation of policies and practices solely focused on SES inefficiencies.

The literature on efficiency/benchmarking of SES is scarce, mostly due to the complexities and methodological hurdles associated with the latter. Besides, the absence of a unified conceptual framework for identifying what goes into the system and the expected outcomes, despite apparent benefits, makes empirical analysis of SES strenuous. Few studies have analyzed SES to a certain degree. Using document analysis and the watershed management model, Erickson (2015) evaluated the efficiency and resilience of SES governance. The author identified primary drivers of productivity to include robust funding to support economic multipliers, and flexibility in addressing emergent transformation. Hossain et al. (2017) made the first attempt to operationalize the safe operating space concept within the scope of specific geographical areas by using a complex systems' dynamic model. Their findings highlight the adverse effects of global policy on sustainable development. For example, the withdrawal of agricultural subsidies would make SES vulnerable because of the continuous impact of the human-environment relationship towards poverty and maintaining sustainable agriculture, as stated in SDGs. More recently, (Manyama et al., 2019) analyzed and mapped the impact of the built environment on socio-ecological services along the Dar es Salaam metropolitan coastline. Panel regression revealed that the relationship between the built environment and vegetation cover is inverse. We found no record applying any benchmarking method to estimate the SES efficiency, which makes this study innovative.

This study attempts to estimate the SES efficiency using Data Envelopment Analysis (DEA). Variables suited for DEA should contextualize the complexities and interconnections of SES. Furthermore, environmental efficiency (Wei et al., 2019), economic system efficiency (Barros and Dieke, 2008), social efficiency (Gutiérrez-Nieto et al., 2009), and resource efficiency (Ibrahim et al., 2019) are all components of SES. Those authors have used DEA to evaluate the performance of each component of SES; thus, we also use DEA in SES analysis. However, DEA does not directly integrate exogenous factors within the SES context into the efficiency analysis, despite their potential impact over efficiency. We tested such an impact on SES efficiency by using the quantile regression technique. In this study, exogenous factors include the human development index, the female labor force, and carbon emissions.

Accordingly, the other part of this study is as follows. Section 2 introduces the details of the adopted DEA model. Section 3 describes the data and variables with the quantile regression econometric model. Section 4 presents the case study findings. Finally, section 5 concludes this study by drawing some policy implications resulting from the empirical analysis.

2. Data Envelopment analysis for the SES efficiency

In the SES framework, several factors and drivers are interconnected, including human well-being, social-economic development, and environmental effects coupled with the three pillars of sustainability (Economic, Social, and Environment). It presents a complicated system that makes complex its holistic evaluation. DEA is a non-parametric frontier-based linear programming efficiency evaluation model with the advantage of addressing complex systems by relaxing their interconnections. It evaluates each system known as the decision-making unit (DMU) by using the resources consumed (inputs) and outputs as evaluating criteria (Emrouznejad and Yang, 2018). One has extensively used DEA for performance assessment in many sectors, including healthcare (Ibrahim and Daneshvar, 2018), transportation (Chang et al., 2013), supply chain (Ibrahim and Daneshvar, 2017), education (Navas et al., 2020), public policies (Ibrahim et al., 2018), and resource management, to name a few.

Consider a production system known as production possibility set (PPS) associated with n $(j = 1, \cdots, n)$ homogeneous DMUs, consuming inputs (x) to produce/deliver outputs (y). Each DMU uses $m(i = 1, \cdots, m)$ inputs to produce $s(r = 1, \cdots, s)$ outputs. Therefore, the PPS is the set of all combinations between inputs making the production of outputs possible: PPS $= \{(x,y) \mid x \text{ can produce } y\}$.

This study uses the directional distance-based DEA model, which is a generalized form of the input-oriented and output-oriented DEA models. The flexibility of the model for input contraction and output expansion gives it added advantages (Li et al., 2019) in the context of this study. Indeed, optimum natural resource utilization requires minimizing resource consumption and increasing output production simultaneously (Lewandowski, 2018).

The directional changes follow the path of d_x and d_y, which are vectors with nonnegative components. Let δ be the distance of the jth DMU to the frontier following the path imposed by d_x and d_y. Hence, the target of the evaluated DMU are as follows: $x_j^* \le x_j - \delta \cdot d_x$ and $y_j^* \ge y_j + \delta \cdot d_y$. The model's objective is to maximize the distance δ while keeping feasible the constraints over targets. The aggregating function estimates the efficiency score, θ_k, as follows (Ibrahim et al., 2019):

$$\theta_k = \left(1 - \frac{1}{m}\delta \sum\nolimits_{i=1}^{m} \frac{d_{x_i}}{x_{k\ddot{A}\pm}}\right) \Big/ \left(1 + \frac{1}{s}\delta \sum\nolimits_{r=1}^{s} \frac{d_{y_r}}{y_{kr}}\right) \quad (1)$$

In this study, we imposed $d_x = x_k$ and $d_y = y_k$ (Chambers et al., 1998). Hence, θ becomes equal to $(1 - \delta)/(1 + \delta)$. A DMU is technically efficient (i.e., $\theta_k = 1$) if and only if $\delta = 0$. Inefficient DMUs has $\theta < 1$(i.e.,$\delta > 0$).

Both composite and straightforward performance indicators are required to integrate the interconnection within SES. Those indicators are typically in ratio and index form. Given the convexity assumption of DEA, these variables present a complication for the DEA application (Emrouznejad and Amin, 2009). Olesen et al. (2015) claim that, by disregarding the DEA convexity, this issue should mitigate. It transforms the linear model to a mixed linear programming model that can be solved by the asymptotic properties of the so-called partial frontiers. Therefore, we consider

$$\hat{\delta}_j^{(k)} = \min\left\{\frac{x_k}{x_j}, \frac{y_j}{y_k}\right\}, j = 1, \cdots, n \quad (2)$$

where

$$\left(x_j, y_j\right) = \exp\left(x_j/d_x, y_j/d_y\right), j = 1, \cdots, n, \tag{3}$$

as proposed by Simar and Vanhems (2012) and Daraio and Simar (2014). By replacing $\widehat{\delta}_j^{(k)}$ of Eq. (2) by δ in Eq. (1), we obtain the non-convex efficiency score for DMU k.

Another possible limitation of DEA is the dimensionality problem. It makes the model sensitive to outliers and extreme data, resulting in SES efficiency underestimation should there outliers exist (Gearhart, 2016) and limiting the discretionary power of the model. There are two partial frontier models to mitigate this drawback: the order-*m* (Cazals et al., 2002) and the order-α (Aragon et al., 2005; Ferreira and Marques, 2017). Both models are equivalent under some circumstances. This study utilizes the order-α model, which assumes a probability $1-\alpha$ of observing DMUs outperforming the frontier, with $\alpha \in (0, 1]$. Implementation of the order-α frontier is as follows:

We first consider the function $\psi_{t+1} = \sum_{j=t+1}^{n} \frac{n-j+1}{n}$. Then, we sort n values of the function $\widehat{\delta}_j^{(k)}$, obtaining the order $\widehat{\delta}_{(1)}^{(k)} \le \cdots \le \widehat{\delta}_{(j)}^{(k)} \le \cdots \le \widehat{\delta}_{(n)}^{(k)}$. Concerning the frontier and the chosen path, the distance, δ_α, of DMU k is as follows:

$$\delta_\alpha = \begin{cases} \widehat{\delta}_{(p)}^{(k)} & if \psi_p > 1-\alpha \ge \psi_{l+1} \\ \widehat{\delta}_{(n)}^{(k)} & if\ \psi_n \ge 1-\alpha \ge 0 \end{cases} \tag{4}$$

Finally, the order-α efficiency score results from inserting Eq. (4) into Eq. (1).

3. Data and variables

3.1. The study region

Countries selected for the case study belong to the Sub-Saharan African (SSA) region. According to the United Nations, Sub-Saharan Africa includes the fifty-one countries that lie south of the Sahara (UN, 2020). 21.2 million sq.km in land area and 10.25 million square kilometres (km) in Agricultural land (Worldbank, 2020). The fragile ecosystem and deterioration of natural habitat in the region increase poverty tendency (Chiotha et al., 2018). Furthermore, it is the region that is disproportionately affected negatively by extreme climate patterns (Cervigni et al., 2015), with agriculture being the most affected sector (Pricope et al., 2013). Other sectors are increasingly feeling the impact as well (Wilhite et al., 2014). These issues call for effective and innovative resource analysis and management to the base improvement of social and economic outcomes of the region.

3.2. Data description for SES efficiency assessment

SES comprises both the socio-economic and cultural well-being of people about their physical and biological environment. The environment can function and support human existence (Ostrom, 2009). Changes in natural resources, natural environment, social environment, and population impact SES (Liu et al., 2016). The human-environmental system concept emphasizes that the social, economic, and cultural nourishment of people depends not only on the human–human relationship but also on the physical-biophysical link (Marten, 2001).

A socio-ecologically or SES efficient nation uses the appropriate amount of natural capital (resources) and adequate human capital (labor) to achieve human and environmental well-being as well as economic and social sustainability (Ochola et al., 2010; Liu et al., 2016). According to the Organization of Economic Corporation and Development (OECD) well-being indicators, the compendium for human well-being includes education, housing, safety, and environmental quality (OECD, 2020).

The standard protocol for SES efficiency or variable for empirical analysis does not exist in the literature (Cox et al., 2020). SES has a plethora of variables either directly or indirectly relevant, which thwarts SES empirical efficiency analysis. Drawing from the studies of Partelow (2019) and Cox et al. (2020), natural resources and their connection to human well-being are contextualized to represent SES inputs and outputs.

We now present a conceptual framework for SES efficiency analysis. The vital resources are inputs, whereas measurable and available human well-being factors are used as outputs for SES (see Fig. 1 and Table 1). Table 2 provides further information regarding some data statistics

Input indexes. Selecting inputs for SES efficiency estimation is a complex process. However, direct and measurable inputs create balance and accountability for the system.

Water. Renewable internal freshwater resources flows refer to internal renewable resources (internal river flows and groundwater from rainfall) in the country.

Energy use. We should consider all forms of energy utilized to account for the total energy consumed in the SES. Thus, we choose energy use as the variable that refers to the use of primary energy before transformation to other end-use fuels. It is equivalent to indigenous production plus imports, and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport.

Agricultural land. We only consider agrarian land to assess the effectiveness of land on SES accurately. It creates a more homogenous comparison among countries because some might have significant land areas. Still, part of them includes areas that do not contribute to SES, e.g., land under market, inland water, and desert. Agrarian land includes (i) arable land, (ii) land under permanent crops or permanent pastures, (iii) land under temporary meadows for mowing or grazing, (iv) land under market or kitchen gardens, and (v) temporarily fallows.

Labor force. The role of humans in the utilization of resources for SES sustainability is evident. Therefore, to account for human inputs to the system, the labor force was utilized as opposed to the population. Labor force comprises people aged 15 or older who supply labor to produce goods and services during a specified period. The variable includes people who are currently employed, the unemployed ones but seeking work, and first-time jobseekers. The studies of Mousavi-Avval et al. (2011) and Mohammadi et al. (2008) have also used the labor force as inputs in system analysis.

Output indexes. The outputs should represent the different dimensions of SES production. Due to the broad nature of SES, we require composite indicators to capture the various interconnection in terms of human well-being such as food production, environmental performance, social (access to electricity), and economics.

Food production index (FPI). Food is a necessity for human survival. Thus, it is a required output when defining SES and its efficiency. The food production index covers food crops that are considered edible and contain nutrients. The index is the sum of price-weighted quantities of different agricultural commodities produced after deductions of amounts used as seed and feed weighted similarly. Using the food production index as an output allows a uniform comparison across countries compared to the food production level (Buhaug et al., 2015).

Environmental Performance Index (EPI). The environment is a recipient of all activities occurring in SES, including industrial activities for economic sustainability or agricultural activities for food production. The EPI is a universal and complete indicator of environmental viability measurement (SEDAC, 2020). Six policy areas define EPI: environmental health, air quality, water resources, biodiversity and habitat, productive natural resources, and sustainable energy. EPI measures proximity-to-target per indicator (established by international agreements, national standards, or scientific consensus), within a range of 0–100. The higher the EPI score, the better the environmental performance of the country.

Access to electricity. Africa is one of the continents with the lowest access to electric power in the world. Access to electricity plays a pivotal role in human development. It is a critical output for sustainable development, a social improvement with a connection to inequality and

Fig. 1. Origin of inputs and outputs for the Socio-ecological system. Note: GDP – gross domestic product.

Table 1
Input-output indexes for Sub-Saharan Africa countries.

Indexes	Sub-Saharan Africa case	Data Source
Input		
Water	Internal freshwater withdrawals, total (billion cubic meters)	WDI
Energy	Energy use (kg of oil equivalent)	WDI
land	Agricultural land (square kilometers)	WDI
Labor	Labor force	WDI
Output		
Food	Food production index (US$)	WDI
Environment	Environmental Performance Index	NASA/SEDAC Columbia university
Human-Wellbeing	Access to electricity	WDI
Economics	GDP (constant 2011 US$)	WDI

1. (WDI) World Development Indicator: https://data.worldbank.org/indicator.
2. NASA/SEDAC (Socioeconomic Data and Applications Center): http://sedac.ciesin.columbia.edu/data/collection/epi/.
3. GDP – gross domestic product.

governance (Sarkodie and Adams, 2020b, 2020a). Hospitals, for instance, as well as other major industries, need access to electricity to operate effectively. Access to electric power is the percentage of the population with access to it.

Gross Domestic Product (GDP). The economic returns of resource utilization are related to national financial interest. It is one of the best indicators to track each nation's economic health (Callen, 2020). SSA is rich with multiple resources that contribute to economic development. Individual outputs of those industries are difficult to assess. They might lead to omission, hence the selection of GDP as an output indicator for the economic sustainability of SES (Ibrahim et al., 2019).

3.3. Potential explanatory variables

This study examines the determining role of selected variables on the SES efficiency of African countries. Notably, we considered a panel of 24 selected SSA countries observed over the experimental period of 2000 to 2014. Thus, the efficiency of SES is the dependent variable. The explanatory variables of this study are the human development index, the female labor force (FLF), the carbon emissions (CEM), and the rate of urbanization (URP). Table 3 provides further information regarding some statistics and sources of the dataset.

SES efficiency. SES efficiency results from the array of input/outputs defined in Table 1. *Source: Author's computation.*

Human development index (HDI). HDI assesses the development of a country regarding the population's (i) lifespan, (ii) education (mean of schooling years for people older than 25 and expected years of schooling

Table 2
Descriptive statistics of input–output for efficiency analysis.

	Common statistics	Labour force	Agricultural land	Internal freshwater withdrawals	Energy use	FPI	GDP	Access to electricity	EPI
	Mean	8364564.875	284048.8151	578.84371	107.02546	84.779167	30,554,953,533	32.146119	44.862907
2000	S.Dev	9391445.564	249546.5504	474.67127	187.12691	11.125673	60,224,438,288	23.115843	6.7653416
	Min.	331,645	1010	129.6497	2.4	62.63	1,939,336,012	6.4814815	30
	Max.	37,993,680	981,250	2424.8816	900	106.27	2.67001E + 11	99	53.568572
2002	Mean	8808001.708	284619.2318	593.57745	107.02546	87.944167	33,819,176,504	35.289792	45.800425
	S.Dev	9906199.232	249240.3256	485.67975	187.12691	8.5012285	66,992,832,484	22.937803	6.8380017
	Min.	353,939	1000	128.83152	2.4	67.18	2,172,521,829	7.8180485	31
	Max.	39,914,966	980,280	2384.1371	900	106.24	2.84357E + 11	99.4	56.315048
2005	Mean	9503192.625	290252.3568	643.65598	107.02546	100.83583	39,654,943,494	38.081293	46.099145
	S.Dev	10714699.2	251409.1109	595.92821	187.12691	4.1458674	78,787,169,924	23.804608	6.5688335
	Min.	394,914	960	127.23008	2.4	89.34	2,200,767,545	6	32
	Max.	42,828,205	974,830	2678.5539	900	110.91	3.22228E + 11	98.77565	56.301307
2007	Mean	9978264.458	292027.9818	668.80115	107.02546	104.4175	44,838,585,366	42.940839	46.73108
	S.Dev	1.27175E + 14	63,415,420,134	432517.21	35016.479	70.636315	7.81106E + 21	553.88449	42.614798
	Min.	431,893	920	126.65076	2.4	85.61	2,210,534,026	11.254148	33
	Max.	45,010,413	968,900	2775.6157	900	122.86	3.58526E + 11	98.385506	55.621891
2010	Mean	10685373.33	293269.2318	707.46127	107.02546	124.01375	51,381,148,206	43.335752	47.508811
	S.Dev	12213815.76	249199.9497	729.92271	187.12691	22.37381	99,780,548,154	23.815935	6.3534942
	Min.	500,221	910	135.35645	2.4	90.24	2,117,039,512	12.686551	34.4
	Max.	48,753,690	968,910	3129.0788	900	168.65	3.75349E + 11	100	57.91183
2012	Mean	11254912.04	296510.8984	684.3232	107.02546	128.14792	56,070,918,040	46.361038	47.792917
	S.Dev	12919295.68	251390.4976	575.57267	187.12691	22.629178	1.07185E + 11	22.21847	6.0871229
	Min.	552,275	870	127.90826	2.4	91.4	2,117,039,512	14.4	34.55
	Max.	51,387,354	968,410	2636.6176	900	176.25	3.98833E + 11	97.82164	57.91
2014	Mean	11918940.88	296327.9818	729.15756	107.02546	134.53958	61,757,786,977	47.708098	38
	S.Dev	13723700.56	250832.5504	661.4829	187.12691	28.73895	1.16707E + 11	23.015153	8.9241704
	Min.	595,863	860	150.01385	2.4	91.1	2,117,039,512	13.5	24.64
	Max.	54,234,993	968,410	2695.4165	900	187.45	4.52285E + 11	97.861351	58.09

Table 3
Data Statistics of explanatory variables.

Common Statistics	Mean	Minimum	Maximum	S.Dev	Skewness	Kurtosis	Jarque Bera
HDI	0.489	0.253	0.786	0.103	0.465	3.123	13.334*
FLF	25.97	0.675	65.381	18.04	−1.292	4.269	23.653*
CEM	1.14	0.058	3.518	0.869	4.38	21.106	68.547*
URP	41.521	14.74	87.651	15.345	0.655	3.631	31.683*

Note: SES, HDI, FLF, CEM, URB are, respectively, the social-ecological index, the human development index, the female labor force, carbon emissions, and urbanization. * represents the 1% (p-value $\leq$ 0.01) statistically significant level for the Jarque-Bera test.

for youngsters), and (iii) living standard (gross national income). *Source: UNDP*.

Female labor force (FLF). FLF is the quotient between females older than 15 and the available labor (regardless of gender) for the production of goods and services. *Source: WDI*.

Carbon emissions (CEM). CEM regards emissions from solid, liquid, and gas energy, and gas flaring measured in kilotons. Source: *WDI*.

Urbanization rate (URP). URP refers to the weight of people living in urban areas in the total population. *Source: WDI*.

3.4. Regression model

Beginning from the work of Wackernagel and Yount, (1998), studies have continued to examine the different perspectives of ecological footprint. Berkes and Folke, (1998), for instance, studied the interactions between the ecological system and social networks. More recently, several social system components, including income, population, human development index, migration, have been studied within the ecological framework (Alola, 2019b, 2019a; Adedoyin et al., 2020; Destek and Sarkodie, 2019; Ike et al., 2020; Dogan et al., 2020). However, to consider the interaction between the ecological and social systems, we examine the impact of human development, the female labor force, and carbon emissions on the SES efficiency. Hence, the conventional linear functional form is as follows:

$$SES = f(FLF, HDI, CEM) \tag{5}$$

The peculiarity and advantages of the quantile regression (QR) approach are situated toward achieving the desired objective of the study. This study implements the QR approach because of the relevance of the entire distribution of the examined series. Explanatory non-discretionary variables also do not follow the Gaussian distribution. In this regard, the QR approach does not estimate an incomplete description of a conditional mean and median distribution (Mosteller and Tukey, 1977). Hence, the implemented QR approach modifies the conditional mean model with fixed effect (FE) of:

$$E[SEI_{it}|(HDI_{it}, FLF_{IT}, CEM_{it}), \alpha_i] = \left(HDI_{it}^T, FLF_{it}^T, CEM_{it}^T\right)\beta + \alpha_i, \tag{6}$$

such that

$$Q_{SEI_{it}}[\tau|(HDI_{it}, FLF_{IT}, CEM_{it}), \alpha_i] = \beta_{1\tau}HDI_{it} + \beta_{2\tau}FLF_{IT} + \beta_{3\tau}CEM_{it} + \alpha_i \tag{7}$$

where t is the year span (2000, 2001, …, 2014) for the country i: 1 = Angola, 2 = Benin, 3 = Botswana, 4 = Cameroon, 5 = Cote d'Ivoire, 6 = Congo Democratic Republic, 7 = Congo Republic, 8 = Eritrea, 9 = Ethopia, 10 = Gabon, 11 = Ghana, 12 = Kenya, 13 = Mauritius, 14 = Mozambique, 15 = Namibia, 16 = Niger, 17 = Nigeria, 18 = Senegal, 19 = South Africa, 20 = Sudan, 21 = Tanzania, 22 = Togo, 23 = Zambia, and 24 = Zimbabwe, and the unobserved country-specific factors is α_i.

As introduced by Koenker and Bassett Jr (1978), the QR approach extends the concept of conventional least-squares by applying different conditional quantile functions such that $\widehat{\beta}(\tau)$ used in Eq. (7) is as follows:

$$\widehat{\beta}(\tau) = arg_{\beta\in\Re^k} min\left[\sum_{i\in\{i:y_i\geqslant x_i\beta\}} \tau|y_i - x_i\beta|\right] + \sum_{i\in\{i:y_i<x_i\beta\}} (1-\tau)|y_i - x_i\beta|] \tag{8}$$

Thus, the conditional quantile of the SES efficiency given each of the explanatory variables x_i is as follows:

$$Q_{SES}(\tau|HDI_i, FLF_i, CEM_i) = (HDI_i, FLF_i, CEM_i)\beta_\tau \tag{9}$$

In this case, each category quantile τ presents the respective slope parameters for the entire distribution of the SES instead of the mean of the conditional distribution as obtainable in Ordinary Least Square (OLS). In this case, we implement the (pooled) OLS and the weighted Fully-Modified OLS (FMOLS) estimation. We then compare their outcomes with the quantile regression estimates. Moreover, we perform a robustness check by incorporating urbanization (URB) in Eq. (9) such that a bootstrap estimate is as follows:

$$Q_{SES}(\tau|HDI_i, FLF_i, CEM_i, URB_i) = (HDI_i, FLF_i, CEM_i, URB_i)\beta_\tau \tag{10}$$

4. Results and discussion

4.1. Efficiency analysis

We pooled the seven years sample to improve the discrimination power of the model by creating a common frontier. Furthermore, we performed the principal component analysis to aggregate inputs and outputs into one variable, each, without redundancy. Fig. 2 shows the average efficiency scores of the 25 evaluated SSA countries. Fig. 3 presents the individual efficiency scores of the states, respectively. The subcontinent showed a steady increase in the SES efficiency from 2000 to 2010. Efficiency became constant between 2010 and 2012 but watched a 10% (average) decrease in 2014. Fig. 4 presents the efficiency of the best performing years (2010 and 2012). The performance trend of countries is consistent in both periods. The mean of EPI and access to electricity were highest in both periods, with minimal water withdrawal (see Table 2).

SSA countries exhibit a relatively inefficient SES across the evaluated period. 55% of the states were inefficient. 11% of the sample showed efficiency below 60%. 2012 was the best performing period, with 80% of the countries being efficient. Table 4 presents the most inefficient countries over the evaluated period. Nigeria and South Africa dominated the list of underperforming SES countries. However, in 2014, South Africa became efficient. The Congo Democratic Republic was always

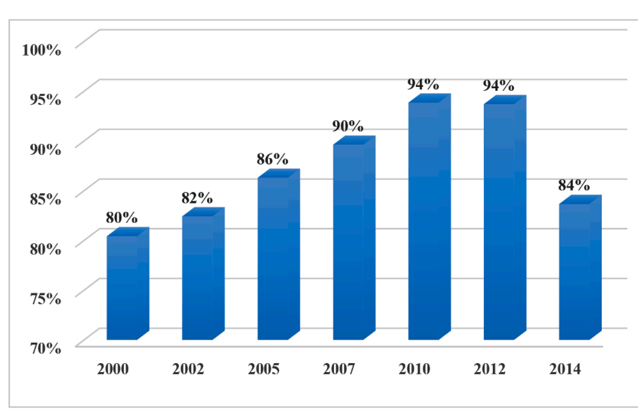

Fig. 2. Average Annual Socio-ecological efficiency.

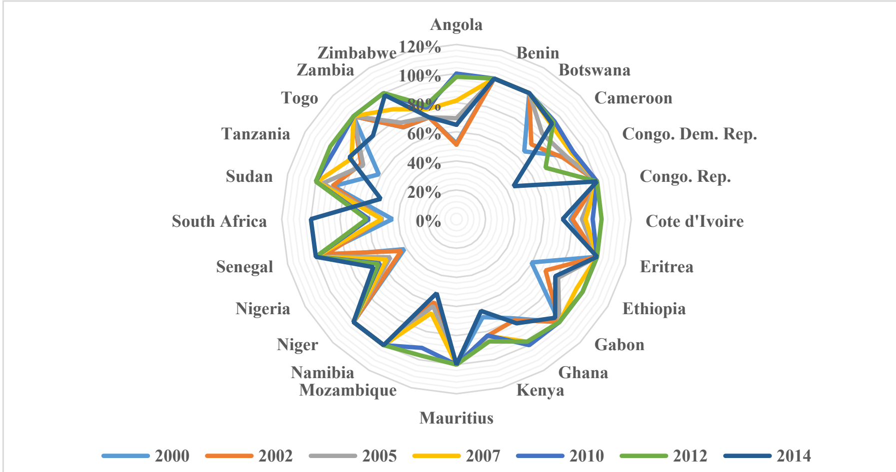

Fig. 3. Annual Socio-ecological efficiency for Sub-Saharan Africa countries.

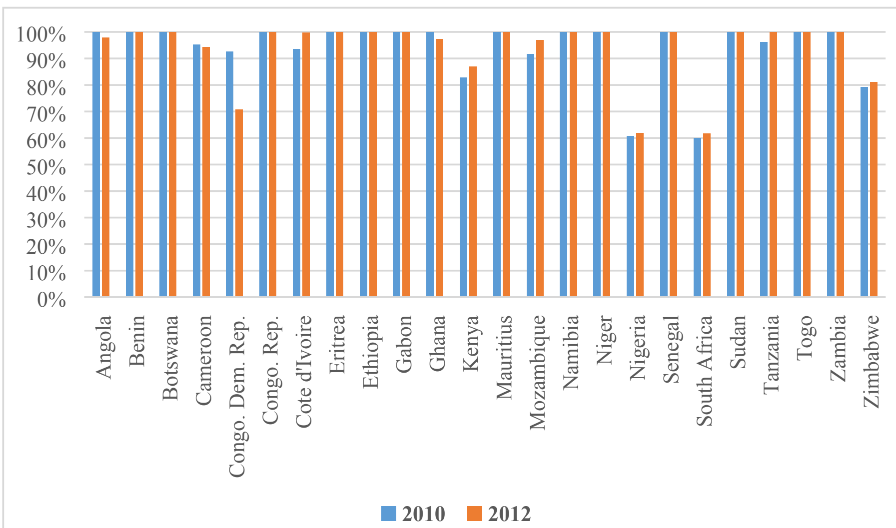

Fig. 4. 2012 Socio-ecological efficiency for Sub-Saharan Africa countries.

slightly above the average efficiency except for 2014. The 55% increase in EPI in 2014 helps to explain the rapid change in SES efficiency of South-Africa when compared to other periods. The sharp drop in SES efficiency of the Congo Democratic Republic may have resulted from the 47% decline in EPI compared to 2012 and other periods.

South-Africa had consistently one of the highest weight of population with access to electric power and GDP but was still among the least efficient countries.

Benin, Botswana, and Eritria were consistently efficient across the evaluated period. Fig. 5 presents a percentage comparison of variables for the top 3 efficient and inefficient countries. Inefficient countries had significantly higher inputs consumption in labour force, agricultural land, and energy use. The efficient and inefficient countries had a relatively equal food production and EPI. However, there is a huge gap in GDP. This infers that both food production and environmental performance play a significant role in ensuring SES efficiency compared to

Table 4
The least efficient Socio-ecological systems.

Year	Countries	Efficiency
2000	Nigeria	41.28%
2002	Nigeria	43.71%
2005	South Africa	50.61%
2007	South Africa	51.32%
2010	South Africa	59.99%
2012	South Africa	61.74%
2014	Congo. Dem. Rep.	45.24%

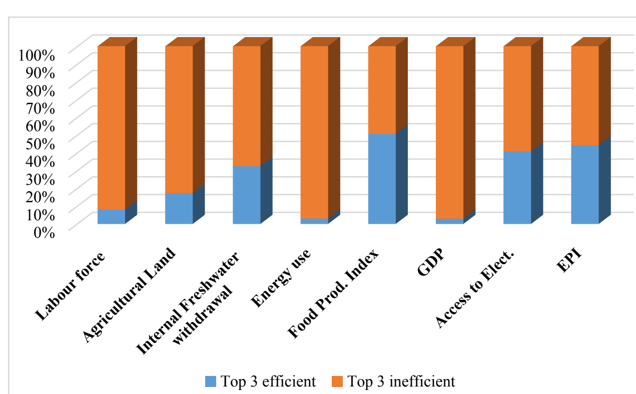

Fig. 5. Comparison between top3 efficient countries.

the weight of the population with access to electricity and GDP. The Large amount of resources consumed by the inefficient countries is indicative of operational and systemic of those countries.

4.2. Regression analysis

Although we do not provide further details of the estimation procedures, Table 3 presents the result of the QR approach estimation. Regarding the illustrated result of the estimation for the pooled OLS, FMOLS, and the quantile regression as depicted in Table 3, we start by comparing the results of the OLS and FMOLS. Except for the lack of significant evidence and type of direction of impact for the FLF (female labor force), the implication from the two approaches is very similar. Considering the superiority of FMOLS to OLS, both the FLF and carbon emissions exert a negative and significant impact (of −0.024 and −0.006, respectively) on the efficiency of the SES. Meanwhile, the impact of HDI on SES efficiency is likely positive (+0.976). Thus, the indicated result sustains the significant evidence of the correlation statistics.

We may expect a positive association between HDI and SES efficiency. Improvements in human health (lifespan), education, and income (all components of HDI) expectedly transcend to more efficient SES. In the current study, there is an increasingly suitably positive and significant impact of HDI across all the quantiles of SES. Illustratively, at 5th, 10th, 25th, 50th, 75th, and 90th, the effect of HDI on SES efficiency is respectively 0.676, 0.060, 0.351, 0.009, and 0.005. The result implies that although the impact of HDI is desirable, it significantly declines toward the upper quantile. A lower value of the impact of HDI on SES at the higher percentile could result from a better interaction between other components of the social system such as population, biophysical characteristics, social organization, knowledge, technology, and the ecological system (nature). The result of the bootstrap approach, especially with urbanization (URB) as an additional variable (see the lower part of Table 5), yields the same conclusion.

Furthermore, the interaction of the female proletariat with the efficiency of SES is noticeably negative (see Table 3) across the quantiles. In the same vein, the result of the bootstrap estimation, even when we include urbanization, yields a similar outcome. Interestingly, the impact of the female labor force on SES efficiency noticeably gets more extensive at the upper quantile. For instance, the impact on 25th quantile is −0.006; it improves to −0.002 at 50th quantile, and, eventually, becomes −0.0002 at the 90th percentile. The negative relationship between the FLF and SES efficiency is not unexpected, especially for the case of nations in SSA. The reason for the unusual observation is likely to be associated with some societal traditions, especially that are culturally rooted in societal norms and beliefs. Most of the SSA countries predominantly experience high gender inequities and other gender-related discriminations. Most women from this part of the continent are left to engage in other activities, such as the informal sector (gender economic exclusion). It, therefore, justifies the no significant or negative impact on the SES. The studies of Asongu and Odhiambo (2020), Asongu and Odhiambo (2019) are some of the recent investigations that have acknowledged the effect of gender exclusion for the specific case of the Sub-Sahara region.

Moreover, the result also implies that carbon emissions are likely associated with reductions in SES efficiency. This evidence upholds when the bootstrap approach is employed. Additionally, the inclusion of urbanization into the regression model also demonstrates the same outcome as the carbon emissions and the female labor force. In a continent highly dependent on coal and fossil fuel and verifying an increasing rate of rural-to-urban movement, the negative impact of both carbon emissions and urbanization was unexpected.

5. Conclusion and policy implications

The naturally existing interdependence between social factors and the ecosystem has continued to be explored for good reasons, but not without producing a handful of undesirable effects. From the human perspective, the unwanted effect resulting from the inefficient or imbalance in the social-ecological interactions is primarily associated with the world global emergencies such as global warming and food insecurity.

This study examines the efficiency of SES in the panel of 24 SSA nations. The framework for SES was not only local but regional as well, and globalization has made a ripple effect of SES more impactful regionally. We also used explanatory variables for those nations' efficiency: the human development index, the female labor force, urbanization, and carbon emissions. Accordingly, we found that social development improves the efficiency of SES across the quantile. However, we also verified a negative and significant effect of the female labor force, carbon emissions, and urbanization across the entire quantile of SES efficiency of the considered sample. This result suggests that sustainable development drive in the region is dependent on the implementation of targeted policy mechanisms.

Indicatively, we can infer a handful of policy suggestions. First, the positive impact of the human development index suggests that a

Table 5
The Ordinary Least Square and Quantile Regression. Dependent variable = Socio-ecological system efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
				Quantile Regression				
Variable	POLS	FMOLS	5th	10th	25th	50th	75th	90th
Constant	0.603*	0.182**	0.550**	0.772*	0.820*	0.863*	1.009*	1.007*
HDI	0.576*	0.976*	0.864*	0.676*	0.600*	0.351*	0.009*	0.005*
FLF	0.001	−0.024*	−0.005	−0.007*	−0.006*	−0.002***	−0.0002*	−0.0002*
CEM	−0.030**	−0.006*	−2.07E−06*	−2.19E−06*	−1.18E−06*	−1.07E−06*	−8.46E−07*	−4.16E−07*

Robustness check with urban population and bootstrapping with 100

	(1)	(2)	(3)	(4)	(5)	(6)
			Quantile Regression			
Variable	5th	10th	25th	50th	75th	90th
Constant	0.563	0.685*	0.813*	0.838*	1.008*	1.007*
HDI	0.889*	0.672*	0.516*	0.259*	0.010*	0.005
FLF	−0.001	−0.006**	−0.007*	−0.001	−0.0002***	−0.0002
CEM	−1.99E−06*	−2.22E−06*	−1.22E−06*	−1.06E−06*	−8.46E−07*	−4.16E−07
URP	−0.001*	0.001	0.001	0.0006	−6.33E−06	−1.69E−05

Note: The lowest Quantile Pseudo R-squared = 0.4406, Raw sum of deviations = 14.10643, Minimum sum of deviations = 7.891089, and number of Observations = 360. HDI, FLF, CEM, and URP are respectively the human development index, female labour force, carbon emissions, and urban population.

consented effort should be directed towards the complement of the region's achievements in health, education, and income growth. Secondly, the study suspect gender economic and social exclusiveness, hence the related policies that pertain to gender participation should be further revisited across the regions. In specific, there should be genuine effort of governments to tackle the increasing level of unharnesssed or unproductivity of most aspects of the informal sector across the continent. In most cases, the female component of the sector comprised of largely the unskilled population, thus becoming a larger component of an unproductive sector of the economy. In such case, an effective skill acquisition program with intensive awrenesss on the benefits of female participation will definitely redirect the negative trend of the female labour participation rate across the African continent and even other similar regions of the world. Policies targeting minimization of resource vulnerability such as strict environmental policies for waste disposal in land and water should have a positive impact on social welfare.

For further research, we propose consideration of individual threats to the natural resources as negative outputs using DEA. It should illustrate the application of DEA to SES research and increase the literature on a national analysis of SES.

CRediT authorship contribution statement

Mustapha D. Ibrahim: Conceptualization, Data, Formal Analysis, Original draft, and Writing. **Andrew A. Alola:** Conceptualization, Formal analysis, and writing. **Diogo Cunha Ferreira:** Validation, Visualization, and Review & editing.

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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