

From non-renewables to renewables and high-tech production: The impact of natural wealth and technology on ecological load capacity in sub-Saharan Africa

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Abstract

In the face of growing sustainability challenges, this study examines the ecological impacts of natural wealth (NR) and tech-driven industrial diversification (TID) in sub-Saharan Africa (SSA). It employs the load capacity factor (LCF), utilizing a panel dataset spanning from 1991 to 2020. The findings reveal that renewable (forest) resources exert a positive and significant influence on LCF, primarily at lower quantiles. When the resource basket is adjusted to include mineral resources, this impact turns negative across all quantiles, with statistical significance evident at the upper quantiles. Further modifications to the resource basket, including energy extraction such as oil, coal, and

natural gas, yield a statistically significant negative impact on LCF across the lower, median, and upper quantiles. Additionally, TID has a positive impact on LCF in the upper quantiles. Robustness analysis confirms that the covariates indeed Granger-cause LCF. This finding also indicates that the causal equation is significantly influenced by past values of NR and TID. The Half-Panel Jackknife estimator reaffirms that, on average, TID has a positive effect on LCF in the region. These findings suggest enhancing growth through renewables and industrial capacity in medium- and high-tech industries as part of broader sustainability strategies in the SSA region.

KEYWORDS

ecological load capacity factor, industrial diversification, medium- and high-tech industries, natural resources, sustainable development

1 | INTRODUCTION

Sub-Saharan Africa (SSA), a region rich in abundant natural resources, has garnered global attention due to its unique economic and environmental challenges. This vast continent boasts a wealth of mineral deposits, fertile lands, and diverse biodiversity, rendering it a significant contributor to the global supply of critical raw materials. However, this abundance of natural resources has often led to a heavy reliance on resource extraction as the backbone of many SSA economies. According to data from the World Bank, SSA stands out as one of the most resource-dependent regions globally, with natural resources accounting for an average of 10% of gross domestic product (GDP) in 2021 (WDI, 2023). This dependence is particularly pronounced for non-renewable resources, primarily oil and coal, as well as for the mineral sector, which encompasses resources such as gold, zinc, iron ore, diamonds, and copper, which collectively accounted for over 38% and 20%, respectively, of the region's merchandise exports in 2021 (WDI, 2023).

The extent of SSA's reliance on natural resources has sparked on-going debates in the academic literature about its implications for the economic, social, and environmental sustainability of the region (Mpuure & Mengba, 2023; Nwani et al., 2023). While natural resources have indeed fuelled economic growth, generating substantial export revenues, employment opportunities, and government income (WDI, 2023), they may also produce negative consequences that can undermine the region's sustainability. First, it discourages investment diversification into other sectors, such as manufacturing, hindering the transition to more economically efficient industries (Nwani et al., 2023). Second, resource extraction contributes to environmental degradation, impacting ecological sustainability through biodiversity loss, deforestation, fisheries collapse, and the accumulation of waste and carbon dioxide (CO₂) emissions (Tiamgne et al., 2022). From an ecological sustainability perspective, SSA countries currently

consume more ecological resources and services than their ecosystems can provide, as reported by the National Footprint and Biocapacity Accounts (NFBA), indicating an ecological deficit of over 35 million global hectares (gha) (NFBA, 2023). This expanding ecological deficit poses risks to economic security and the region's ability to ensure the well-being of its population. Prioritizing short-term gains over the long-term support of ecosystem services poses significant challenges to achieving sustainable development goals (SDGs), particularly those focused on poverty reduction and improved health outcomes, as these goals heavily rely on ecological resources and the services they provide, such as water, forests, and biodiversity (Tiamgne et al., 2022).

Among the sustainability challenges posed by natural resource dependence, diversification contributes to fostering economic resilience even though not all forms of diversification lead to sustainable development and resilient economies (El Anshasy & Khalid, 2023). Industrial diversification, particularly in medium- and high-tech industries, has emerged as a promising pathway for enhancing economic resilience and reducing reliance on natural resources (Ghosh et al., 2023; Shahzad et al., 2022; Wang et al., 2024). These industries, characterized by innovation, technological advancement, and high-value production, have the potential to drive economic growth while minimizing the ecological footprint associated with resource extraction (Aziz et al., 2023). Compared with traditional resource extraction sectors such as mining and energy, medium- and high-tech sectors, including information technology, biotechnology, renewable energy, and advanced manufacturing, may place lower demands on the ecological environment (Aziz et al., 2023). They place greater emphasis on human capital, intellectual property, and innovation, reducing their reliance on the overexploitation of natural resources (Ghosh et al., 2023; Shahzad et al., 2022; Wang et al., 2024). Remarkably, the region has yet to fully harness the potential for industrial diversification in medium- and high-tech industries, despite the evident advantages this transition offers. This represents a critical gap in SSA's development trajectory, especially considering the pressing ecological concerns that continue to mount.

The complex interplay between resource dependence and ecological sustainability has long been a global concern and has attracted significant empirical attention (Mpuure & Mengba, 2023). In SSA, existing studies have often employed CO₂ emissions and the ecological footprint as measures of environmental sustainability, overlooking the supply side, namely, biocapacity (see Iorember & Yusoff, 2023; Usman et al., 2022). However, both CO₂ emissions and the EF only consider the demand (or output) side of nature while ignoring the supply (or input) side (Pata et al., 2023). Nonetheless, recent research has employed the load capacity factor (LCF) as a measure of environmental sustainability because it accounts for both the supply and demand sides, thereby making it a more thorough indicator of environmental sustainability (Guloglu et al., 2023; Okezie et al., 2023; Pata & Isik, 2021). The SDGs, which highlight the need to maintain a sustainable ecosystem in the air, land, and sea, are strongly related to the LCF. Therefore, policymakers may find it useful to analyze environmental challenges using the LCF indicator as a guide.

Furthermore, prior research has predominantly relied on aggregated metrics to assess the region's economic reliance on natural resources, failing to account for the distinct policy implications associated with renewable and non-renewable resources. Additionally, while existing studies have highlighted the challenges posed by natural resource dependence, they have often fallen short of providing sustainable diversification strategies to overcome this curse. Using robust econometric techniques, this study aims to shed light on the delicate balance required to secure a prosperous, environmentally responsible, and sustainable future. To achieve this aim,

this study divides biocapacity by the ecological footprint to derive a sustainability measure (LCF) that gauges the region's capacity to sustain natural ecosystems and support its growing population without depleting the ecological environment or causing irreversible environmental damage (see Dogan & Pata, 2022). Furthermore, this study offers perspectives on how SSA could use its natural resources and technological breakthroughs to achieve sustainable development goals while addressing pressing environmental issues and promoting socio-economic equity across the region. To achieve this objective, the study provides answers to the following research questions:

- i. What is the relationship between SSA's load capacity factor (LCF) and economic reliance on natural resources, and how much does this dependence affect the region's ecological sustainability?
- ii. How does technology-driven industrial diversification affect the load capacity factor (LCF) of SSA, and is there any evidence that this diversification significantly improves the region's ecological sustainability?

This study contributes to the literature in three key areas. First, the model analyzed in this study reconciles sustainability issues associated with increasing human footprints and declining biocapacity, two dimensions of ecological accounting. This approach resolves conflicting policy suggestions prevalent in the literature and provides a comprehensive understanding of how SSA countries can strike a balance between economic demands and climate concerns. Second, this study examines the resource dependence effect from the perspective of diversity in the composition of the natural resource basket. By constructing different baskets of natural resources, the empirical models identify and distinguish the impact mechanisms and varied policy implications of different types of natural resources more effectively. Third, to inform policy deliberations, this study extends the empirical analysis to reveal how industrial diversification, with an emphasis on higher capacity in medium- and high-tech industrial output, can contribute to resolving sustainability dilemmas in SSA. The empirical insights can, therefore, offer valuable guidance for policymakers and support efforts to achieve long-term environmental resilience and prosperity in SSA and beyond.

The structure of this study is as follows: Section 2 provides a review of related studies, Section 3 outlines the empirical steps and methods employed, Section 4 presents and discusses the results, and finally, Section 5 offers the conclusion, policy insights, and limitations of the study.

2 | LITERATURE REVIEW

2.1 | Theoretical background

The resource curse hypothesis credited to the seminal work of Auty in 1993 posits that nations endowed with vast natural resources commonly face sluggish economic and development than their counterparts with lesser natural resource endowments (Auty, 1993). This incident could have a considerable influence on ecological deterioration. There are several ways in which the resource curse phenomenon could undermine the ecosystem. First, nations with vast natural resources tend to concentrate more on the extractive sectors resulting in unsustainable utilization of these resources. The environmental repercussions of these activities are enormous as

they can result in water contamination, biodiversity loss, deforestation, and soil erosion (Yadav et al., 2024). Second, resource-endowed economies could have lax ecological standards owing to the influence of dominant extractive industries. These industries that generate revenues from resource extraction might influence environmental agencies in the economies they operate to make laws that are not strict leading to enhanced ecological damage (Xiang et al., 2024). Third, resource-endowed economies could experience frequent economic uncertainty owing to the unanticipated shifts in global market prices. As a result of this economic insecurity, they may be forced to make unsustainable decisions that only prioritize immediate economic gain against long-term environmental stewardship (Li et al., 2024). Fourth, the expansion of revenue from the extraction of natural resources can result in increased corruption activities and weak governance system. This could hinder ecological preservation endeavors as public officials may be given kickbacks to ignore ecological infractions or even to grant approvals to projects with adverse ecological effects. Fifth, these nations with vast natural resources could overlook other economic sectors like agriculture and manufacturing resulting in a narrow economic base (Xiang et al., 2024). This excessive reliance on resource extraction could engender continuous ecological destruction. Sixth, the struggle for resource control could instigate socio-political conflicts which could trigger damage to natural habitats and infrastructure thereby degrading the ecosystem (Li et al., 2024).

On the other hand, Michael Porter's hypothesis asserts that environmental standards and sustainability initiatives can trigger competitiveness and innovation in industries. This theory indicates that rigorous eco-regulations can propel innovation within high-tech industries resulting in improved ecological sustainability (Li & Shao, 2023). There are several ways in which this proposition can be utilized to explain the ecological quality effects of the high-tech industry. First high-tech is renowned for fostering innovation in sustainable technologies like green energy and eco-friendly appliances. This hypothesis aver that industries can obtain a strategic market edge via innovation. In the realm of sustainable environmental health, this innovation can trigger the development of procedures and products that substantially lower carbon footprints (Wu & Lin, 2021). Second, Porter equally contends that industry rivalry inspires enterprises to enhance quality and efficiency. Within the high-tech industry, where there is a prevalence of competition among firms in the global markets, firms are expected to align with global ecological guidelines. Consequently, this could engender the uptake of sustainable manufacturing techniques, green technologies and waste mitigation tactics, hence encouraging ecological stewardship (Rubashkina et al., 2015).

2.2 | Past literature

2.2.1 | Natural resources and the environment

Prior related studies have majorly utilized carbon dioxide (CO₂) emissions, the ecological footprint (EF) and the load capacity factor (LCF) as indicators of ecological sustainability. Our discussion in this section covers these dominant environmental metrics. Focusing on the nexus between natural resources (NR) and CO₂ emissions, Tufail et al. (2021) in advanced economies, Saud et al. (2022) in MENA nations and Jahanger et al. (2022) in emerging economies confirmed that NR lowers CO₂ emissions thereby contributing to a healthier ecosystem. Regarding the connection between NR and EF, Zafar et al. (2019) and Liu et al. (2022) reported that NR promotes ecological quality by reducing EF in the USA and developed economies

respectively. These indicators employed in the foregoing studies have been widely utilized in environmental literature, however, they are often criticized for providing only a narrow assessment of environmental quality. To sidestep the shortcomings associated with these metrics, LCF has emerged as a broader environmental sustainability indicator covering multiple aspects of resource utilization and ecological strain (Kartal, 2024; Pata et al., 2023). Given that the LCF incorporates the impacts of both demand- and supply-oriented initiatives on the ecosystem, recent research attention has been directed toward using LCF as a surrogate for ecological quality. For instance, Guloglu et al. (2023) and Sun et al. (2024) utilized LCF to reveal that NR fosters environmental protection in OECD and 17 economies respectively. These outcomes reinforce the critical role of NR in mitigating ecological decline.

On the flip side, there is other evidence that highlights that NR may not always boost ecological health. For instance, Wang, Zhang, and Li (2022) and Sun et al. (2020) discovered that NR damages the ecosystem by intensifying carbon emissions in 208 economies and 88 nations respectively. For studies on EF, Hassan et al. (2019) in Pakistan and Hussain et al. (2022) in China showed that NR broadens EF thereby reducing ecosystem balance. Concentrating on LCF research, Pata and Isik (2021), Ni et al. (2022) and Erdogan (2023) in China, resource-driven economies and Africa respectively found that NR compromises ecological stability by reducing LCF.

Consequently, the study tests the following null hypothesis:

H1. Economic reliance on NR has no significant negative effect on LCF.

2.2.2 | High-tech industries and the environment

Shahzad et al. (2022), Wang et al. (2024), and Xu and Lin (2017, 2018) in China reported that high-technology industries (HTIs) improve the environment by reducing environmental pollution. Likewise, Aziz et al. (2023) discovered in Saudi Arabia that HTI promotes ecological balance. Avenyo and Tregenna's (2022) study across 68 economies documented that HTI lower emission levels relative to low-tech industries. Similar studies conducted across 10 nations and advanced economies respectively by Ghosh et al. (2023) and Wang, Chen, and Teng (2022) yielded the same outcome. In contrast, some studies have raised concerns regarding the sustainability of HTI. For instance, Du et al. (2022) in MINT nations and Khan et al. (2024) in APEC economies reported that ecological damage is worsened by HTI.

However, numerous research has assessed the influence of industrial structure upgrading on ecological stability with most highlighting its enhancing effect on ecological quality. For instance, Zhu (2022) documented that China's industrial structure upgrading reduces carbon emissions. Likewise, Zhao et al. (2023) unveiled that improving the industrial structure is an efficient tactic for promoting carbon emission mitigation in China. Yang et al. (2021) and Zhao et al. (2021) also confirmed this outcome in China.

Given the preceding discussions, the study evaluates the following null hypothesis:

H2. The HTI has no significant positive impact on LCF.

2.3 | Evaluation of the literature

A review of prior related studies revealed numerous gaps in the literature. First, while past research has concentrated on the effects of NR on the environment, there has been limited

exploration of the role played by HTI in promoting environmental sustainability, especially in Africa. Considering the region's position as a focal point for climate change repercussions and the increasing sustainability obstacles in the region, a comprehensive study of Africa is warranted. Second, prior studies have predominantly utilized environmental performance surrogates such as CO₂ emissions and EF, which only capture aspects of the ecosystem demand side (Kartal, 2024; Pata et al., 2023). Hence, a more comprehensive approach, such as the LCF, which circumvents these limitations, is necessary to address this gap. Third, prior research has heavily relied on aggregated metrics to evaluate natural resource rents (Hussain et al., 2022; Saud et al., 2022; Zafar et al., 2019), neglecting the impact of disaggregated measures on environmental sustainability. Last, prior research has largely applied linear econometric models (Hussain et al., 2022; Liu et al., 2022; Tufail et al., 2021), neglecting the asymmetric and nonlinear dynamics in the interplay among variables. Hence, alternative modeling techniques that can account for these complexities should be explored. Given the deficiencies in the literature, this study represents a comprehensive endeavor to examine the impact of NR and HTI on the LCF in Africa. By delving into these connections, this research not only enriches the literature but also furnishes decision-makers and environmental scientists with alternative policy measures to advance sustainable development objectives.

3 | METHODS

3.1 | Theoretical model

The model formulation is grounded in the STIRPAT (Stochastic Impacts by Regression on Population [represented by P], Affluence [represented by A], and Technology [represented by T]) framework, as proposed by Dietz and Rosa (1994). The STIRPAT equation, which is used to analyze environmental impact drivers, can be expressed as follows:

$$I_t = \varphi P_t^\alpha A_t^\beta T_t^\delta. \quad (1)$$

This study defines the impact component (I) using the load carrying measure of the ecological environment. The impact of technology is assessed through the lens of industrial structure diversification, with a focus on higher capacity for medium- and high-tech output. An important expansion of the traditional STIRPAT equation in this study is the incorporation of the degree of economic reliance of SSA countries on natural resources. Considering these definitions, Equation (1) can be algebraically transformed to establish an empirical model that will guide this analysis:

$$\ln LCF_{i,t} = \varphi + \alpha \ln P_{i,t} + \beta \ln A_{i,t} + \delta \ln NR_{i,t} + \eta \ln TID_{i,t} + u_{it}. \quad (2)$$

The insertion of $\ln$ in Equation (2) indicates the use of natural logarithmic values for computation. The subscripts i and t correspond to country i th in period t , while u represents the stochastic error term. The ecological load capacity factor is denoted as LCF, and the NR and TID serve as indicators of economic reliance on natural resources and technology-driven industrial diversification, respectively. The constant term φ and coefficients α , β , δ , and η are also indicated. Different formulations of Equation (2) can be devised to investigate how the combination

of forest, energy, and mineral resources influences the ecological effects of the NR basket within the SSA region. These specific equations are outlined as follows:

$$\ln LCF_{i,t} = \varphi + \alpha \ln P_{i,t} + \beta \ln A_{i,t} + \delta \ln NR - TR_{i,t} + \eta \ln TID_{i,t} + u_{it}. \quad (3)$$

$$\ln LCF_{i,t} = \varphi + \alpha \ln P_{i,t} + \beta \ln A_{i,t} + \delta \ln NR - FR_{i,t} + \eta \ln TID_{i,t} + u_{it}. \quad (4)$$

$$\ln LCF_{i,t} = \varphi + \alpha \ln P_{i,t} + \beta \ln A_{i,t} + \delta \ln NR - FMR_{i,t} + \eta \ln TID_{i,t} + u_{it}. \quad (5)$$

$$\ln LCF_{i,t} = \varphi + \alpha \ln P_{i,t} + \beta \ln A_{i,t} + \delta \ln NR - FER_{i,t} + \eta \ln TID_{i,t} + u_{it}. \quad (6)$$

The NR impact factor is defined in various forms. In Equation (3), NR-TR represents a measure of rents from all resources, encompassing forest, fossil energy (coal, oil, minerals), and mineral resources. Different combinations or combinations of these resources can be derived to facilitate more informed policy formulation. In Equation (4), the NR-FR quantifies rents exclusively from forest (renewable) resources, excluding the economic contributions of other resources. This approach is taken because all SSA countries extract forest resources. In Equation (5), the NR-FMR captures the combined rents from both forest and mineral resources. This specification is aimed at examining how the proportion of minerals in the resource basket influences the NR-LCF relationship. In Equation (6), NR-FER represents the combined rents derived from forest, oil, coal, and natural gas. By constructing this variable, it becomes possible to elucidate how the extraction of fossil energy impacts the NR-LCF relationship.

3.2 | Data

A panel dataset comprising 28 sub-Saharan African nations spanning the years 1991 to 2020 was assembled. The selection process is presented in Figure 1, primarily based on data availability.

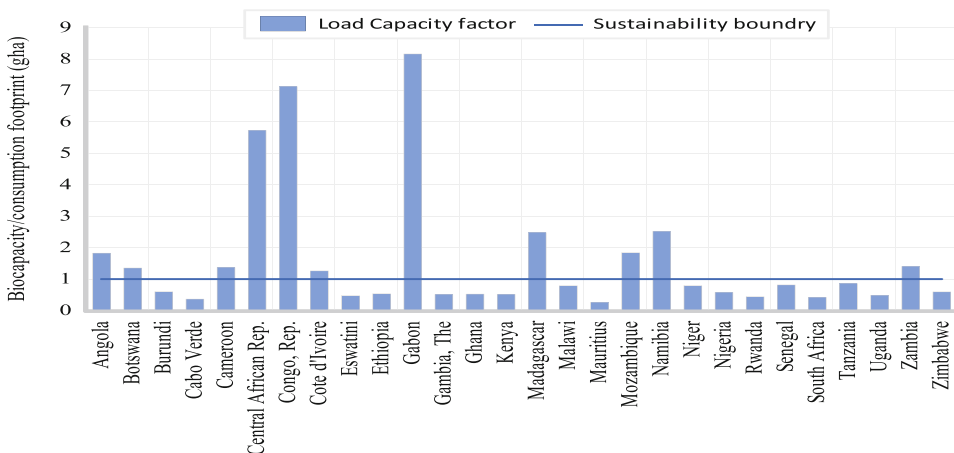


FIGURE 1 Selected countries and their LCF estimates in 2020. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/for.13161)]

TABLE 1 Variables and definitions.

Variables	Identification	Computation and data collection	Mean	Median	Maximum	Minimum
LCF	Ecological Load Capacity Factor	Biocapacity (in global hectares) divided by ecological footprint (in global hectares), data are from NFBA (2023)	2.196	0.841	24.246	0.212
P	Population size	Population, total; Data are from WDI (2023)	21,692,321	12,836,671	208,000,000	372,721
A	Affluence	GDP per capita (constant 2015 US\$), Data are from WDI (2023)	1976.391	1208.573	10956.950	190.333
NR-TR	Economic reliance on Natural Resources	Total natural resources rents (% of GDP), Data are from WDI (2023)	11.284	7.310	59.684	0.002
NR-FR	Forest resources	Forest rents (% of GDP), Data are from WDI (2023)	5.554	3.775	40.408	0.002
NR-FMR	Forest and Mineral resources	Forest plus Mineral rents (% of GDP), Data are from WDI (2023)	6.111	4.249	40.492	0.002
NR-FER	Forest, Coal, Oils and natural gas	Forest plus the sum of Coal, Oils and natural gas rents (% of GDP), Data are from WDI (2023)	10.727	6.535	59.683	0.002
TID	Technology-driven industrial diversification	Medium and high-tech manufacturing value added (% manufacturing value added), Data are from WDI (2023)	11.519	9.587	77.684	0.666

The load carrying factor (LCF) serves as a metric that quantifies the connection between biocapacity and the ecological footprint, as defined by Dogan and Pata (2022), Okezie et al. (2023), and Pata and Kartal (2023). Accordingly, an increase in the LCF indicates a greater environmental carrying capacity, suggesting an improved sustainability status. Table 1 presents a comprehensive overview of the definitions and measurements of all variables, together with their respective data sources. Additionally, it offers fundamental descriptive statistics. Upon initial analysis of the LCF distribution, as depicted in Figure 1, it becomes evident that a significant proportion of nations possess an LCF that falls below the established sustainability threshold. However, certain countries, namely, the Central African Republic, the Congo Republic, Gabon, Madagascar, Mozambique, and Namibia, demonstrate LCF values that surpass 1. This observation indicates an imbalanced allocation of LCF scores within the panel dataset. The distributional plots in Figure 2 provide additional evidence to corroborate this observation. Graphical representation A illustrates the greater degree of peakness in the distribution of LCF in comparison to a normal distribution. All of the explanatory variables exhibit notable departures from a symmetric distribution.

3.3 | Estimation protocol

This study employs the method of moments quantile regression (MMQReg) estimator, developed by Machado and Silva (2019). The MMQReg methodology demonstrates efficacy in

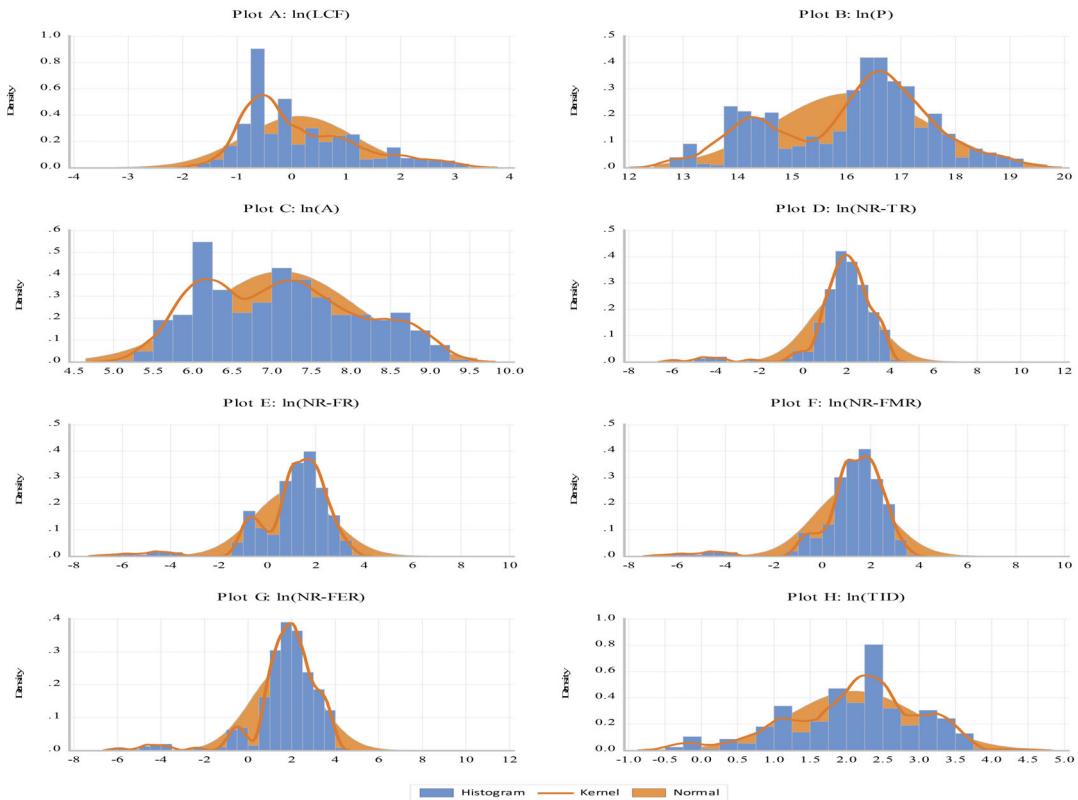


FIGURE 2 Distributional plots. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jrde.13161)]

addressing fixed effects within panel quantile models, enabling the estimation of diverse subsets of the conditional distribution, encompassing distinct quantiles of the dependent variable. In line with the model specifications in Equations (3)–(6), the following quantile specifications are considered for empirical estimation:

$$Q_{\ln LCF_{it}}(\tau|\beta_i, \varepsilon_{it}, X_{it}) = \varphi_0 + \varphi_1 \ln P_{it} + \varphi_2 \ln A_{it} + \varphi_3 \ln NR - TR_{it} + \varphi_4 \ln TID_{it} + \varepsilon_{it}. \quad (7)$$

$$Q_{\ln LCF_{it}}(\tau|\beta_i, \varepsilon_{it}, X_{it}) = \varphi_0 + \varphi_1 \ln P_{it} + \varphi_2 \ln A_{it} + \varphi_3 \ln NR - FR_{it} + \varphi_4 \ln TID_{it} + \varepsilon_{it}. \quad (8)$$

$$Q_{\ln LCF_{it}}(\tau|\beta_i, \varepsilon_{it}, X_{it}) = \varphi_0 + \varphi_1 \ln P_{it} + \varphi_2 \ln A_{it} + \varphi_3 \ln NR - FMR_{it} + \varphi_4 \ln TID_{it} + \varepsilon_{it}. \quad (9)$$

$$Q_{\ln LCF_{it}}(\tau|\beta_i, \varepsilon_{it}, X_{it}) = \varphi_0 + \varphi_1 \ln P_{it} + \varphi_2 \ln A_{it} + \varphi_3 \ln NR - FER_{it} + \varphi_4 \ln TID_{it} + \varepsilon_{it}. \quad (10)$$

The $Q_{\ln LCF_{it}}(\tau|\beta_i, \varepsilon_{it}, X_{it})$ definition in Equations (7)–(10) depicts the quantile distribution of LCF, taking into account the distributional effects of P, A, TID, and the NR-TR. In the specifications in Equations (8)–(10), the impact of NR on the LCF is adjusted to account for the separate roles of renewable (forest) and non-renewable (fossil energy and mineral) resources in the composition of the resource basket in the SSA region.

4 | EMPIRICAL FINDINGS

4.1 | Findings

Panel data series underwent unit-root and cross-sectional dependency tests. Results in Table 2 indicate strong evidence against cross-sectional independence, except TID. Cross-sectional-dependent errors were observed across countries. Variables showed stationarity in first differences

TABLE 2 Variable validation tests.

Variable	Panel A	Panel B			
	Pesaran (2004)	Pesaran (2007) Panel unit root tests			
	CS dependence test	Level specification		1st difference specification	
	Statistics	CIPS	Truncated CIPS	CIPS	Truncated CIPS
lnLCF	64.697***	−1.822	−1.822	−5.193***	−4.610***
lnP	104.769***	−4.639***	−2.107	−2.866***	−2.657***
lnA	33.617***	−1.274	−1.274	−2.735***	−2.706***
lnNR-TR	19.138***	−1.209	−1.209	−4.044***	−4.010***
lnNR-FR	34.712***	−1.600	−1.600	−3.208***	−3.194***
lnNR-FMR	21.871***	−1.545	−1.545	−3.185***	−3.122***
lnNR-FENR	19.79***	−1.493	−1.493	−4.303***	−4.182***
lnTID	1.264	−2.488***	−1.955	−4.608***	−3.340***

*** $p < .01$.

TABLE 3 Slope homogeneity and cointegration tests.

	Test specification	Algorithm	Model 1: NR-TR	Model 2: NR-FR	Model 3: NR-FMR	Model 4: Using NR-FENR
Panel A	Slope homogeneity	Hashem Pesaran and Yamagata (2008)				
		Delta tilde ($\tilde{\Delta}$)	27.102*** (0.000)	29.626*** (0.000)	28.841*** (0.000)	28.129*** (0.000)
		Adjusted delta tilde ($\tilde{\Delta}_{Adj}$)	30.301*** (0.000)	33.123*** (0.000)	32.245*** (0.000)	31.449*** (0.000)
Panel B	Panel cointegration	Westerlund (2007) Error-correction-based test				
		Gt	−4.023*** (0.000)	−3.866*** (0.000)	−3.970*** (0.000)	−3.946*** (0.000)
		Ga	−9.348 (0.380)	−8.142 (0.660)	−8.389 (0.650)	−9.404 (0.260)
		Pt	−18.615*** (0.010)	−18.845*** (0.000)	−18.767*** (0.000)	−18.891*** (0.000)
		Pa	−9.807** (0.050)	−9.054 (0.210)	−8.280 (0.270)	−10.633** (0.040)

Note: Robust p-value in parentheses.
*** $p < .01$, ** $p < .05$.

(see Panel B of Table 2). Slope heterogeneity and long-term coevolution were explored (see results in Table 3). The results revealed long-term relationships. MMQreg estimator is used to address distributional asymmetry. Robustness was ensured with bootstrap analysis adjusting for cross-sectional and temporal dependencies (see Table 4; Figure 3).

Starting with demographic changes, the findings reveal a significant decrease in the ecological load capacity factor due to shifts in population size, broadly affecting quantile distributions. Specifically, a 1% change in population size results in a 0.658%, 0.633%, and 0.606% reduction in the ecological load capacity factor at the 10th, 50th, and 90th quantiles, respectively. This underscores that within SSA, population growth poses a substantial challenge to achieving environmental sustainability. This conclusion aligns with previous research, as affirmed by Dimnwobi et al. (2021) for Africa. Consequently, policymakers must prioritize awareness programs to educate the burgeoning population about the detrimental consequences of compromised environmental quality. Additionally, the implementation of strategic birth control measures could help mitigate observed ecological deficits (Dimnwobi et al., 2021).

By analyzing the relationship between economic affluence and LCF in SSA, the results reveal complex dynamics. Economic affluence generates statistically insignificant parameter estimates at the lower quantiles of the LCF distribution. However, a significant negative impact becomes evident at the upper quantiles of the LCF distribution. A 1% change in per capita GDP leads to a 0.066% and 0.114% reduction in LCF at the 60th and 90th quantiles, respectively. This discovery underscores what numerous previous studies have pointed out—the detrimental environmental consequences of economic growth trajectories in developing economies (Uche et al., 2023). Given these findings, it is imperative to advocate for strategies within SSA countries to reduce the ecological footprint and enhance the region's biocapacity. A sustainable

TABLE 4 Distributional effects (1000 bootstrap replications with DOF adjustment).

Variables	(1) Location	(2) Scale	(3) Qtile_10	(4) qtile_20	(5) qtile_30	(6) qtile_40	(7) qtile_50	(8) qtile_60	(9) qtile_70	(10) qtile_80	(11) qtile_90
lnP	−0.632*** (0.034)	0.017 (0.018)	−0.658*** (0.043)	−0.651*** (0.039)	−0.645*** (0.037)	−0.639*** (0.035)	−0.633*** (0.034)	−0.626*** (0.035)	−0.621*** (0.037)	−0.614*** (0.039)	−0.606*** (0.046)
lnA	−0.052 (0.033)	−0.040** (0.018)	0.011 (0.040)	−0.006 (0.036)	−0.020 (0.034)	−0.034 (0.033)	−0.050 (0.032)	−0.066** (0.033)	−0.080** (0.034)	−0.096** (0.037)	−0.114*** (0.042)
lnNR-TR	−0.081*** (0.014)	−0.035*** (0.007)	−0.027* (0.015)	−0.042*** (0.014)	−0.054*** (0.012)	−0.066*** (0.013)	−0.080*** (0.013)	−0.094*** (0.015)	−0.105*** (0.015)	−0.120*** (0.017)	−0.136*** (0.019)
lnTTID	0.010 (0.010)	0.013** (0.006)	−0.011 (0.012)	−0.005 (0.011)	−0.001 (0.011)	0.004 (0.010)	0.009 (0.010)	0.014 (0.011)	0.019 (0.012)	0.024* (0.013)	0.030** (0.015)
Constant	10.794*** (0.444)	0.156 (0.223)	10.553*** (0.566)	10.619*** (0.509)	10.672*** (0.482)	10.726*** (0.448)	10.788*** (0.433)	10.850*** (0.448)	10.902*** (0.465)	10.965*** (0.475)	11.037*** (0.569)
Observations	840	840	840	840	840	840	840	840	840	840	840

Note: Standard errors are in parentheses.
*** $p < .01$; ** $p < .05$; * $p < .1$.

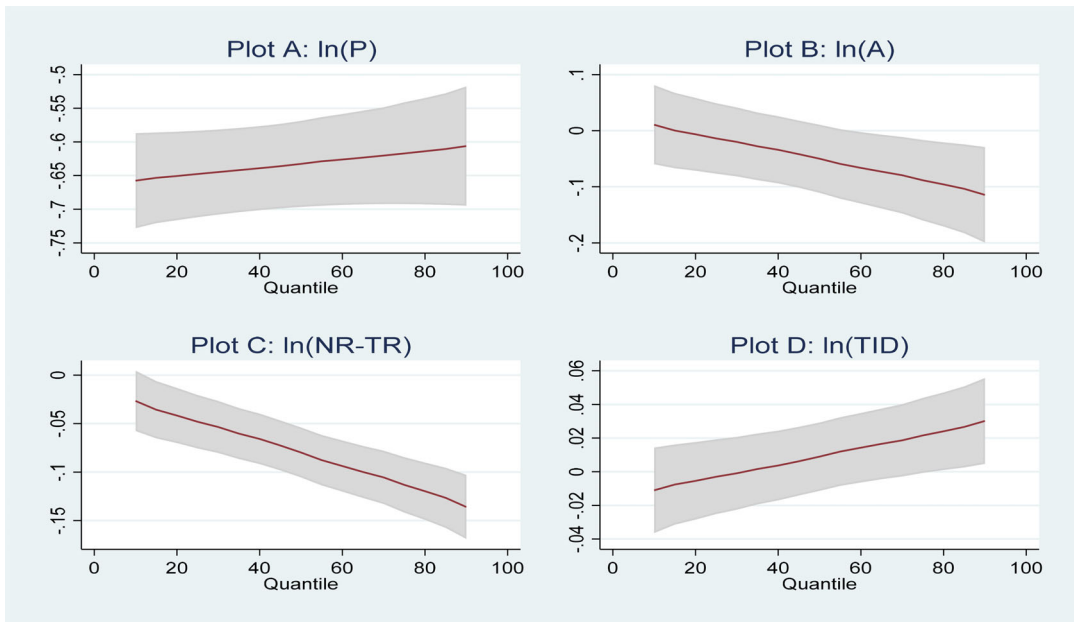


FIGURE 3 Quantile plots (aggregated analysis). [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/rode.13161)]

step for improved ecological space is divesting to technologies that depend less on natural resources.

Turning attention to the focal variables of interest within this study, the results reveal a significant negative coefficient for the NR-TR across various quantiles. Consequently, the null hypothesis I is reject (as outlined in Section 2.1). When considering the construction of the LCF metric, it becomes apparent that economic reliance on natural resources expands the ecological footprint beyond biocapacity—nature's inherent capacity to regenerate ecological resources. From a theoretical standpoint, a growth path that heavily depends on natural resources undermines ecological sustainability (Gylfason, 2001). These findings are consistent with those of Hassan et al. (2019) in Pakistan, and Ni et al. (2022) in economies highly reliant on resources. However, it is worth noting that there are studies that have reported divergent results, including Jahanger et al. (2022) in developing countries and Guloglu et al. (2023) in OECD countries. When examining the parameter estimates across the quantiles, it becomes evident that NR exerts a more pronounced impact on LCF at the upper quantiles. For instance, a 1% increase in total natural resource rents leads to a reduction in LCF of 0.027% at the 10th quantile, 0.080% at the 50th quantile, and 0.136% at the 90th quantile. This implies that as countries progress economically with a growth strategy heavily reliant on natural resources, they impose a heavier burden on ecological load capacity. As a result, NR hampers the expansion of eco-efficient sectors, thereby constraining opportunities for research, development, and innovation in environmentally friendly technologies (Gylfason, 2001). Given these outcomes, it is imperative to highlight that SSA depends heavily on natural resources, unlike some other countries that are less dependent on natural resources. In this instance, strategies that emphasize alternative income generation paths other than natural ones are essential for curtailing the harmful impacts of resource rents on LCF in SSA. Notably, the literature (Guloglu et al., 2023)

underlines notable ecological vitality in countries that rely less on natural resources. Hence, the remaining option for SSA is to diversify its income sources away from natural resources.

The coefficient associated with TID exhibits a positive trend at both the median quantile (50th) and the upper quantiles (60th–90th) in the analysis. However, statistical significance is only observed at the 80th and 90th quantiles. Specifically, a 1% increase in the presence of medium- and high-tech industries within the industrial landscape results in a modest yet significant increase in LCF of 0.024% and 0.030% at the 80th and 90th quantiles, respectively. As a result, the null hypothesis II is rejected (as outlined in Section 2.2). This discovery aligns with the findings of previous studies conducted by Li et al. (2019) and Xu and Lin (2018) in China; Aziz et al. (2023) in Saudi Arabia; and Avenyo and Tregenna (2022) in emerging and developing nations. This finding underscores the potential of industrial diversification into medium- and high-tech sectors as a promising avenue for enhancing ecological resilience and sustaining load capacity, particularly in the face of sustainability challenges arising from natural resource dependence (Shahzad et al., 2022; Yang et al., 2021; Zhao et al., 2021). Of particular note is the phenomenon observed at higher quantiles, where the influence of NR on LCF is more pronounced. In this context, TID exhibits a remarkable capacity for mitigating adverse effects. TID is characterized by advanced manufacturing activities in fields such as information technology, biotechnology, and renewable energy. These industries inherently impose lower demands on the ecological environment than traditional sectors such as mining and energy exploration (Aziz et al., 2023). This is primarily due to the emphasis on innovation, technological advancement, and high-value production within TID, which reduces their reliance on the exploitation of the ecological environment (Shahzad et al., 2022). Following this discovery and in agreement with the submissions of the extant literature, SSA countries must ensure that TID is improved for overall environmental progress. The modest pleasant effects observed at the 80th and 90th quantiles suggest that there is a need for improvements in the potential of TID to improve LCF in the region.

To consider the distinct policy implications associated with fossil fuels, minerals, and forest resources, various baskets of natural resources were constructed. The findings from this step are presented in Table 5 (see also visual representations in Figure 4). Starting with the baseline basket, NR-FR, composed exclusively of forest resources, the results in Panel A reveal that NR-FR exhibits a positive and significant coefficient only at the 10th and 20th quantiles, with estimated positive impacts of 0.038% and 0.031%, respectively. The coefficient becomes statistically insignificant across the 30th to 90th quantiles. Subsequently, the composition of the basket was adjusted to include mineral resources (NR-FMR). In Panel B, the results indicate that the coefficient becomes negative across all quantiles but achieves statistical significance only at the 70th, 80th, and 90th quantiles, with estimated negative impacts of 0.030%, 0.035%, and 0.042%, respectively. This implies that mineral extraction weakens the load capacity of the region. Further adjustments were made to the basket to include oil, coal, and natural gas, resulting in NR-FER. In Panel C, the results show that the negative coefficient becomes statistically significant across the lower, median, and upper quantiles, with estimated negative impacts ranging from 0.031% at the 10th quantile to 0.146% at the 90th quantile. The ecological degradation caused by the NR is primarily driven by energy extraction in the region. This underscores the need for structural diversification into sectors that rely more on renewable energy sources. As the results suggest, medium- and high-tech industries offer SSA economies a sustainable way to strike a balance between their growing economic needs and ecological demands.

TABLE 5 Mix of natural resource basket (1000 bootstrap replications with DOF adjustment).

Variables	(1) Qtile_10	(2) qtile_20	(3) qtile_30	(4) qtile_40	(5) qtile_50	(6) qtile_60	(7) qtile_70	(8) qtile_80	(9) qtile_90
Panel A: Forest resources									
lnP	−0.646*** (0.040)	−0.641*** (0.036)	−0.638*** (0.035)	−0.633*** (0.034)	−0.629*** (0.033)	−0.623*** (0.035)	−0.619*** (0.037)	−0.614*** (0.043)	−0.607*** (0.045)
lnA	0.038 (0.043)	0.026 (0.038)	0.016 (0.037)	0.004 (0.034)	−0.008 (0.034)	−0.022 (0.037)	−0.035 (0.039)	−0.048 (0.044)	−0.066 (0.047)
lnNR-FR	0.038* (0.020)	0.031* (0.018)	0.025 (0.017)	0.018 (0.017)	0.011 (0.016)	0.002 (0.019)	−0.005 (0.020)	−0.012 (0.022)	−0.023 (0.024)
lnTTID	−0.018* (0.011)	−0.011 (0.011)	−0.005 (0.010)	0.002 (0.011)	0.009 (0.011)	0.017 (0.012)	0.024* (0.013)	0.031** (0.015)	0.042** (0.017)
Constant	10.103*** (0.537)	10.147*** (0.491)	10.180*** (0.458)	10.222*** (0.454)	10.263*** (0.437)	10.313*** (0.455)	10.357*** (0.472)	10.402*** (0.538)	10.467*** (0.590)
Panel B: Including mineral resources									
lnP	−0.652*** (0.040)	−0.647*** (0.037)	−0.643*** (0.034)	−0.638*** (0.033)	−0.634*** (0.033)	−0.628*** (0.036)	−0.623*** (0.036)	−0.617*** (0.042)	−0.610*** (0.046)
lnA	0.012 (0.041)	0.001 (0.035)	−0.008 (0.033)	−0.018 (0.033)	−0.028 (0.033)	−0.040 (0.036)	−0.051 (0.036)	−0.063 (0.042)	−0.078* (0.047)
lnNR-FMR	−0.000 (0.017)	−0.005 (0.016)	−0.009 (0.014)	−0.014 (0.015)	−0.019 (0.014)	−0.025 (0.016)	−0.030* (0.016)	−0.035** (0.018)	−0.042** (0.021)
lnTTID	−0.017 (0.012)	−0.010 (0.011)	−0.004 (0.010)	0.003 (0.010)	0.009 (0.011)	0.017 (0.012)	0.024* (0.013)	0.032** (0.014)	0.042** (0.016)
Constant	10.422*** (0.523)	10.447*** (0.497)	10.468*** (0.454)	10.493*** (0.445)	10.515*** (0.423)	10.545*** (0.459)	10.570*** (0.464)	10.598*** (0.538)	10.633*** (0.583)

(Continues)

TABLE 5 (Continued)

Variables	(1) Qtile_10	(2) qtile_20	(3) qtile_30	(4) qtile_40	(5) qtile_50	(6) qtile_60	(7) qtile_70	(8) qtile_80	(9) qtile_90
Panel C: Including coal, oil and natural gas									
lnP	−0.657*** (0.042)	−0.652*** (0.037)	−0.646*** (0.036)	−0.641*** (0.034)	−0.636*** (0.033)	−0.630*** (0.034)	−0.626*** (0.038)	−0.620*** (0.040)	−0.614*** (0.047)
lnA	0.010 (0.041)	−0.008 (0.036)	−0.025 (0.034)	−0.042 (0.033)	−0.057* (0.032)	−0.077** (0.033)	−0.092** (0.036)	−0.110*** (0.039)	−0.129*** (0.044)
lnNR-FER	−0.014 (0.015)	−0.031** (0.015)	−0.047*** (0.014)	−0.063*** (0.014)	−0.078*** (0.015)	−0.097*** (0.016)	−0.111*** (0.017)	−0.128*** (0.017)	−0.146*** (0.020)
lnTTID	−0.008 (0.013)	−0.003 (0.011)	0.001 (0.011)	0.006 (0.010)	0.010 (0.011)	0.016 (0.011)	0.020* (0.012)	0.025* (0.013)	0.030** (0.015)
Constant	10.520*** (0.564)	10.614*** (0.499)	10.703*** (0.477)	10.795*** (0.443)	10.880*** (0.429)	10.987*** (0.427)	11.067*** (0.472)	11.161*** (0.491)	11.267*** (0.572)
Observations	840	840	840	840	840	840	840	840	840

Note: Standard errors are in parentheses.
*** $p < .01$; ** $p < .05$; * $p < .1$.

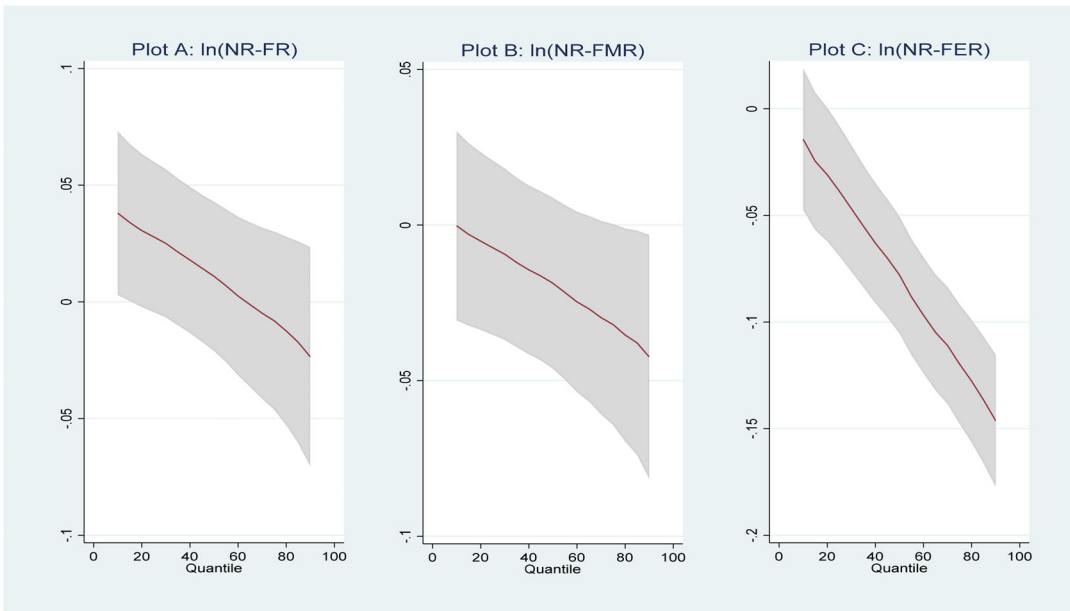


FIGURE 4 Quantile plots (disaggregated analysis). [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jrde.13161)]

4.2 | Robustness test

The Half-Panel Jackknife (HPJ) Wald-type test, developed by Juodis et al. (2021), is employed to enhance the robustness of the empirical findings. This technique demonstrates superior size and power performance compared to other similar methods found in the literature and is capable of estimating multivariate and heterogeneous panel data models (Xiao et al., 2023). By utilizing the bootstrap variance option, which accounts for cross-sectional dependence, the Wald test algorithm is used to determine the presence of Granger causality. It employs the bias-corrected pooled estimator to elucidate how selected covariates influence the equation, utilizing cross-sectional heteroskedasticity-robust standard errors. The results are presented in Table 6, with a summarized visualization in Figure 5.

Columns (1) to (4) of the specifications examine whether P, A, NR, and TID Granger cause LCF. The HPJ Wald statistic is statistically significant in these specifications, rejecting the null hypothesis that the covariates do not Granger-cause LCF in SSA. Furthermore, the regression output of the bias-corrected pooled estimator in Panel B indicates that the test outcome of the multivariate equation is significantly influenced by past values of NR and TID. The coefficient estimates suggest that technology-driven industrial diversification has a positive effect on LCF in the region. The estimates for NR-FR and NR-FMR are both found to be insignificant. However, when oil, coal, and natural gas are introduced into the resource mix (as shown in column 4), a significant coefficient estimate emerges. This implies that the ecological load of natural resource extraction in the region is significantly influenced by fossil energy extraction. Another noteworthy finding is the bidirectional positive relationship between natural resources and affluence (as observed in columns 6 and 7). As illustrated in Figure 5, diversifying the region's industrial output capacity through medium- and high-tech industries is a critical step toward sustaining the ecological load capacity of the region.

TABLE 6 JKS multivariate non-causality test.

Equations	(1) lnLCF	(2) lnLCF	(3) lnLCF	(4) lnLCF	(5) lnP	(6) lnA	(7) lnNR-TR	(8) lnTID
Panel A: Non-causality test								
HPJ Wald test	13.687***	12.893**	13.032**	11.502**	4.697	9.530**	22.294***	4.458
p-Value	.008	.012	.011	.022	.320	.049	.000	.348
Panel B: Panel Jackknife estimates of Selected covariates								
lnP	−0.009 (0.097)	−0.005 (0.097)	−0.014 (0.100)	−0.006 (0.094)		0.015 (0.040)	−0.204 (0.175)	−0.194 (0.140)
lnA	−0.102 (0.102)	−0.106 (0.108)	−0.105 (0.104)	−0.109 (0.105)	0.007 (0.011)		0.266* (0.147)	0.047 (0.242)
lnNR-TR	−0.038*** (0.014)				0.002 (0.002)	0.021* (0.011)		−0.029 (0.088)
lnNR-FR		−0.014 (0.017)						
lnNR-FMR			−0.026 (0.018)					
lnNR-FER				−0.036* (0.014)				
lnTID	0.014** (0.007)	0.016** (0.008)	0.015* (0.008)	0.015** (0.008)	−0.001 (0.002)	−0.007 (0.012)	0.002 (0.057)	
lnLCF					−0.004 (0.014)	−0.026 (0.039)	−0.432** (0.169)	−0.295 (0.195)
Number of ID	28	28	28	28	28	28	28	28

Note: H_0 : Selected covariates do not Granger-cause; H_1 : H_0 is violated; Standard errors in parentheses.

*** $p < .01$; ** $p < .05$; * $p < .1$.

5 | CONCLUSION AND POLICY REMARKS

5.1 | Conclusion and policy implications

This study examines the ecological impact of natural resource wealth and industrial diversification in a selection of SSA countries, with a particular focus on the role of medium- and high-technology industries. It utilizes the ecological load capacity factor (LCF), relying on a panel dataset spanning from 1991 to 2020, and the novel method of moments quantile regression technique, along with the bootstrap variance procedure. Considering the distinct impacts associated with the various baskets of natural resources, the findings show that forest resources, which form the baseline basket, improve LCF at lower quantiles, while adjusted baskets that include mineral resources and oil, coal, and natural gas reduce LCF at various quantile distributions. Specifically, the extraction of mineral resources induces a reduction in LCF in the upper quantile, while the combination of oil, coal, and natural gas reduces LCF in the upper, middle, and lower quantiles. Therefore, this study concludes that economic reliance on non-renewable

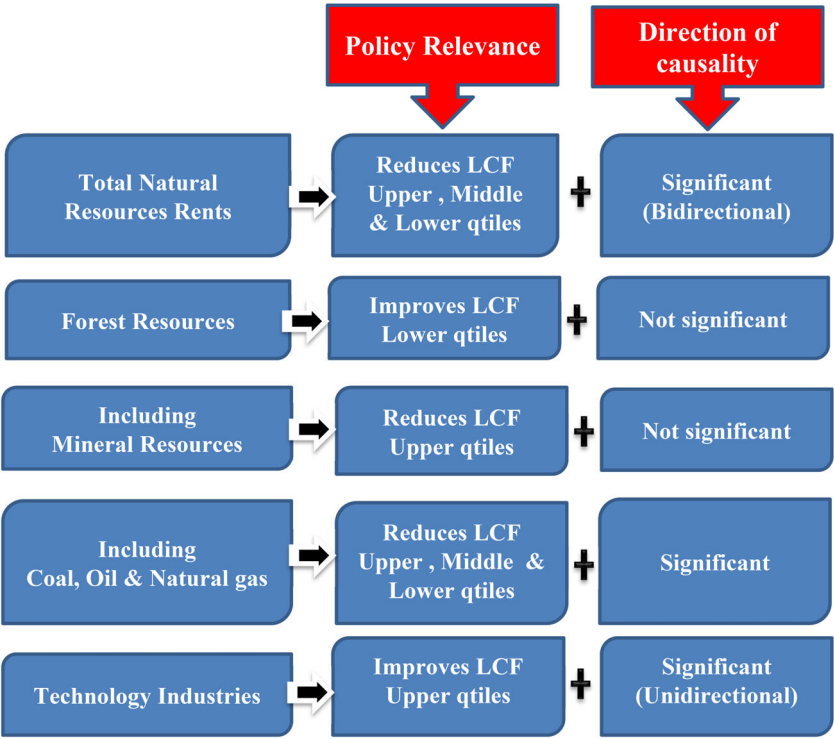


FIGURE 5 Summary of findings. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jrde.13161)]

resources lowers LCF. Furthermore, the results reveal that technology industries exert a significant positive impact on LCF at both the median quantile and the upper quantiles. However, statistical significance is only observed at the 80th and 90th quantiles. Consequently, this study concludes that technology-driven industrial diversification has a significant positive impact on LCF.

Additionally, to confirm the robustness of the empirical findings, this study implements a multivariate Granger causality technique in heterogeneous panels. The findings show that under a multivariate system, the joint predictive power of the impact model is significantly influenced by natural resource extraction and technology-driven industrial diversification. The bias-corrected pooled estimator reaffirms that, on average, technology-driven industrial diversification has a positive effect on LCF in the region. Furthermore, a bidirectional causal relationship exists between LCF and natural resource extraction, and unidirectional causality exists from technology-driven industrial diversification to LCF. In conclusion, the findings demonstrate that while economic dependence on natural resources dampens LCF, technologically driven industrial diversification has the ability to reduce the reliance on the exploitation of the ecological environment and, implicitly, offers the means of achieving environmental sustainability in SSA.

Regarding policy implications, the findings have at least two policy ramifications that could improve ecological sustainability in SSA. First, the findings show that natural resources lower the ecological load capacity factor. More so, the effect of natural resources on ecological sustainability improves with forest resources and deteriorates with mineral and energy extraction. Therefore, adopting sustainable habits, encouraging conservation efforts such as afforestation,

shifting toward the use of renewable energy sources, and passing and enforcing laws that control the wise use of natural resources will ensure ecological sustainability.

Second, the findings stipulate that technology industries exhibit a significant positive impact on the ecological load capacity factor at both the median quantile and the upper quantiles in the analysis. This highlights the possibility of economic diversification into medium- and high-tech sectors as a possible avenue for improving ecological resilience and maintaining load capacity, especially in the face of sustainability constraints caused by natural resource dependence. High-tech firms develop and invest in renewable energy sources that produce energy with fewer carbon emissions, thereby ensuring ecological sustainability. In this light, policymakers are invited to leverage the technological path to produce environmentally friendly and biodegradable materials that can replace conventionally dangerous compounds that degrade the environment.

That is, as countries develop economically with a growth strategy that is primarily dependent on natural resources, they place greater pressure on their ecological load capacity, which further restricts the growth of eco-efficient industries. Natural resources are abundant in SSA, and they have historically contributed significantly to the economies of many of the countries in the region. However, the reliance on natural resources for economic expansion is no longer sustainable. Moreover, the results show that the effect of natural resources on ecological sustainability improves with forest resources and deteriorates with mineral and energy extraction. This is understandable because large-scale forests can be found in SSA, where they serve as a habitat for a variety of animals and help regulate the climate. Therefore, adopting sustainable habits, encouraging conservation efforts such as afforestation, shifting toward the use of renewable energy sources, and passing and enforcing laws that control the wise use of natural resources will ensure ecological sustainability.

Second, the findings stipulate that technology industries exhibit a significant positive impact on the ecological load capacity factor at both the median quantile and the upper quantiles in the analysis. This highlights the possibility of economic diversification into medium- and high-tech sectors as a possible avenue for improving ecological resilience and maintaining load capacity, especially in the face of sustainability constraints caused by natural resource dependence. High-tech firms develop and invest in renewable energy sources that produce energy with fewer carbon emissions, thereby ensuring ecological sustainability. Moreover, they inherently impose lower demands on the ecological environment than traditional sectors such as mining and energy exploration. In this light, policymakers are invited to leverage the technological path to produce environmentally friendly and biodegradable materials that can replace conventionally dangerous compounds that degrade the environment.

5.2 | Limitations and directions for future research

Although this present analysis offers useful insights into the topic, its scope is restricted because it exclusively concentrates on SSA, which may limit the generalizability of the findings to other regions or countries with different economic structures, resource endowments, and industrial development trajectories. Expanding the geographical scope of the analysis could enhance the broader applicability of the results. Second, the study period is limited to 1991 to 2020, which may not fully capture long-term trends and dynamics in the relationships among natural wealth, industrial diversification, and ecological sustainability. Extending the analysis to include a longer time frame could provide a more comprehensive understanding of these

complex interactions. The use of LCF as a proxy for ecological sustainability, while widely accepted, may not capture the full complexity of environmental impacts. Incorporating additional indicators of ecosystem health, biodiversity, or resource depletion could provide a more nuanced assessment of the ecological implications of natural wealth and industrial diversification. Finally, complementing the current approach with other econometric techniques or qualitative methods could further strengthen the robustness of the findings and deepen the understanding of the underlying mechanisms involved.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data used for this study are from open access databases and freely available online: 2023 National Footprint and Biocapacity Accounts, *Global Footprint Network*. Available online: <https://data.footprintnetwork.org/>; WDI available at <https://databank.worldbank.org/source/world-development-indicators>; SDG Tracker: <https://ourworldindata.org/grapher/total-manufacturing-value-added-from-high-tech>.

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