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South African Insights on the Validity of the Environmental Kuznets Curve using Economic Complexity and Environmental Degradation: The Role of ICT Development

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ABSTRACT

This study aims to assess the effect of economic complexity (EC) on environmental degradation and evaluate the applicability of the Environmental Kuznets Curve in the South African context between 2000 and 2025. The study also examines the interaction effect of Information and Communication Technology (ICT) development. This analysis uses the ARDL estimation technique. The results reveal an inverted U-shaped relationship between EC and environmental degradation in the long run. The turning point occurs at a complexity index of 1.262, which lies within the EC data range (−2.8–1.274). In contrast, short-run estimates indicate a monotonic positive relationship, with the implied turning point of 1.53 lying outside the observed data range. This indicates that EC initially exacerbates environmental degradation. However, once EC exceeds 1.262, the economy's structure appears to favour fewer polluting activities. The results also indicate that ICT development in South Africa erases the detrimental effect of EC in the long run. Furthermore, the results show that human capital and renewable energy reduce environmental degradation in the long run in South Africa. The results offer policy implications for policymakers and the government to promote environmental sustainability.

Keywords: Environmental Degradation, Economic Complexity, ICT Development, Kuznets Curve, Interaction Terms, South Africa
JEL Classifications: C22, O44, Q53, Q56

1. INTRODUCTION

The environmental Kuznets curve (EKC) is a significant hypothesis that guides environmental policy in any economy, and its updating is essential for growth and environmental policy. Previously, the EKC has been tested using conventional measures of growth, such as Gross Domestic Product (GDP) or GDP per capita (Tenaw and Beyene, 2021; Xing et al., 2023). However, in the current era, the growth of any economy is determined by the diversity, sophistication, and ubiquity of its economic structure. Thus, EC predicts an economy's long-term growth, resilience, and ability to generate quality employment (Maulidar et al., 2025)

Furthermore, Can and Gozgor (2017), Doğan et al. (2019) and Neagu and Teodoru (2019) suggest that EC is a robust index of economic prosperity that encompasses knowledge and skill upgrades, product diversity, and ubiquity. In line with this, the COP26 summit in Glasgow in 2021 reinforced global commitments to reduce environmental degradation, particularly greenhouse gas emissions, and to promote a structural transition toward sustainable economies (United Nations Framework Convention on Climate Change [UNFCCC], 2022). Hence, achieving these goals requires understanding how changes in EC affect the environment. Therefore, a reassessment of the EKC hypothesis using EC is imperative, as it determines the relationship between an economy's complex structure, productive knowledge, and its environmental

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trajectory. Indeed, an analysis of the EKC using EC determines whether the economy can expect environmental improvements to occur naturally as it becomes more complex, or whether it is not on a path to permanent ecological damage.

As most studies on EKC have concentrated on cross-country analysis, this study aims to evaluate the EKC in the context of South Africa. This follows South Africa's ranking among the 11th- to 14th-largest carbon and greenhouse gas emitters globally and the largest in Africa, contributing 1.1% of total worldwide emissions (Worldometer, 2026). Again, the country accounts for over 40% of the continent's total carbon emissions (Energy Council of South Africa, 2025). Subsequently, South Africa's per capita emissions are relatively high due to a historic reliance on coal as its primary energy source (Cassim et al., 2004; Yongli, 2019).

The Growth Lab at Harvard University (2026) and Observatory of Economic Complexity (OEC) (2026) rank South Africa between 58th and 77th globally on the Economic Complexity Index (ECI), which measures the diversity and technological sophistication of a country's exports. Specifically, the OCE ranks South Africa 60th out of 130, 24th out of 97, and 22nd out of 138 and 47Th out of 172 countries for trade, technology, research, and software complexities, with EC scores of 0.01 (2024), 0.93(2021), 1.23 (2024) and 0.49 (2025), respectively.

Compared to a decade earlier, South Africa's economy has become less complex, dropping nine positions in the EC ranking (Olaniyi and Odhiambo, 2025). South Africa's worsening complexity has been driven by a lack of export diversification (Ncanywa, 2024) This structural stalling highlights a unique empirical paradox. While the conventional EKC hypothesis assumes a steady forward movement toward economic sophistication, assessing the curvilinear effects reveals how a stagnating or retreating structural transformation imprints onto the country's ecological blueprint. Again, this decline in productive sophistication underscores the urgency of this analysis, as it allows policymakers and the government to determine whether South Africa's low-performing complexity traps it on the carbon-intensive side of the pollution peak. Moreover, this stagnation suggests that productive sophistication alone may not be sufficient to flatten the EKC. It therefore warrants examining whether complementary capabilities, such as Information and Communication Technology (ICT) development, can moderate this relationship and help flatten the environmental trajectory even when structural transformation is hindered.

ICT development in South Africa has seen significant improvements in mobile phone and internet usage, as well as broadband subscriptions, since 2000 (GSMA, 2026). Subsequently, over 92% of households own a working mobile cellular, and about 73% of these subscriptions are smartphones (Kemp, 2026), making cell phones the primary tool for accessing the digital economy. Again, internet penetration has reached 76% of the population, representing 51.7 million users. ICT, in terms of fixed broadband subscriptions, skyrocketed from 1.4 million in 2023 to 2.7 million in 2024, representing a more than 4,200% increase in fibre adoption (GSMA, 2026). As ICT continue to advance in South Africa, assessing its moderating role on the impact of EC on environmental depletion is crucial given its capacity to catalyse structural transformation, which in turn drives sustainable production and mitigates overall environmental impacts

The empirical literature on the effect of EC on environmental degradation is centred on cross-country and panel data analyses, including global and regional studies of developed and developing economies, primarily the BRICS, African, and Asian economies. Again, studies examining the Environment Kuznets Curve have relied on conventional growth measures such as GDP per capita or GDP, which offer a limited perspective on economic development by capturing the volume of economic activity without reflecting the underlying structural composition and technological capabilities highlighted by economic complexity. Moreover, empirical literature has focused on the direct effects of EC on environmental degradation, overlooking the role of complementary factors, such as human capital and ever-changing technological advancement, in the ECI_environmental degradation nexus.

The current paper contributes to the existing literature in threefold. First, the study substitutes the traditional GDP proxy with EC to examine the EKC hypothesis and assess the effect of productive sophistication across different developmental stages. Assessing the EKC hypothesis using EC addresses the hollow nature of GDP by shifting the focus from the volume of economic activity to the quality and sophistication of South Africa's industrial output. Moreover, identifying the turning point allows policymakers and governments to anticipate when capital surpluses for investing in green technologies will occur. Second, while cross-country and panel studies, such as the BRICS, SADC, and Sub-Saharan Africa, include South Africa, they fail to account for the country's unique energy-intensive mineral-energy complex. This study provides an empirical examination of the environmental degradation effects of EC, while evaluating the moderating impact of ICT development within the South African context. Thus, a specific study within the context of South Africa allows interpretation of the EKC results through the lens of local South African policies such as the Just Energy Transition Implementation Plan (JET IP), which aims to transition the economy from fossil fuels to cleaner energies and accelerate decarbonisation of key economic sectors (Just Energy Transition [JET], 2025).

The subsequent section presents the literature review. The third section delineates the data and methodology used in this study. The third section presents empirical results, and the last section concludes the paper.

2. LITERATURE REVIEW

The relationship between EC and environmental degradation is grounded in the EKC framework, which stems from Kuznets's (1955) hypothesis linking income inequality and economic growth. Subsequently, the environmental aspect was incorporated, following Grossman and Krueger (1994), who found a similar inverted-U-shaped relationship between environmental pollution and economic growth. The EKC hypothesises that economic development initially worsens environmental degradation until it reaches a threshold at which it reduces pollution or environmental

degradation, probably due to technological efficiency and environmental awareness (Grossman and Krueger, 1994; 1996). Consistently, Kearsley and Riddel (2010) and Soumyananda (2010) indicate that the early stages of development are concentrated in agrarian production, which has little detrimental impact on the environment. However, as economies undergo structural changes, countries shift toward industry-based manufacturing processes, in which fossil fuel consumption increases due to intensive production (Soumyananda, 2010). This eventually damages the environment. Nonetheless, once economies reach a threshold level of income, they shift their production systems toward technology-based production. Therefore, the reallocation of factors of production from traditional to modern sectors minimises carbon emissions by facilitating the adoption of green technologies and sustainable production processes. Thus, the main argument is that as economies move toward more modern, sophisticated productive processes, such as the introduction of cleaner energy sources, environmental damage is minimised.

This study also considers the moderating role of ICT development on the economic complexity-environmental degradation nexus, based on technology development theory. The Technology Development Theory suggests that technology modalities, such as ICT development, serve as digital infrastructure that accelerates, connects, and optimises complex networks (Schumpeter, 1934; Hidalgo and Hausmann, 2009). ICT also enhances energy and resource productivity, allowing complex economies to lower the pollution intensity of their manufacturing (Khan and Ximei, 2022). Again, technology development shifts productive structure away from resource extractive, hardware-heavy manufacturing toward high complexity, weightless digital services, virtual business networks and knowledge economies such as e-commerce, which decouples economic sophistication from physical resource depletion (Khan and Ximei, 2022).

2.1. Empirical Literature

Studies that validate the environmental Kuznets curve hypothesis have focused on conventional development indicators (Doğan et al., 2019; Adedoyin et al., 2021; Ahmad et al., 2021; Boleti et al., 2021; Martins et al., 2021; Adebayo et al., 2022), often treating EC as a direct effect. However, incorporating EC into EKC validation is increasingly prevalent. Thus, empirical evidence has confirmed this relationship across several economic groupings and regions, notably within emerging economies (Ahmad et al., 2021), E7 (Chu et al., 2023), G7 (Khan et al., 2022), OECD (Wang et al., 2023) and energy-importing countries (Naimoğlu and Akal, 2024). Again, the hypothesis holds true in the global analysis of the environmental impacts of EC across 119 countries (Adedoyin et al., 2021). Nonetheless, the fluctuating effects of EC have been documented in Portugal, Ireland, Italy, Greece and Spain (PIIGS), BRICS and European emerging economies (Agozie et al., 2022; Marco et al., 2022; Balsalobre-Lorente et al., 2023). These studies document evidence of both inverted U-shaped and N-shaped EKC, confirming that EC first increases environmental degradation, then reduces it as it increases, and then increases it again.

Empirical literature indicates that EC exacerbates environmental degradation in countries with high economic complexity. For example (Abbasi et al., 2021), Adebayo et al. (2022), Martins et al. (2021) and Rafique et al. (2022) utilised cross-sectional ARDL (CS-ARDL), generalised methods of moments (GMM) and Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) methods to assess the impact of EC on environmental degradation in top EC countries, indicating that sophisticated productive structures worsen carbon emissions and ecological footprint between 1980 and 2019. While these studies (Martins et al., 2021; Adebayo et al., 2022) confirm the EKC effect using a GDP measure, none of the studies validates the EKC using economic complexity. These outcomes are also supported by Ren et al. (2025), who document a stronger positive effect of EC on carbon emissions in countries with high EC than in those with low EC between 2001 and 2019.

Again, in more advanced economies such as G-7 countries, studies show that moving toward sophisticated production yields mixed environmental effects. For example, using ecological footprint as an indicator for environmental quality, the FMOLS and DOLS analyses by Khan et al. (2022) substantiate an inverted-U-shaped EKC between 1996 and 2019, in which EC initially increases the ecological footprint but then reduces it after reaching a certain threshold. Again, Khan and Ximei (2022) indicate that EC and ICT-exports intensify the ecological footprint from 2001 to 2018. Nevertheless, when using carbon footprint and carbon emissions, Murshed et al. (2022) reveals that EC mitigated these metrics in 1995 and 2016.

In OECD economies, studies indicate that the environmental effects of EC depend strongly on internal developments. Thus, using the FMOLS estimation technique, (Majeed et al., 2022) validated the inverted-U-shaped EKC, confirming that sophisticated production increases carbon emissions, particularly in countries with low carbon emissions. Again, the fixed-effects analysis of Aluko et al. (2023) suggests that EC intensifies environmental damage when incomes are low but reduces it as economies grow. Moreover, Wang et al. (2023) reveals with the STIRPAT model that EC effectively reduces the ecological footprint only after an economy increases its renewable energy consumption to above 44.6% and its human capital score to above 2.60. At the same time, Şanlı and Gülbay Yiğiteli (2024) indicates with the asymmetric analysis that sophisticated production structures exert less environmental pollution than traditional production modes.

Regardless of the utilisation of different estimation techniques such as CS-ARDL and quantile regression, the empirical literature in emerging economies is in consensus that EC is a primary driver of environmental outcomes, with most works confirming a non-linear relationship. Thus, Ahmad et al. (2021), Chu et al. (2023) and Naimoğlu and Akal, (2024) suggest that the initial stages of sophisticated production worsen the ecological footprint and carbon emissions, and the advanced stages help reduce them. Again, Ahmad et al. (2021), suggest that EC in emerging economies requires institutional quality to act as a catalyst for environmental stability. However, Balsalobre-Lorente et al. (2023) report that EC acts as a shield against pollution caused by increasing globalisation, yet the relationship exhibits an N-shaped pattern. At the same time, Kazemzadeh et al. (2023)

highlights a contrast: fixed-effects models suggest that EC worsens environmental pressure, whereas quantile regression indicates that EC generally reduces ecological footprint across most emission levels between 2000 and 2016.

The global empirical literature on the effects of EC and environmental degradation remains inconclusive. However, a common finding across several studies is that the environmental impacts of EC vary with levels of development. For example, quantile regression and GMM analyses by Doğan et al. (2019) and Adedoyin et al. (2021) suggest that EC worsens carbon emissions in low- and middle-income economies, whereas it enhances environmental performance in high-income economies. Consistently, Bucher et al. (2023)and Ashraf (2024) suggest that EC worsens environmental degradation in the short run. Furthermore, studies (Ashraf, 2024; Dada et al., 2025; Ren et al., 2025) indicate that the detrimental environmental effects of EC can be mitigated by complementary factors such as political stability, human capital, and energy efficiency. Nevertheless, in African economies, Dada et al. (2025) find that different types of globalisation, including social and economic globalisation, exacerbate the detrimental effects of EC on environmental degradation, whereas political globalisation enhances the positive effects of EC on the environment.

Empirical studies are in consensus that EC does not act alone. Thus, its environmental impact depends on other structural factors. Nevertheless, studies that analysed the effect of complementary factors on the environmental degradation and EC nexus most emphasised the moderating effects of institutional quality (Ahmad et al., 2021) globalization (Dada et al., 2025), income level (Ahmed et al., 2022; Aluko et al., 2023; Alsabhan and Tahir, 2024), energy consumption structure (Wang et al., 2023) and urbanisation (Agozie et al., 2022; Balsalobre-Lorente et al., 2022) while the moderating effect of human capital remains limited to OECD and Belt and Road Initiative (BRI) countries (Wang et al., 2023; Ashraf, 2024). These studies advocate that human capital mitigates the adverse impacts of EC on ecological footprint.

Studies on the moderating effect of ICT development on the economic complexity-environmental degradation nexus are still limited, as most studies focus on its direct effects on the environment. A notable study on the interaction effect of ICT and economic growth in Vietnam indicates that ICT reduces the long-run environmental impact of growth. More so, Dada (2025) indicates that ICT reduces the positive effect of the informal economy on environmental degradation. Indeed, studies that assess the direct effects of ICT and technological development on the environment indicate that ICT reduces environmental degradation and pollution (Khan and Ximei, 2022; Kazemzadeh et al., 2023; Wang et al., 2023; Sadaoui et al., 2025)

Even though the effects of EC on environmental degradation are limited in the context of South Africa, insights can be drawn from studies that include South Africa as part of broader analyses across the G20 and BRICS countries and in the global context. Thus, Sun et al. (2025) examined the roles of renewable energy, ECI, fintech, green finance, green growth, and economic performance in G20 economies amid sustainability efforts, using the Method of Moments Quantile Regression (MMQR) between 2000 and 2021. The results suggest that ECI, Green growth, and Fintech reduce the ecological footprint over 4 quantiles. However, renewable energy, natural resources and governance significantly enhance the ecological footprint. South Africa was also incorporated into the multi-country panel analysis by examining the relationship between global EC, environmental degradation, energy consumption and sustainable development across 119 countries between 1995 and 2026, using the system GMM estimator (Adedoyin et al., 2021). The results suggest that EC increases carbon emissions among low-income groups, while significantly decreasing emissions in upper-middle- and high-income groups. However, for the combined group, the EKC was validated, and ECI significantly lowers carbon emissions. The study also indicates that GDP worsens emissions across all income groups.

Furthermore, the empirical literature on BRICS economies, in which South Africa is a member, yields conflicting results on the effect of EC on the environment. Agozie et al. (2022) confirms non-linear and fluctuating effects, documenting evidence of inverted-U-shaped and N-shaped environmental Kuznets relationships between ECI and carbon emissions, and of detrimental effects when ECI interacts with urbanisation. In contrast, Adebayo (2023) argues that EC benefits ecological quality, whereas traditional growth reduces it. At the same time, Alsabhan and Tahir (2024) argue that EC degrades environmental quality. Nonetheless, the studies are in consensus that the implications of EC are shaped by other intervening variables. Thus, its influence on the environment is contingent upon other structural factors such as urbanisation and income levels (Agozie et al. 2022; Alsabhan and Tahir, 2024). These discrepancies in the results might be driven by the choice of estimation techniques (2SLS for endogeneity; AMG for cross-sectional dependence) and by the measurement of environmental quality (load capacity factor; carbon emissions).

In the specific context of South Africa, the EKC has been confirmed using the traditional production-based measure, economic growth. Again, there are limited studies on the environmental impacts of economic complexity, and none have validated the EKC from this lens. A notable study that evaluated the effect of EC on environmental degradation in South Africa, Udeagha and Muchapondwa (2022) examined the moderating effect of economic policy uncertainty on the EKC using an ARDL model from 1960 to 2020. The study examined the effect of EC, yet the validity of the EKC was not tested with a sophisticated measure of production. The study indicated that environmental quality is deteriorated by energy intensity, economic complexity, non-renewable energy use, and trade openness. The study suggests that the use of renewable energy and technological innovation improves environmental quality. Also, the interaction between ECI and economic policy uncertainty improves environmental quality.

Even though the EKC has been widely tested, the literature remains limited in three respects. First, most theoretical and empirical studies have relied on conventional measures of economic development, particularly GDP per capita, to examine the relationship between EC and environmental degradation. This

provides a limited insight into how the structure of production affects environmental outcomes. By utilising EC as an alternative measure of development, the current study offers a different perspective on the EKC hypothesis, capturing an economy's knowledge intensity and diversification. Second. While recent studies have begun to explore the direct effects of EC in ENVD, there is scant evidence on the possibility of a curvilinear relationship, and even less on factors that may condition this nexus, particularly in developing economies. Third, much of the existing empirical literature is derived from cross-country and regional panel analyses. Such analysis, while useful, often obscures country-specific trajectories. This paper contributes by focusing on South Africa as a single country case, thereby providing evidence grounded in the country's unique structural and environmental context. Based on these gaps, this study formulates the following hypotheses:

- H_1: EC escalates environmental degradation in the early stages in South Africa, while mitigating it as complexity advances.
- H_2: The effect of EC on environmental degradation in South Africa is moderated by ICT development.

3. DATA AND METHODOLOGY

The study utilised time-series data to assess the EKC hypothesis in South Africa using EC between 2000 and 2025. The EC data were obtained from the Observatory of Economic Complexity (OEC) database. The study derives the EC index from the two EC sub-indices, technology complexity (ectech) and trade complexity (ectrd), using principal component analysis (PCA). The study employs the KMO, Bartlett's test of sphericity (Tobias and Carlson, 1969; Nkansah, 2018), and the explained and unexplained variances to assess whether each constituent qualifies for inclusion in the single index. In this study, environmental degradation is proxied by per capita carbon emissions, which are considered the most significant contributor to environmental degradation due to their role in global warming since the Industrial Revolution, as recommended by the Intergovernmental Panel on Climate Change (IPCC) (World Meteorological Organization [WMO], 1988). The data for carbon emissions were obtained from the Global Economy database. Based on the empirical literature, the study includes ICT development as the moderating variable and renewable energy consumption, human capital as control variables. The data for the explanatory variables were retrieved from the Global Economy database, World Penn Tables 11.0, and IEA Energy Statistics Database.

3.1. Model Specification

The current paper adopts the model of Ahmed et al. (2022) which analysed the effect of EC on environmental degradation, measured by the ecological footprint, with the moderating effect of economic growth in India between 1970 and 2011. The model is expressed as:

$$EF_t=\sigma_0+\delta_1 G_t+\delta_2 EI_t+\delta_3 POP_t+\delta_4 ECP_t+\delta_5 INT_t+\delta_6 FD_t+\mu_t \quad (1)$$

where:

EF represents ecological footprint, G denotes economic growth measured by GDP 2010 constant US dollars per capita form, EI is energy intensity measured by energy consumption per unit of GDP in per capita, POP represents population growth, ECP is economic complexity, FD represents financial development measured by domestic credit to private sector as a percentage of GDP, INT denotes the interaction term of EC with economic growth, u is the disturbance term. Although the study examined the effects of EC on the environment, it focused only on its linear effect and the moderating effect of economic growth. The current study extends the above model by accounting for the curvilinear relationship between EC and environmental degradation in South Africa. That is to examine the effects of the developmental stages of the sophisticated production structure on environmental degradation. Following Ahmed, the current study also considers the moderating effect of ICT development, as ICT is the primary driver of cleaner environmental technologies. Also, the study considers human capital as one of the explanatory variables, as it has been recognised as a key factor for cleaner production skills. Again, renewable energy consumption is considered the renewable energy variable, in line with South Africa's Just Energy Transition Partnership (JETP) (JET, 2025) commitments to accelerate the shift toward cleaner energy sources. Following the model of the current study takes the form:

$$lenvd_t=\alpha_0+\gamma_1 lec_t+\gamma_2 lec_t^2+\gamma_3 lict_t+\gamma_4(lec*ict)_t+\gamma_5 lhuc_t +\gamma_6 lrecn_t+\varepsilon_t \quad (2)$$

where:

$lenvd_t$ represents the log environmental degradation at time t, measured by carbon dioxide emissions per capita (*C02pc)*. To facilitate interpretation as elasticities or percentage changes, all variables are log-transformed (*l*). *lec* represents the EC, which encompasses knowledge and skill upgrades, product diversity, and ubiquity (Can and Gozgor, 2017; Neagu and Teodoru, 2019). The EC is proxied by ECI, which is generated from two sub-indices: economic complexity in trade (ectrd) and in technology(ectech). The PCA shows that the ECI was appropriate as indicated by a significant Bartlett test of sphericity (Chi^2 = 16.893, P = 0.000) (Appendix 4), consistent with the guidelines of Tobias and Carlson (1969), and a high intervariable correlation of 0.858 (Appendix 3). The principal components accounted for 85.8% of the total variance. Again, both variables loaded positively and equally on the first component with a loading of 0.7071. Even if the KMO measure was 0.50, this is typical for a two-variable PCA. lec_t^2 represents the quadratic term of economic complexity, which captures the non-linear effect of EC on environmental degradation. The turning point of this quadratic specification is derived by setting the first derivative of the dependent variable with respect to *lec* equal to zero:

$$\frac{\partial lenvd}{\partial lec}=\gamma_2+\gamma_3 ec_t^2=0 \quad (3)$$

Therefore, the vertex is expressed as:

$$-\frac{\gamma_2}{2\gamma_3} \quad (4)$$

Hence, the relationship is U-shaped if the coefficient on EC is negative and the coefficient on its square is positive. Conversely, it is inverted U-shaped if the coefficient on EC is positive and that

on its square is negative (Pham et al., 2024). As the variables are in log form, the quadratic coefficients represent elasticities. To interpret the turning point in its natural units, the vertex in logs is transformed back to levels by using the exponential transformation, calculated as:

$$ec_{tp} = exp^{ec_{tp}} \quad (5)$$

where:
exp denotes the exponential function with the base $e = 2.718828$ and *tp* represents a turning point in logs. This step is needed to revert the logarithmic transformation, since the exponential function is the inverse of the log function (Wooldridge, 2020).

lict is Information and Communication Technology which captures technology development, it is proxied by the ICT index derived from three indicators, including mobile phone usage (mcs), internet usage (itu), and fixed broadband subscriptions (fbs). The suitability of PCA was validated by the KMO measure of sampling adequacy of 0.780 and a significant Bartlett test of sphericity ($Chi^2 = 96.439$, $P = 0.000$) (Appendix 4). Also, the first principal component had an eigenvalue of 2.849 and explained by 94.97% of the total cumulative variance (Appendix 3). All three variables loaded positively and above 0.50 on the first component (Appendix 3), indicating that they contribute significantly to the index. $lec*ict_t$ is the interaction term between and the moderating variable ICT. Hence, the effect of EC on environmental degradation, conditional on ICT, is derived as:

$$\frac{\partial lenvd}{\partial lec} = \gamma_2 + \gamma_4 ict \quad (6)$$

Thus, the parameters γ_3 and γ_4 signifies the direct and interaction effects of economic complexity, respectively. *lhuc* is human capital which captures education or skill level. *recn* represents renewable energy consumption, which captures the share of clean energy,

3.2. Estimation Technique

According to Nelson and Plosser (1982), most time series are differenced-stationary processes; thus, using differenced variables in regression leads to a loss of relevant information about the equilibrium relationship between the variables. Nonetheless, cointegration estimators, such as the ARDL approach, reparameterise the non-stationary series into an Error Correction Model to capture the short-run dynamics and the long-run relationship of the underlying variables. Therefore, to assess both the short-run and the long-run relationship between EC and environmental degradation in South Africa, this study employs the autoregressive distributed lag (ARDL) estimation technique. This estimation technique is consistent and efficient for determining the long-run relationship between non-stationary series and series with different orders of integration (Shin et al., 2014; Nkoro and Kelvin, 2016). Furthermore, the ARDL approach allows for the selection of optimal lag orders and appropriate information criteria, thereby enhancing efficiency and consistency in small samples (Pahlavani et al., 2005; Nkoro and Kelvin, 2016).

The ARDL technique is a more statistically significant method for determining cointegration in small samples (Pahlavani et al., 2005). Therefore, utilising this estimator retains the relevant long-run information in the differenced variables via cointegration, thereby integrating short-run dynamics with long-run equilibrium (Shin et al., 2014; Kripfganz and Schneider, 2023). While other cointegration techniques require all regressors to be integrated of the same order, the ARDL can be applied whether the regressors are stationary in levels or in first differences. That is, whether the series are all unit-root or all stationary, or mixed. Indeed, ARDL allows for cointegration, which is a preferred approach for modelling meaningful relationships for forecasting and policy implementation. Therefore, the model for this study is expressed as:

$$\begin{aligned}\Delta lenvd_t = {} & \gamma_0 + \sum_{i=0}^{p}\gamma_{1i}\Delta lenvd_{t-i} + \sum_{i=0}^{q}\gamma_{2i}\Delta lec_{t-i} + \sum_{i=0}^{q}\gamma_{3i}lec^2_{t-i} \\ & + \sum_{i=0}^{p}\gamma_{4i}\Delta lict_{t-i} + \sum_{i=0}^{q}\gamma_5\Delta(lec*lict)_{t-i} + \sum_{i=0}^{q}\gamma_{6i}\Delta lhuc_{t-i} \\ & + \sum_{i=0}^{q}\gamma_{7i}lrecn_{t-i} + \varphi_1 lenvd_{t-1} + \varphi_2 lec_{t-i} + \varphi_3 lec^2_{t-1} \\ & + \varphi_5 lict_{t-1} + \varphi_6(lec*ict)_{t-1} + \varphi_4 lhuc_{t-1} + \delta_7 lrecn_{t-1} \quad (6)\end{aligned}$$

In which:
$\Delta lenvd$ represent the log of environmental degradation, $\Delta lenvd_{t-1}$ is the lagged variable of environmental degradation. Δ denotes the first difference operator, which calculates the change in a variable from one period to the previous period. γ_1–γ_7 represent the short-run coefficients, while ϕ_1–ϕ_7 are the long-run coefficients. *p* and *q* are the lag lengths of the explained and explanatory variables, respectively. *i* denotes the lag order and ε_t is the error term. The short-run relationship is estimated with an Error Correction Model (ECM) of the form:

$$\begin{aligned}\Delta lenvd_t = {} & \gamma_0 + \sum_{i=0}^{p}\gamma_{1i}\Delta lenvd_{t-i} + \sum_{i=0}^{q}\gamma_{2i}\Delta lec_{t-i} + \sum_{i=0}^{q}\gamma_{3i}ec^2_{t-i} \\ & + \sum_{i=0}^{q}\gamma_{4i}\Delta lict_{t-i} + \sum_{i=0}^{q}\gamma_{5i}\Delta(lec*lict)_{t-i} + \sum_{i=0}^{q}\gamma_{6i}\Delta lhuc_{t-i} \\ & + \sum_{i=0}^{q}\gamma_{7i}\Delta lrecn_{t-i} + \phi ECT_{t-1} + \varepsilon_t \quad (7)\end{aligned}$$

Where:
φ is the speed of adjustment, ECT_{t-1} is the error correction term. Table 1 outlines the definitions and sources for the variables under consideration.

In line with the literature summarised in Table 1, EC is expected to have a positive sign, while its square term (ec^2) is expected to have a negative sign, indicating an inverted U-shape. ICT, human capital, renewable energy consumption, and the interaction term between CE and ICT are all expected to have a negative effect on environmental degradation. The next section presents the empirical results.

Table 1: Definition and source of variables

Variable	Definition	Literature	Expected sign	Data source
envd	Environmental degradation is the deterioration of the environment through pollution and depletion of natural resources, making it less able to support life. It is measured by Carbon dioxide emissions per capita (C02pc)	Abbasi et al., 2021	Dependent variable	Global Economy Database (GED)
ec	Economic complexity is the measure of a country's productive knowledge, reflected in diversity and sophistication of the products it can make and exports. It is measured by the ECI, which is generated from two sub-indices: EC in trade and in technology, using PCA	Stojkoski et al., 2023	+	Authors calculation with data from GED
ec^2	Squared term of EC	Agozie et al., 2022	-	Author's calculations using data from GED
ict	ICT development index, generated from three ICT indicators, including fixed broadband subscription (%), internet usage (%) and mobile cellular usage per 100 people	Khan and Ximei, 2022; Kazemzadeh et al., 2023	-	Author's calculations using data from GED
huc	Human capital development proxied by average years of schooling and returns to education	Wang et al., 2023; Ashraf, 2024	-	Penn World Tables Version 11.0
recn	Renewable energy consumption (%total final energy consumption)	Udeagha and Muchapondwa, 2022	-	International Energy Agency (IEA) Energy Statistics Data
eci_ict	The interaction term of EC and ICT development	Dada et al., 2025	-	Author's calculations using data from GED

Source: Author

4. EMPIRICAL RESULTS

Given the relatively short sample period of <30 years, the Schwarz Information Criterion (SIC) is employed for lag selection, as it tends to select more parsimonious models and reduce overfitting (Kilian, 2001; Dougadir et al., 2026). Again, to preserve degrees of freedom, the maximum lag length is limited to 1. Moreover, the study's model is specified with a limited number of regressors to maintain model parsimony. The empirical results are presented in the following sequence: descriptive statistics to summarise the characteristics of the data, correlation coefficients, variation inflation factor to check multicollinearity, stationarity test to ensure appropriate model specification, bounds test for cointegration, the short and long run results, the diagnostic assess the model reliability and sensitivity results for robustness of the results. The following table presents the descriptive statistics for all variables considered.

Table 2 indicates that environmental degradation, as measured by carbon emissions per capita, averages 7.94, with a minimum of 5.75 and a maximum of 9.55 between 2000 and 2025. The EC and ICT indices may not reflect the actual averages of the EC and ICT variables; the summary statistics report descriptive statistics for individual constituents of each index. Table 2 shows that the average value of trade EC and technology complexity is 0.3 and 1.0, respectively, between 2000 and 2025. Trade complexity ranged from 0.05 to 0.47, while technology complexity ranged from 0.75 to 1.20 between 2000 and 2025. ICT development has been improving, particularly in mobile phone usage, with a mean of 113.9 and a range from 17.7/100 people in 2000 to 117.69 per 100 people in 2025. Also, internet usage averaged 39%, with a range of 5.35% to 76.5% between 2000 and 2025. However, the fixed broadband subscription rate is notably constrained, averaging 1.72% (minimum 0.01%, maximum 4.1%) between 2000 and 2025. The summary statistics indicate an average human capital of

Table 2: Descriptive statistics

Variable	Obs	Mean	Standard deviation	Min.	Max.
envd	26	7.943	1.012	5.75	9.550
ec	26	4.69e-09	1.310	−2.846	1.274
ectrd	26	0.269	0.1310	0.0513	0.473
ectech	26	1.039	0.121	0.754	1.194
ict	26	1.00e-09	1.688	−2.516	2.536
itu	26	39.039	28.528	5.350	76.450
fbs	26	1.716	1.261	0.010	4.080
mcs	26	113.887	52.810	17.680	177.69
huc	26	2.975	0.183	2.648	3.309
recn	25	9.796	2.354	7.600	16.20

Source: Author

2.97% (ranging from 2.65 to 3.31) between 2000 and 2025. There is a notable improvement in renewable energy consumption, with an average of 9.8, with a minimum of 7.6 and a maximum of 16.2.

The paper checks for multicollinearity to avoid linear dependence among the explanatory variables. Thus, the correlation coefficients (Appendix 1) for the variables under consideration show that all the variables under consideration are below 0.8, and the variance inflation factor analysis shows that all the variables have a VIF (Appendix 2) below 10 with a mean VIF of 5.62, confirming the absence of severe multicollinearity. Again, this study mean-centred both the squared variable and the interaction terms before regression to avoid multicollinearity.

Even though the ARDL cointegration technique does not require pre-testing for stationarity, this study checks for the presence of a unit root in the underlying variables' series to avoid structural estimation issues when variables are integrated of order two. The stationarity properties were assessed using the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) approaches, both with intercept and trend specifications, as presented in Table 3.

As shown in Table 3, all variables become stationary after first differencing, with none integrated of order two. This validates the application of the ARDL approach, which is appropriate when variables are I(0), I(1) or a mix, but not I(2) (Demirhan, 2020; Wstabdullah et al., 2022). To test for cointegration, given the less than 30-year period, this study uses the asymptotic bounds of Pesaran et al. (2001) in Table 4 to infer a long-run relationship between variables under consideration.

Table 4 shows that both the F-statistic and T-statistic from the ARDL bounds test surpass both lower and upper critical values at the 1% and 5% significance levels. On this basis, the absence of cointegration is rejected, suggesting that a stable long-run relationship exists among the variables under consideration. This justifies estimating both short- and long-run specifications within the ARDL framework (Ojiako, 2020; Gulaliyev et al., 2025). Table 5 presents the empirical results regarding the short-run effect of EC on environmental degradation in South Africa.

The ECT is negative and significant at the 1% level, with a coefficient of −70. This confirms the existence of a long-run cointegration relationship among the variables. This implies that about 70% of the disequilibrium from the previous period is corrected in the current period. The short-run analysis indicates that the relationship between EC and environmental degradation is monotonic. The estimated EKC turning point is 1.53, which is above the maximum observed ECI of 1.27. Thus, within the sample period, increases in ECI are associated with higher levels of environmental degradation. This suggests that the level of sophistication required for structural change to reduce environmental degradation is not attained in the short term. This result reflects a phase of industrial diversification and the expansion of more resource- and energy-intensive activities. The positive effect of EC on environmental degradation is consistent with Nathaniel et al. (2022) and Ren et al. (2025), who suggest that EC is associated with environmental degradation in emerging countries and in countries with high economic complexity.

Table 5 indicates that renewable energy has a positive and significant effect on environmental degradation in the short term. Thus, a 1% rise in renewable energy consumption corresponds to a 0.2% increase in environmental degradation (P<0.01). This suggests that expanding renewable energy capacity temporarily increases environmental degradation. This result is consistent with Sun et al. (2025), who suggested that renewable energy significantly enhances the ecological footprint.

The long-run results indicate a significant positive EC and a negative EC-squared, confirming an inverted U-shaped ECK relationship between EC and environmental degradation. The estimated turning point is 1.262 ($e^{0.2324}$). This implies that environmental degradation increases with EC up to 1.262. Thus, beyond this threshold, further increase in EC is associated with a decrease in emissions. This indicates a structural shift in the economy toward a more knowledge-intensive and less environmentally intensive production structure. This result corroborates the EKC theory, which hypothesises that economic development initially worsens environmental degradation until it reaches a threshold at which it begins to decline. Again, this inverted U-shaped relationship aligns with Ahmad et al. (2021), Khan et al. (2022), Chu et al. (2023), Wang et al. (2023) and Naimoğlu and Akal (2024), which confirms the inverted U-shaped relationship across several economic groupings and regions, notably within emerging, G-7, OECD and emerging importing economies.

Empirical results reveal that ICT development has a negative direct effect on environmental degradation, yet the effect is insignificant. However, the moderation effect of ICT development on EC is statistically significant impact, whereas the main effect of EC is positive and significant. This result indicates that ICT enhances the environmental sustainability of EC in South Africa. Again, this result shows that ICT enables cleaner production processes, more efficient resource use, and smart industrial monitoring, ultimately decoupling complex economic activities from environmental damage. This result aligns with Dada et al. (2025), who suggest that ICT reduces the positive effect of the informal economy on environmental degradation.

Table 3: Stationarity test results

Variable	Specification (s)	ADF 1 (0)	ADF 1 (1)	PP 1 (0)	PP 1 (1)	Order
lenvd	Constant+Trend	−1.303	−6.494***	−1.502	−7.609***	1 (1)
lec	Constant+Trend	−2.594	−5.152***	−2.624	−4.661***	1 (1)
lec^2	Constant	−0.349	−3.867**	−0.568	−3.765**	1 (1)
lict	Constant Trend	−0.955	−2.640*	−0.560	−2.753**	1 (1)
lhuc	Constant+Trend	−2.348	−5.966***	−2.290	−6.506***	1 (1)
lrecn	Constant+Trend	−0.907	−4.258**	−0.900	−4.262**	1 (1)
lec_lict	Constant	−0.684	−3.206**	−0.605	−3.185**	1 (1)

*P<0.1, **P<0.05, ***P<0.01. Source: Author's compilation using EViews

Table 4: Bounds test

Test	Statistic	K	Test	Statistic	k
F-bounds	8.361299	6	t-bounds	−9.876664	6
Signif.	1 (0) Lower	1 (1) Upper	Signif.	1 (0) Lower	1 (1) Upper
10%	2.12	3.23	10%	−2.57	−4.04
5%	2.45	3.61	5%	−2.86	−4.38
2.5%	2.75	3.99	2.5%	−3.13	−4.66
1%	3.15	4.43	1%	−3.43	−4.99

Source: Author

Table 6 shows that human capital development and renewable energy consumption are environmental degradation-reducing factors in South Africa. Specifically, a 1% increase in human capital and renewable energy consumption reduces environmental degradation by 1.5% and 0.5%, respectively (P<0.01). The adverse effect of human capital development on environmental degradation implies that higher levels of human capital, often operationalised through education, literacy and skill development, foster environmental literacy. This enhances informed energy choices among individuals and firms, encouraging the adoption of clean technologies and reducing carbon-intensive consumption patterns, thereby mitigating environmental degradation. This finding aligns with Roy (2026), who suggested that enhancing human capital significantly reduces carbon dioxide emissions, thereby mitigating environmental degradation.

The negative effect of renewable energy consumption indicates that increased use of renewable energy reduces the embedded carbon content. This result supports South Africa's JET-IP, which suggests that scaling up renewable energy actively reduces environmental damage rather than serving as a neutral substitute. Consistently, the result aligns with Işık et al. (2023) and Pal et al. (2026) suggesting that consumption of renewable energy fosters a more rapid reduction in carbon dioxide emissions, thereby reducing environmental degradation in G7, BRICS, and energy-consuming countries. To confirm that the estimated coefficients are unbiased, non-spurious, and statistically reliable for policy analysis and forecasting, this study applies the diagnostic checks presented in Table 7.

Table 5: Short-run coefficients

Variable	ARDL (1, 0, 1, 1, 0, 1, 1)			Prob. value
	Coeff.	Standard error	T-statistic	
d (lec)	0.065**	0.028	2.299	0.047
d (lec^2)	−0.076***	0.012	−6.167	0.000
d (lict)	−0.001	0.017	−0.047	0.964
d (lhuc)	0.021	0.099	0.208	0.840
d (lrecn)	0.207***	0.062	3.358	0.008
Interaction term				
d (lec_lict)	−0.0002	0.009	−0.021	0.984
ECT(-1)	−0.697***	0.071	−9.877	0.000
C	5.042***	0.511	9.863	0.000
Adjusted sample period		2001-2025		
Number of observations		25 after adjustments		
Maximum lag for Dep.var		1		
Lag length for the dynamic regressors		1		
Information criterion for model selection		SIC		

d represents the first difference operator; l represents logarithm, ec _economic complexity; ec^2 is the square term of economic complexity; ict_information and communication technology; huc_human capital development; recn_renewable energy consumption; lec_lict_interaction of EC with ICT development; ECT_error correction term; C_constant; SIC Schwarz Information Criterion. *P<0.1, **P<0.05, ***P<0.01. Source: Author

Table 6: Long-run coefficients

Variable	ARDL (1, 0, 1, 1, 0, 1, 1)			Prob. value
	Coeff.	Std.Error	T-statistic	
lec	0.093	0.027	3.450	0.007
lec^2	−0.201	0.044	−4.533	0.001
lhuc	−1.544	0.459	−3.367	0.008
lict	−7.03E-05	0.023	−0.003	0.998
lrecn	−0.534	0.078	−6.824	0.000
Interaction term				
lec_lict	−0.090	0.024	−3.798	0.004
Turning point				
Calculated vertex (x*)	0.2324 in logs 1.262 in levels			
Sample range	−2.8-1.27			
Nature of curve	The inverted U-shape EKC hypothesis is supported			

*P<0.1, **P<0.05, ***P<0.01. Source: Author

The diagnostic test results in Table 7 confirm statistical reliability and econometric adequacy of the estimated model. The adjusted R-squared value of 0.94 indicates that 94% of the variation in environmental degradation is explained by the explanatory variable, while the F-statistic P-value confirms joint statistical significance. The LM test (P = 0.13) and the Breusch-Pagan test (P = 0.96) confirm the absence of higher-order serial correlation and heteroscedasticity, respectively. Moreover, the Jarque-Bera test (P = 0.72) (Appendix 5) indicates that the residuals are normally distributed, and the Ramsey RESET test P-value confirms proper functional specification without omitted non -linear terms. Moreover, the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests (Appendix 6) confirm parameter stability, as the plots remain within the 5% critical bounds. For robustness checks, the study utilised the Fully Modified Least Squares (FMOLS) approach, as shown in Table 8, to confirm the consistency of the results.

Table 7: Diagnostic checks

Diagnostic test	Test statistic	Inference
Adjusted R-squared	0.945	The model fits the observed data closely
F-Statistic	32.163 (0.000)	Explanatory variables exert a statistically significant effect on the dependent variable
Durbin-Watson (DW) Statistic	2.630	Absence of first-order serial correlation
Jarque-Bera Normality Test	0.468 (0.719)	The error term closely follows a normal distribution
LM Serial Correlation Test	2.7621 (0.130)	No higher-order serial correlation
Breusch-Pagan Heteroscedasticity Test	0.334 (0.955)	Evidence of constant error variance
Ramsey RESET Test	1.511 (0.169)	Correct functional form

P-values are in parentheses. Source: Author

Table 8: Sensitivity analysis

Variable	Coef.	Standard error	t-Statistic	Prob.
lec	0.011	0.023	−0.498	0.626
lec^2	−0.034	0.022	1.586	0.135
lict	−0.099	0.020	4.931	0.000
lhuc	−0.593***	0.170	3.500	0.004
lrecn	−0.344***	0.056	−6.142	0.000
Interactions				
lec_lict	−0.069	0.052	−1.343869	0.195
C	2.719***	0.416	6.538485	0.000

*P<0.1, **P<0.05, ***P<0.01. Source: Author

The FMOLS results in Table 8 are consistent with the ARDL in terms of the direction of effects, particularly for renewable energy, which remains negative and significant. However, some disparities emerge: ICT becomes significant, human capital changes sign, and the interaction and EKC terms lose significance. These discrepancies are expected, given that FMOLS requires large sample sizes for optimal performance, whereas the ARDL approach remains well-suited for finite sample sizes and mixed integration (Pesaran et al., 2001; Nkoro and Kelvin, 2016). Therefore, the ARDL estimates are preferred for inference in this study, with FMOLS serving as a robust check.

5. CONCLUSION

The study examined the applicability of the EKC in South Africa, using EC and environmental degradation, as well as the role of ICT development. The results reveal a monotonic relationship between EC and environmental degradation in the short run. Also, the short-run analysis suggests that renewable energy consumption worsens environmental degradation. At the same time, empirical results confirm the EKC relationship in the long run. Thus, EC worsens environmental degradation but decreases it once a higher threshold of productive sophistication is attained. The results also indicate that ICT development reduces the detrimental effect of ECI on environmental degradation. Furthermore, the results show that human capital development and renewable energy consumption are factors reducing environmental degradation in South Africa. These results have the following policy implications.

5.1. Policy Implications

The monotonic relationship in the short run and the U-shaped relationship in the long run imply that the process through which EC reduces environmental degradation is not immediate, but it unfolds over time as the structure of the South African economy changes.

The insignificant direct negative effect of ICT and the significant negative interaction effect between EC and ICT on environmental degradation imply that ICT alone does not directly affect environmental degradation. However, a positive main effect of EC and a negative interaction term between EC and ICT suggest that EC often entails industrial processing, energy-intensive manufacturing, and a diversified supply chain, which initially worsens environmental degradation. Yet the integration of ICT mitigates these adverse effects and effectively neutralises the polluting generating activities associated with higher economic complexity.

The negative effect of human capital on environmental degradation implies that an educated workforce is better equipped to develop, implement, and maintain clean technologies, thereby shifting the energy mix away from carbon-intensive fuels toward renewables. Again, highly environmentally literate individuals lead to stronger public support for environmental protection policies and greater environmental responsibility.

The positive short-run effect of renewable energy consumption suggests that renewable energy expansion temporarily exacerbates environmental degradation. This suggests that building renewable energy infrastructure, such as wind turbines and solar PV farms, requires carbon-intensive manufacturing, civil engineering, and raw material extraction. These activities generate immediate emissions and land deterioration before clean electricity production starts. However, the environmental degradation during this energy transition is not a sign of policy failure, but rather an unavoidable structural cost before long-run term operational decarbonization takes effect. Indeed, the negative effect of renewable energy consumption suggests that green power serves as a critical structural substitute for carbon-intensive fuels in South Africa. This validates that fostering renewable energy consumption is an effective policy lever for achieving national decarbonisation targets without compromising overall economic output.

5.2. Policy Recommendations

Given the short-run monotonic relationship alongside a long-run inverted-U-shaped EKC, the South African government and policymakers should adopt a targeted dual strategy. Thus, policy should prioritise the enforcement of clean production benchmarks for resource-intensive manufacturing during early-stage product diversification, while directing research and development incentives, subsidies, and tax credits exclusively toward high-technology, knowledge-intensive, and sophisticated sectors such as advanced electronics and green hydrogen processing, to foster South Africa's transition toward the complexity threshold. To achieve decoupling, policy should aim to raise EC above the estimated long-run threshold of 1.262 by diversifying into cleaner, higher-value-added, and knowledge-intensive products and processes.

Based on the negative interaction term between EC and ICT development, policy should incentivise digital adoption, such as Internet of Things (IoT) sensors, automation, and energy management, as well as digital technologies, within highly complex, energy-intensive manufacturing and export sectors to reduce their environmental footprint. Again, the South African government should subsidise research, development, and enterprise adoption of digital innovations, particularly those designed for pollution monitoring, industrial waste management, or resource optimisation across expanding, sophisticated economic sectors.

To leverage the beneficial effects of human capital, the government and policymakers should prioritise expanding specialised vocational programs, such as work-integrated learning, tailored to green technologies, energy management systems, and solar installations. Again, the government should implement targeted adult education and community outreach programs focused on household efficiency and green technologies, to foster the transition from carbon-intensive appliances.

To mitigate immediate environmental pressures from renewable energy expansion, the South African government and energy policymakers should not rely on capacity deployment alone; rather, investment in renewable energy should prioritise Battery energy storage systems and grid stabilisation to prevent efficiency losses from baseline coal-fired power plant operations. Again, there is a

need for strict life-cycle carbon standards for new projects under the Renewable Energy Independent Power Producer Procurement (REIPPPP) to ensure that variable clean power immediately replaces the baseline coal generation rather than activating carbon-intensive dynamic cycling. Given that renewable energy consumption directly reduces environmental degradation in South Africa, the government and policymakers should immediately remove the primary bottlenecks that prevent higher rates of renewable energy consumption and grid access. There is a need to fast-track the expansion of transmission lines and the integration of battery storage. Specifically, unlocking transmission capacity in resource-rich regions such as the Western and Northern parts of South Africa will allow solar and wind to deliver maximum clean power to the national grid, enabling industries and households to substitute fossil fuels with clean energy at scale.

5.3. Limitations and Areas of Further Study

While cross-country panel studies predominate in the environmental economics literature, this study focuses on South Africa to address the empirical gap in country-specific structural insights. The study utilised the OEC complexity data, which was fully available from 2000 to 2025. To maintain statistical power and preserve degrees of freedom over a 26-year period, the empirical design prioritised model parsimony within an ARDL framework, restricting the lag length to one and omitting other interaction terms and dummy variables, while confirming estimation reliability through rigorous diagnostic checks and FMOLS robustness tests. Thus, future studies can build upon these findings by assessing longer time horizons as data become available, incorporating additional within-country moderating mechanisms such as human capital, and exploring sectoral- and provincial-level environmental dynamics.

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APPENDICES

Appendix 1: Correlation coefficients

	lc02pc	leci_c	lict_c	lhc	lrecn	leci_ict
lenvd	1.000					
lec_c	0.891*	1.000				
lict_c	−0.569*	−0.739*	1.000			
lhc	0.327*	0.119	0.431*	1.000		
lrecn	−0.495*	−0.230*	−0.394*	−0.777*	1.000	
lec_lict	0.685*	0.636*	−0.188*	0.420*	−0.400*	1.000

Source: Author's computations

Appendix 2: Variance inflation factor

Variable	VIF	1/VIF
lict_c	9.43	0.106
lrecn	7.53	0.133
lec_c	5.03	0.199
lhc	4.02	0.249
lec_lict	2.11	0.473
Mean VIF	5.62	

Source: Author's computations

Appendix 3: Principal components and eigenvectors: EC and ICT indices

Variable	Component	EC_2-components				Comp 1	Unexplained
		Eigenvalue	Difference	Proportion	Cumulative		
ntrdec	Comp1	1.716	1.432	0.858	0.858	0.707	0.142
ntechec	Comp2	0.284		0.142	1.000	0.707	0.142
Variable	**Component**	**ICT_3-components**				**Comp 1**	**Unexplained**
		Eigenvalue	**Difference**	**Proportion**	**Cumulative**		
nfbs	Comp1	2.849	2.759	0.949	0.949	0.575	0.0576
nitu	Comp2	0.091	0.030	0.030	0.979	0.577	0.0529
nmcs	Comp3	0.060		0.020	1.000	0.580	0.0404

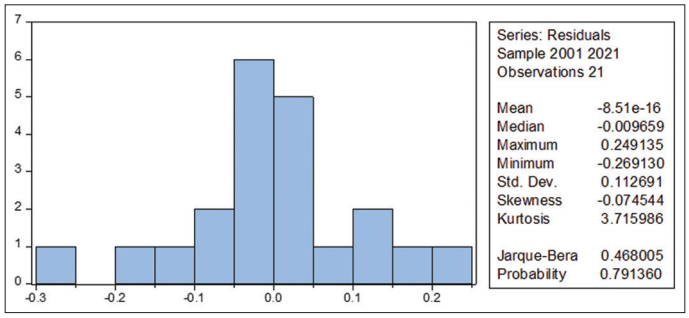
Source: Author's computations

Appendix 4: Diagnostics for PCA

Index	Bartlett test	KMO test
ec-2-components	0.000	0.500
ict- 3-components	0.000	0.780

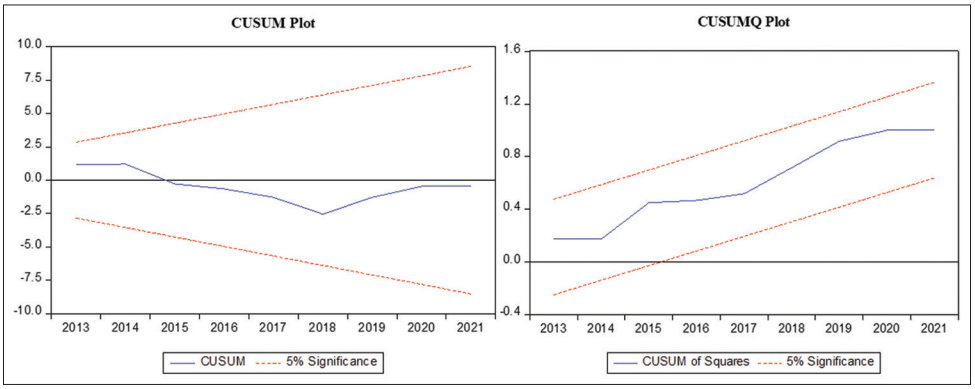
Source: Authors computations

Appendix 5: Histogram



Source: Author

Appendix 6: CUSUM plots



Source: Author