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Searching for Sustainable Footprints: Does ICT increase CO2 emissions?

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Abstract

Generally, the revolutionary idea behind using information and communication technology (ICT) has improved potential productivity in many industries, particularly in Africa. ICT is an essential tool in the oil and gas industry and plays a complementary role in technological dynamics and cross-sectoral productivity. For the educational sector, ICT facilitates research and development as well as in imparting knowledge. ICT remains the password to essential inputs required for any given output in terms of improved productivity and economic development. With regard to employment creation, ICT accounts for more than 50% of employment globally. Despite the significant role of ICT in the economy, evidence shows that more than 90% of carbon emissions have been linked to ICT production, installation, and usage. This study aims to determine whether ICT causes environmental sustainability in Nigeria and South Africa. The methodological contribution of the study lies in combining the STIRPAT framework and time series based on the VAR/VEC Granger causality, enabling the study to uncouple the dynamic interaction among environmental sustainability indicators. The findings show that ICT has contributed to South Africa's environmental sustainability, whereas evidence in Nigeria is relatively mixed. Therefore, the study recommends the urgent need to provide intervention programs tailored toward investing in environmental infrastructure to mitigate the threat of climate change in Nigeria.

Keywords: CO2 emissions; ICT; Economic development; Sub-Saharan Africa
JEL Classification : C52 ; O38 ; O40 ; O55 ; P37

1. Introduction

Researchers attempting to explain the role of information and communication technology (ICT) on environmental sustainability have empirically wrestled with multifaceted considerations in energy and environmental sciences (Strazicich & List, 2003, Shobande 2020; Shobande & Asongu, 2022). While climate policy remains a global concern, many researchers addressing the problem have used the stochastic impacts by regression on population, affluence, and technology (STIRPAT) framework to analyse the role of ICT on environmental sustainability. Despite the empirical literature's growth, evidence on Granger causality between the factors is still missing. This is not surprising, given the complexity and socioeconomic factors surrounding the discussion on using ICT to combat climate change. This study explores whether ICT causes environmental sustainability in Nigeria and South Africa. The study aims to achieve three purposes. First, it provides an avenue to check whether ICT can help mitigate climate change effects among the countries. Second, it provides an avenue to appraise, compare and learn from the policies adopted in fighting climate change in these countries. Third, it contributes to accumulating empirical literature seeking to address the multifaceted problem of climate resurgence and serves as a reference for future studies. The selection of Nigeria and South Africa is premised on the fact that while much literature has focused on Sub-Saharan Africa, as apparent in the following paragraph, little is known specifically on the two largest economies in Africa that are based in SSA (i.e., Nigeria and South Africa).

Recent work by Asongu et al. (2017, 2018), Amir et al. (2019), Danish (2019), Ahmed et al. (2020), Shahbaz et al. (2018, 2019), Khan et al. (2020), Shobande (2019, 2020) have provided the energy and environment community with important findings on the link between ICT and environmental sustainability. While these scholars' findings have a number of profound implications for climate change, they provide a deeper insight into the consequence of investment in, production of and utilisation of ICT, which deserve a critical examination, especially in two leading economies in Africa (i.e. Nigeria and South Africa). For example, Amir et al. (2019) find no evidence on the connection between ICT and environmental sustainability indicators; whereas few studies have found evidence that ICT does promote environmental sustainability (Danish et al., 2019; Ahmed et al., 2020, Avom et al., 2020). A cursory look at these studies shows that mixed evidence is reported. As a way of reconciling their empirical evidence, it is imperative to re-examine these studies, particularly in Nigeria and South Africa in order to provide insights into the nexus between ICT and CO2 emissions.

Four reasons motivated Nigeria and South Africa as candidates for investigating whether ICT causes environmental sustainability. First, ICT is growing rapidly due to the number of megacities in Nigeria and South Africa. Therefore, it is important to understand its implication for environmental sustainability. Second, cities are often attracted to use advanced ICT infrastructure for productivity because they are most prosperous for the economy. In contrast, production and usage of this ICT infrastructure can increase carbon emissions depending on the nature of technology, raising several environmental concerns (Rex et al. 2022; Dong et al., 2020; Wang et al. 2022; Shobande & Shodipe, 2019). For Africa, Nigeria and South Africa have the major hub of industrial productivity, which account for a significant proportion of carbon emissions in the continent. Consequently, there is an urgent need to check whether ICT can help mitigate the impact of carbon emissions in these countries. Third, population growth is connected with high ICT penetration, which may impact environmental sustainability. Similarly, the population in Nigeria and South Africa, respectively, has been projected to double in the next decades, implying ICT infrastructure, production, and usage, as well as environmental consequences. Fourth, the current revolution in higher education has provided an avenue for a paradigm shift in the education system to virtual or e-learning, which implies that there will more use of ICT, as such knowledge of environmental sustainability is crucial (Raman et al., 2019; Cajiroglu & Gokoglu, 2019; Sholihn et al., 2020; Montiel et al., 2020; Rex et al., 2021). Thus, the complexity of learning activities combined with ICT implication is viewed as a fundamental important factor. Moreover and policymakers have demanded for more information before investment in ICT infrastructures.

In extant literature, ICT can affect environmental sustainability in many ways. ICT can help to reduce carbon emissions by substituting environmentally friendly technology with a traditional product that is highly polluted (Wang et al., 2022; Shobande & Asongu, 2022). For example, the financial sector's transformation through e-banking can help reduce overcrowding in the bank, which helps mitigate human-caused carbon emissions. In contrast, ICT can be harmful to the environment. Another example is the production and installation of ICT equipment that have been linked to carbon-emitting properties which may have serious environmental and health effects on the population. Some studies have shown that ICT equipment production, use, and disposal are responsible for 2% of the world's carbon emissions (Rex et al., 2021; Riahi et al., 2007; Nykvist & Whitmersh, 2008).

This study contributes to the empirical literature on environmental sustainability in three ways. First, it investigates whether ICT causes environmental sustainability in Nigeria and South Africa. Second, it employs a time series approach within the remit of a VAR/VEC Granger causality framework. The findings show there is the existence of cointegration between ICT and environmental sustainability. Similarly, ICT unidirectionally Granger causes environmental sustainability in South Africa, whereas a bidirectional nexus observed in Nigeria. Furthermore, the variables' convergence speeds to their long-term mean are relatively high in South Africa, whereas it is relatively slow in Nigeria. Based on the findings, Nigeria and South Africa should continue investing in ICT infrastructure as it can help promote environmental sustainability.

The rest of the study is structured as follows. The corresponding literature is provided in Section 2. Section 3 covers the data and research method, whereas section 4 presents the results and discusses the findings. Section 5 concludes with a policy recommendation.

2.Literature Review

This section presents the empirical literature on the connection between ICT and indicators of environmental sustainability. It aims to provide a concise view of the various controversies surrounding the nexus and ends with a testable hypothesis.

Related Studies

The long-standing debate in empirical literature attempting to provide information that will help address climate change is whether ICT can help promote environmental sustainability. Major empirical studies have implemented different econometric approaches which are contextualised in the STIRPAT framework. Dietz and Rosa (1997) developed and implemented a STIRPAT framework to provide a solution for environmental sustainability and discovered that ICT and population are crucial for promoting a sustainable environment. Ahmed et al. (2020) investigate the criticality of ICT and human capital in environmental sustainability using a STIRPAT framework and continuously updated fully modified (CUP-BC) as well as a continuously updated bias-corrected (CUP-FM) model for Latin America and Caribbean countries. Their empirical results confirmed that ICT causes the indicator of environmental sustainability (i.e., carbon emission). In contrast, Asongu et al. (2018), observed ICT and indicators of environmental sustainability in Sub Saharan Africa (SSA) and found no evidence on the nexus between ICT and environmental sustainability.

Asongu et al. (2017) examined the role of ICT in inclusive human capital development tailored towards environmental sustainability using the Generalised Method of Moments (GMM). They reported that ICT promotes environmental sustainability in SSA. Avom et al. (2020) examined the role of ICT on the indicator of environmental sustainability between 1996 and 2014. They reported 21 SSA countries in which ICT affects environmental sustainability indicators through mechanisms such as energy consumption. In contrast, Nguyen et al. (2020) investigate the impact of innovation and ICT on environmental sustainability using the fully modified least squares (FMOLS) method and reported that ICT is harmful to the environment among the G20 countries. Focusing on Tunisia, Amri et al. (2019) assessed the connection between ICT, total factor productivity, and environmental sustainability indicators and found no evidence connecting ICT and sustainability.

Wang et al. (2022) assessed how ICT agglomeration affects carbon emissions in China and reported that ICT agglomeration has a positive effect on carbon emission through increasing economies of scale. Shobande and Asongu (2022) examine the role of education and ICT in promoting environmental sustainability in the Eastern and Southern African countries using a third-generation time series methodology. The findings of the authors confirmed that education and investment in clean technology can help promote environmental quality in Africa. Ollo-lopez and Aramendia-Muneta (2012) show that ICT can reduce carbon emissions through improvements in innovation and competition.

Evidently, the above empirical studies have provided deep insights into the connection between ICT and environmental sustainability indicators. While the evidence remains mixed, it is important to note that most of these studies have implemented different econometric methods that reflect the mixed evidence reported. Moreover, most of the studies are cross-sectional, or panel-related and there is sparse evidence on country-specific studies focusing on the attendant nexus. To complement existing efforts and provide new information that will help tackle climate change and promote environmental sustainability, this study aims to determine whether ICT causes environmental sustainability in Nigeria and South Africa.

Hypothesis Tested
Given the inconclusive evidence from the empirical literature review above, the hypothesis tested in this study is stated as:

ICT (mobile penetration per 100 people) contributes to environmental sustainability in terms of Carbon (CO_2) emissions per capita

The hypothesis is important for Africa's largest economies, particularly for Nigeria and South Africa. The two countries harbour big cities with giant multinational ICT industries which have revolutionised their economies. Similarly, Nigeria and South Africa have witnessed an increase in ICT infrastructure investment, which raises several concerns on whether ICT can promote environmental sustainability in these countries. The investigation will provide information that can help policymakers decide on the further investment of ICT infrastructure and compliance with climate change agreement (United Nations Framework Convention on Climate Change (UNFCCC)).

3.Data and Methodology

This section describes the data and methodology used. It aims to provide information on the sources and description of the data used, empirical strategy and time series modelling, and the method of estimation implemented.

3.1Data

The study focuses on Nigeria and South Africa using annual series data sourced from World Development Indicators (WDI) for the period 1980 to 2017. The indicator used is well captured in the STIRPAT framework. The variables used are indicators of environmental impact captured using carbon dioxide (CO_2) emissions per capita, population, GDP per capita (Affluence), and technology is proxied with mobile phone subscription. Two additional variables were included to capture human capital (education and health) and the sources and descriptions are as follows.

Carbon (CO_2) per capita: This measures carbon dioxide (CO_2) emissions (metric tons per capita). CO_2 emission has been a major interest to environmentalists. It makes up the largest share of greenhouse gases that contribute to climate change and has serious global warming implications. The CO_2 emission per capita is sourced from the international Energy Agency (IEA) (see Asongu et al., 2017; Ahmed et al., 2020, Lee et al., 2020).

ICT: It is measured with mobile phone penetration (per 100 people) to represent the quality of telecommunication technology in the country. It is an important indicator of ICT, and the data are available from WDI of the World Bank (Asongu et al., 2017).

Population: it is measured as population growth (annual %). It is an important indicator of demography, and data are available from WDI of the World Bank (Aldy, 2006).

Income: It is measured as per capita income (current US$). It is a measure of overall wellbeing, and data are available from WDI of the World Bank.

Education Quality: It is measured as a pupil-teacher ratio. The indicator is used to access the quality of education, and data are available from WDI of the World Bank.

Health: It is measured with life expectancy at birth, total (years). It is described as the mean number of years a newborn is expected to live if mortality pattern remains constant. Data are available from WDI of the World Bank.

3.2 Methodology

The empirical strategy used in this study is framed in the STIRPAT model, whereas the time series approach is based on VAR/VEC Granger causality. Three reasons motivated the use of these empirical strategies. First, the STIRPAT model contains an important indicator which provides a better framework for environmental impact assessment which has been used by multidisciplinary studies (Kuriyama, 2016; Troster, 2018). Second, the VAR/VEC Granger causality helps determine and uncoupled the transitory (short) and persistent (long) run effects among factors that appeal to the objective of this study (Zhang, 2010; Kuriyama, 2016; Troster, 2018). Third, the VAR/VEC Granger causality framework treats all the variables as endogenous, which enable an assessment of their speeds of convergence and directions of causality (Sinha et al., 2018; Mills & Patterson, 2009).

Initial Model Specification

Following the STIRPAT framework used by Ahmed et al. (2020), the stochastic functional relationship between ICT and environmental sustainability is stated as:

$$I = f\ (P, A, T), \tag{1}$$

where I is an environmental impact model for $Carbon\ dioxide\ (CO_2)\ emissions$, P is population growth; A is an affluence proxy in terms of income per capita, T is technology proxied with ICT.

Time Series Modelling

The model in equation (1) is used to capture the stochastic form, which is specified as:

$$I_{i,t} = \phi_0 P_{i,t}^{\sigma_1} A_t^{\sigma_2} T_{i,t}^{3} \upsilon_{i,t}. \tag{2}$$

Equation (2) can be linearised and specified as:

$$\log I_{i,t} = \phi_0 + \sigma_1 \log P_{i,t} + \sigma_2 \log A_{i,t} + \sigma_3 \log T_{i,t} + \upsilon_t, \tag{3}$$

where, i is the index of country, t is time, ϕ_0 is the constant parameter, σ_{1-3} are not only parameters but elasticities of the variables and υ_t is the error term. Equation (4) that follows is characterized by the inclusion of a control covariate for human capital (education and health). Thus, the model becomes:

$$\log I_{i,t} = \phi_0 + \sigma_1 \log P_{i,t} + \sigma_2 \log A_{i,t} + \sigma_3 \log T_{i,t} + \tau \log X_{i,t} + \upsilon_{i,t}, \tag{4}$$

where, X is used to capture education and health with associated parameters represented as τ. In order ensure uniformity identity with the proxies, Equation (4) is respecified as:

$$\log CO_{2i,t} = \beta_0 + \beta_1 \log Pop_{i,t} + \beta_2 \log Income_{i,t} + \beta_3 \log ICT_{i,t} + \beta_4 \log Life_{i,t} + \beta_5 \log Edu_{i,t} + \mu_{i,t}. \tag{5}$$

From Equation (5), the variables are represented by CO_{2t} for CO_2 emissions per capita (environmental impact), Pop is population growth, $income$ is GDP per capita, ICT is Technology and $Life$ is health capturing life expectancy, and Edu is education quality.

Granger Causality Test

Two conditions must be satisfied before the Granger causality test can be implemented. First, the series must be stationary at first difference (Brook, 2019). The second is that the variable must be cointegrated. Similarly, the cointegration theory provides a yardstick for assessing the short and long run fluctuations, which are explained by the vector error correction model (Troster et al., 2018). Consequently, the core relationship between the short run and long run effects as well as the speeds of convergence are summarised in Equations (6) to(11) as follows.

$$\begin{aligned}\log CO_{2i,t} = {} & \beta_{10} + \sum_{k=1}^{q} \beta_{11ik} \log CO_{2i,t-k} + \sum_{k=1}^{q} \beta_{12ik} \log Pop_{i,t-k} \\ & + \sum_{k=1}^{q} \beta_{13ik} \log Income_{i,t-k} + \sum_{k=1}^{q} \beta_{14ik} \log ICT_{i,t-k} + \sum_{k=1}^{q} \beta_{15ik} \log Life_{i,t-k} \\ & + \sum_{k=1}^{q} \beta_{16ik} \log Edu_{i,t-k} + \alpha_{1i} ECM_{it-1} + \mu_{1i,t}, (6)\end{aligned}$$

$$\begin{aligned}\log Pop_{i,t} = {} & \beta_{20} + \sum_{k=1}^{q} \beta_{21ik} \log pop_{i,t-k} + \sum_{k=1}^{q} \beta_{22ik} \log CO_{2i,t-k} \\ & + \sum_{k=1}^{q} \beta_{23ik} \log Income_{i,t-k} + \sum_{k=1}^{q} \beta_{24ik} \log ICT_{i,t-k} + \sum_{k=1}^{q} \beta_{25ik} \log Life_{i,t-k} \\ & + \sum_{k=1}^{q} \beta_{26ik} \log Edu_{i,t-k} + \alpha_{2i} ECM_{it-1} + \mu_{2i,t}, (7)\end{aligned}$$

$$\log Income_{i,t} = \beta_{30} + \sum_{k=1}^{q} \beta_{31ik} \log income_{i,t-k} + \sum_{k=1}^{q} \beta_{32ik} \log Pop_{i,t-k} + \sum_{k=1}^{q} \beta_{33ik} \log CO_{2i,t-k} + \sum_{k=1}^{q} \beta_{34ik} \log ICT_{i,t-k} + \sum_{k=1}^{q} \beta_{35ik} \log Life_{i,t-k} + \sum_{k=1}^{q} \beta_{36ik} \log Edu_{i,t-k} + \alpha_{3i} ECM_{it-1} + \mu_{3i,t}, (8)$$

$$\log ICT_{i,t} = \beta_{40} + \sum_{k=1}^{q} \beta_{41ik} \log ICT_{i,t-k} + \sum_{k=1}^{q} \beta_{42ik} \log Pop_{i,t-k} + \sum_{k=1}^{q} \beta_{43ik} \log Income_{i,t-k} + \sum_{k=1}^{q} \beta_{44ik} \log CO_{2i,t-k} + \sum_{k=1}^{q} \beta_{45ik} \log Life_{i,t-k} + \sum_{k=1}^{q} \beta_{46ik} \log Edu_{i,t-k} + \alpha_{4i} ECM_{it-1} + \mu_{4i,t}, (9)$$

$$\log Life_{i,t} = \beta_{50} + \sum_{k=1}^{q} \beta_{51ik} \log Life_{i,t-k} + \sum_{k=1}^{q} \beta_{52ik} \log Pop_{i,t-k} + \sum_{k=1}^{q} \beta_{53ik} \log Income_{i,t-k} + \sum_{k=1}^{q} \beta_{54ik} \log ICT_{i,t-k} + \sum_{k=1}^{q} \beta_{55ik} \log CO_{2i,t-k} + \sum_{k=1}^{q} \beta_{56ik} \log Edu_{i,t-k} + \alpha_{5i} ECM_{it-1} + \mu_{5i,t}, (10)$$

$$\log Edu_{i,t} = \beta_{60} + \sum_{k=1}^{q} \beta_{61ik} \log Edu_{i,t-k} + \sum_{k=1}^{q} \beta_{62ik} \log Pop_{i,t-k} + \sum_{k=1}^{q} \beta_{63ik} \log Income_{i,t-k} + \sum_{k=1}^{q} \beta_{64ik} \log ICT_{i,t-k} + \sum_{k=1}^{q} \beta_{65ik} \log Life_{i,t-k} + \sum_{k=1}^{q} \beta_{66ik} \log CO_{2i,t-k} + \alpha_{6i} ECM_{it-1} + \mu_{6i,t}, (11)$$

where q represents the lag length for the differenced variables and ECM_{it} is the speed of convergence of the variables to their long term mean values while α is the elasticity or velocity in the respective equations.

4. Empirical Results

This section presents results of the estimated model and also discusses the corresponding findings. It compares the attendant results with previous studies as well as discusses the implications of the findings.

Summary statistics

In time series analysis, it is customary to begin with the descriptive statistics to understand the prior information of the series before commencing any analysis. This section presents the summary statistics of the series showing the mean values and the standard deviations in Table 1.

Table 1.

Summary Statistics

Variables	Nigeria (1)		South Africa (2)		Obs.
	Mean	Std. Dev.	Mean	Std. Dev.	
CO_2	7.83	3.11	15.4	7.2	39
ICT	21.7	31.3	47.74	58.9	39
Income	1032.64	718.5	3375	1419	39
Pop	1.15	0.35	4.35	1.85	39
Life	47.3	2.4	58.9	3.2	39
Edu	14.0	5.75	13.7	5.7	39

Notes: *Carbon dioxide emissions per capita (CO_2), information and communication technology (ICT), GDP per capita income (Income), life expectancy at birth (Life), population growth (Pop), education (Edu).*

Table 1 reports the summary statistics of the variables indicating the mean values and standard deviations for Nigeria and South Africa. For Nigeria, Column 1 shows that for the CO_2 indicator, the mean value and corresponding standard deviation are respectively, 7.83 and 3.11. In Column 2 for South Africa, the corresponding mean value and standard deviation for CO_2 are respectively, 15.40 and 7.20.

Unit root test

This section presents the results of the unit roots test of the variables used for Nigeria and South Africa. The unit root test is important for a several reasons. First, the test provides information on mean, variance and autocorrelation of the variables used. Second, the test enables us to separate stationary and non-stationary series, which helps determine the best approach to use in the series analysis. Philips Perron (PP) developed a robust unit root test that accounts for an automatic correction for autocorrelation implemented as reported in Table 2.

Table 2.

Philip Perron Unit Root Test

Variables	Nigeria		South Africa	
	1(0)	1(1)	1(0)	1(1)
CO_2	-0.95	-6.6***	1.07	2.95**
ICT	2.24	-3.57**	1.91	-4.85***
Income	-1.4	-7.37***	-0.88	-3.79***
Pop	3.0	-4.5***	-1.49	-5.5**
Life	0.28	-2.98**	-1.49	-5.1**
Edu	-0.78	-6.6***	-0.80	-6.1***
Test critical Values	1%	-3.6		
	5%	-2.94		
	10%	-2.6		

Notes: *Carbon dioxide emissions per capita (CO_2), information and communication technology (ICT), GDP per capita income (Income), life expectancy at birth (Life), population growth (Pop), education (Edu).** and *** denote significance levels of 5% and 1% respectively.*

According to the results of the unit roots test, all the variables are not stationary at level. So, we transform by taking the first difference in order to prevent spurious results. After differencing, the variables become stationary. This poses many implications, particularly the key environmental sustainability indicator (Carbon emissions). First, the lack of stationarity of carbon emissions shows that ambitious policy on climate change should mitigate the long-term effects rather than the short-term consequence. The results are consistent with the empirical literature (Sun & Wang, 1996; Strazicich & List, 2003; Shahbaz et al., 2018).

VAR Lag Selection Criteria

One obvious result from the unit root test is that the series is not stationary until it is first differenced. This section used several criteria to check the optimal lags and determined how quick the variables revert back to their long term mean. The optimal lag selection criteria implemented is based on Hannan-Quinn information criterion, Akaike information criterion, and Schwarz information criterion and the results are reported in Table 3.

Table 3.
VAR Lag Length Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
			Nigeria			
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1577.494	NA	6.0029	85.59429	85.85552	85.68639
1	-1170.763	659.5647	1.2221	65.55475	67.38336	66.19942
2	-1055.451	149.5937*	1.9719*	61.26762*	64.66361*	62.46487*
			South Africa			
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1889.379	NA	1.2637	102.4529	102.7141	102.5450
1	-1473.264	674.7798	1.5428	81.90618	83.73479	82.55085
2	-1349.836	160.1231*	1.6126*	77.18033*	80.57632*	78.37758*

Notes: **Indicates lag order selected by the criteria. LR: sequentially modified LR test statistic FPE: Final Prediction Error. HQ: Hannan-Quinn Information Criterion. AIC: Akaike Information Criterion. SC: Schwarz Information Criterion. Each test is at the 5% significance level.*

According to the results, lag 2 is the optimal lag length in both countries when all the criteria are considered. For Nigeria, the AIC stood at 61.26 being the lowest, whereas in South Africa, the AIC is roughly 77.18.

Cointegration test

Just immediately after the optimal lag lengths of these factors have been uncovered, other questions on whether the variables can converge to their long run mean values become apparent. In the time series world, two main conditions must be satisfied before cointegration tests can be implemented, based on non-stationarity of the series and optimal lag length identified. This study used the multivariate cointegrated method suggested by Johansen (1991) to assess the variables' potential convergence and the corresponding results are presented in Table 3.

Table 3.

Results for Johansen Cointegration Tests for Nigeria and South Africa

Hypothesised No of CE	Eigen value	Trace Statistics	Critical Value 5%	Prob**
		Nigeria		
None*	0.90	181.7	95.75	0.0000
At most 1*	0.65	94.5	65.81	0.0002
At most 2	0.51	55.15	47.84	0.0089
		South Africa		
Hypothesised No of CE	Eigen value	Trace Statistics	Critical Value 5%	Prob**
None*	0.96	313.8	117.7	0.0000
At most 1*	0.86	191.8	88.8	0.0000
At most 2*	0.72	120.72	63.8	0.0000
At most 3	0.57	73.76	42.9	0.0000
Trace test indicates cointegrating(s) at the 0.05 level				

Notes: *The asterisk *denotes statistical significance at the 5% level.*

For Nigeria, the Johansen cointegration tests suggest that the variables are cointegrated. The trace test indicates 2 cointegration equations are present, which is statistically significant at the 5% level. Consistently, cointegration among the variables was confirmed for South Africa with the Trace test statistics admitting 3 cointegrated equations among the variables.

VAR/VEC Granger Causality Tests

The Granger causality proposed and developed by Granger (1969) is used in this analysis. Two reasons justified the implementation. First, the series are stationary at first difference. Second, evidence of cointegration is confirmed among the variables. Therefore, this section discusses, implements, and presents the finding of the VAR/VEC Granger causality tests for Nigeria and South Africa. Table 4 presents the VAR/VEC Granger causality tests of Nigeria and South Africa.

Table 4.

VAR/VEC Granger Causality test

Independent Variables	*The Direction of Causality for Nigeria* Dependent variables						*Long run*
	ΔCO_{2t}	ΔICT_t	$\Delta Income_t$	ΔPop_t	$\Delta Life_t$	ΔEdu_t	ΔECT_{t-i}
$\mathbf{\Delta CO_{2t-k}}$	-	11.40** (0.00)	1.79 (0.60)	1.02 (0.16)	0.3 (0.29)	0.5 (0.41)	-0.024** (0.00 [-3.45]
$\mathbf{\Delta ICT_{t-k}}$	10.5** (0.00)	-	12.96** (0.00)	0.7 (0.19)	6.4** (0.00)	13.24** (0.00)	-0.006** (0.00) [-2.91]
$\mathbf{\Delta Income_{t-k}}$	11.23** (0.00)	6.2** (0.00)	-	14.7*** (0.00)	10.67** (0.00)	0.3 (0.74)	-0.30
$\mathbf{\Delta Pop_{t-k}}$	10.33** (0.00)	8.96** (0.00)	0.4 (0.87)	-	29.4** (0.00)	17.9*** (0.00)	0.035** (0.00) [6.01]
$\mathbf{\Delta Life_{t-k}}$	1.57 (0.68)	9.8** (0.00)	5.4** (0.0)	0.22 (0.38)	-	3.7* (0.00)	-0.052 (0.01) [-5.32]
$\mathbf{\Delta Edu_{t-k}}$	14.23*** (0.00)	10.7*** (0.00)	10.6*** (0.00)	4.09* (0.00)	21.4*** (0.00)	-	0.0089** (0.00) [14.2]
Independent Variables	*The direction of Causality for South Africa*						*Long run*
	ΔCO_{2t}	ΔICT_t	$\Delta Income_t$	ΔPop_t	$\Delta Life_t$	ΔEdu_t	ΔECT_t
$\mathbf{\Delta CO_{2t-k}}$	-	2.1 (0.10)	0.1 (0.74)	6.16*** (0.00)	9.5** (0.00)	1.6 (0.26)	-0.0026** (0.00) [-5.2]
$\mathbf{\Delta ICT_{t-k}}$	6.1*** (0.00)	-	8.3** (0.00)	31.31*** (0.00)	2.0 (0.45)	6.2** (0.00)	-0.0043** (0.00) [-3.9]
$\mathbf{\Delta Income_{t-k}}$	13.7*** (0.00)	10.7*** (0.00)	-	11.7*** (0.00)	1.5 (0.22)	11.58** (0.00)	-0.017 (0.00) [-0.45]
$\mathbf{\Delta Pop_{t-k}}$	8.5** (0.00)	0.03 (0.36)	0.1 (0.24)	-	5.4*** (0.00)	1.03 (0.92)	-0.008** (0.00) [9.12]
$\mathbf{\Delta Life_{t-k}}$	7.9*** (0.00)	0.26 (0.32)	0.5 (0.12)	61.4*** (0.00)	-	12.67** (0.00)	0.0002** (0.00) [7.19]
$\mathbf{\Delta Edu_{t-k}}$	12.5** (0.00)	1.07 (0.44)	3.4* (0.01)	5.8** (0.00)	3.2* (0.03)	-	0.0005** (0.00) [3.35]

Notes: *Carbon dioxide emissions per capita (CO_2), information and communication technology (ICT), GDP per capita income (Income), life expectancy at birth (Life), population growth (Pop), education (Edu).*
*** and *** denote significance levels of 5% and 1% respectively.*

The results of the VAR/VEC Granger causality for Nigeria are presented from five standpoints. First, ICT bidirectionally Granger causes environmental sustainability (CO_2). Second, income, education, life (health) unidirectionally Granger cause environmental sustainability. Third, bidirectional causality exists between income education and ICT. Fourth, ICT unidirectionally Granger cause education. Fifth, the vector error correction (VEC) term is negative and statistically significant. The elasticity/velocity is relatively slow, indicating that the variables are slow to converge to their long term mean values.

The results of the VAR/VEC Granger causality for South Africa are summarised in five perspectives. First, ICT, income, and education unidirectionally Granger cause environmental sustainability (carbon emissions). Second, bidirectional Granger causality exists between population growth, life (health) and environmental sustainability. Third, bidirectional Granger causality exists between ICT and income. Fourth, income, ICT, and life (health) unidirectionally granger causes education. Fifth, the vector error correction (VEC) term is negatively and statistically significant. Still, the elasticity/velocity is relatively high, suggesting that the variables quickly converge to their long term mean values.

Table 5 compares the long run results on the impact of ICT on carbon emission in Nigeria and South Africa. The table suggests that carbon emissions in the previous period contribute significantly to deteriorate the environment in the next period. This provides evidence of inertia in carbon emissions in Nigeria. Specifically, a 1% increase in carbon emissions is correlated to a 3.19% increase in future emissions. While South Africa also has evidence to support this, Nigeria's carbon emissions are more than 1% greater than those of South Africa. ICT negatively contributes to reduce carbon emissions in Nigeria and South Africa. When compared to Nigeria, South Africa has a higher coefficient of ICT contribution to carbon emissions. Also, an increase in economic growth contributes to increase in carbon emissions in Nigeria. On the contrary, an increase in economic growth contributes significantly to reduce carbon emissions in South Africa. Table 6 compares the short run results on the impact of ICT on carbon emissions in Nigeria and South Africa.

Table 5
Long Run Results on the Impact of ICT on CO_2 in Nigeria and South Africa

Nigeria			South Africa		
Dependent variable: ln CO_{2t}			Dependent variable: ln CO_{2t}		
Variable	Coefficient	T-statistics	Variable	Coefficient	T-statistics
Constant	3.19**	2.84	Constant	2.18*	1.86
lnCO_{2t-1}	0.266**	4.27	lnCO_{2t-1}	0.359**	-2.54
lnICT	-0.65***	-7.32	lnICT	-1.78**	-2.60
ln Income	0.012*	1.86	ln Income	-0.42**	-3.75
lnPop	0.0036**	3.69	lnPop	0.0018**	2.84
lnLife	1.34**	-3.54	lnLife	-0.26	-0.61
lnEdu	0.73	0.85	lnEdu	-0.002*	-1.88
Diagnostic tests			Diagnostic tests		
R^2		0.87	R^2		0.95
Adj R^2		0.83	Adj R^2		0.91
F-statistics		1482*	F-statistics		3801*
Normality LM test		0.436(0.852)	Normality LM test		1.55(0.426)
ARCH LM test		0.026(0.764)	ARCH LM test		0.637(0.843
W. heteroskedasticity test		0.461(0.813)	W. heteroskedasticity test		0.302(0.251)
Ramsey Reset		0.429(0.524)	Ramsey Reset		0.141(0.758)

Notes. *, **, and *** indicates significance at 10%, 5% and 1%, respectively, while *p-values* are shown in parentheses in lower segment.

Table 6
Short Run Results on the Impact of ICT on CO_2 in Nigeria and South Africa

Nigeria			South Africa		
Dependent variable: ΔlnCO_{2t}			Dependent variable: Δln$Cabon_{2t}$		
Variable	Coefficient	T-statistics	Variable	Coefficient	T-statistics
Constant	-0.071	-0.56	Constant	-0.047	-0.14
ΔlnCO_{2t-1}	0.0063**	3.05	ΔlnCO_{2t-1}	0.37*	1.84
ΔlnICT	-0.43***	-4.62	ΔlnICT	0.08**	3.93
ΔlnIncome	1.57***	6.28	ΔlnIncome	0.003	1.22
ΔlnPop	0.006**	2.17	ΔlnPop	0.0001**	3.56
ΔlnLife	1.94	0.44	ΔlnLife	-0.031**	-2.84
ΔlnEdu	-0.016**	-3.64	ΔlnEdu	0.05	0.11
ECT_{t-1}	-0.006**	-2.78	ECT_{t-1}	-0.015**	-4.08
Diagnostic tests			Diagnostic tests		
R^2		0.88	R^2		0.77
Adj R^2		0.86	Adj R^2		0.65
F-statistics		15.26**	F-statistics		32.39**
Durbin Watson		1.95	Durbin Watson		2.06
Normality test		0.16(0.539)	Normality test		0.23(0.619)
Breusch-Godfrey LM test		1.89(0.196)	Breusch-Godfrey LM test		1.73(0.130)
ARCH LM test		0.072(0.758)	ARCH LM test		0.084(0.721)
W. Heteroskedasticity		0.471(0.670)	W. Heteroskedasticity		0.374(0.86)
Ramsey RESET		1.30(0.285)	Ramsey RESET		0.103(0.406)

Notes. *, **, and *** indicates significance at 10%, 5% and 1%, respectively, while *p-values* are shown in parentheses in lower segment.

Table 6 shows that a 0.0063% increase in present carbon emissions is correlated with a 1% increase in previous emissions. However, a1% increase in the previous carbon emission is linked with roughly 0.37% current carbon emissions in South Africa. Similarly, a 1% increase in ICT is associated with 0.43% carbon emissions in Nigeria. On the contrary a 1% increase in ICT is linked to 0.08% carbon emissions in South Africa.

The coefficients of the error correction terms have negative signs and are statistically significant at 1% level of significance. The lagged of the error correction term confirms that there is evidence of a long run relationship among the variables. This implies that the speed of convergence of changes in carbon emissions from short run towards a long span is roughly 6% in Nigeria and 15% in South Africa. This evidence shows that changes in carbon emissions from a short-term perspective to a long-term perspective are accelerating at the quickest rates in South Africa compared to Nigeria. The attendant evidence from sensitivity analysis indicates that the short run model passes nearly all the diagnostic tests, notably: the LM test for serial correlation and the White test for heteroskedasticity as well as the ARCH and residual normality tests. Moreover, as apparent from the bottom of the table, there is no evidence of non-normality of the residual in the short run model. This implies that the errors are normally distributed with zero mean and variance. Similarly, there is no evidence of autoregressive conditional heteroskedasticity.

An important lesson from the results is that South Africa has invested in critical ICT infrastructure, which is reflected in the findings from environmental sustainability indicators. In contrast, evidence from the Nigerian counterpart is mixed. Clearly, the ICT that was expected to be a blessing turned out to impact the environment. One plausible explanation to the result may be the nature of energy use or the ICT infrastructure's rebound effects. In either case, the country needs urgent investment in essential ICT infrastructure to correct the delay in convergence speed quickly.

5 Concluding implications and future research directions

The search for appropriate climate change policy remains hotly debated among multidisciplinary studies and environmental experts. Yet, a particular strand of empirical literature that provides the ultimate solution is still missing. This study contributes to the existing empirical literature by investigating whether ICT causes environmental sustainability in Nigeria and South Africa. The methodological contribution of the study lies in combining the STIRPAT framework and time series based on the VAR/VEC Granger causality, enabling us to uncouple the dynamic interaction among environmental sustainability indicators. Comparably, evidence shows that ICT plays a key role in environmental sustainability indicators in South Africa, whereas mixed evidence is observed for Nigeria. The study recommends the urgent need to provide intervention programs tailored toward investing in environmental infrastructure to mitigate the threat of climate change in Nigeria. For South Africa, improving the investment of key ICT infrastructure can further help the country promote environmental sustainability. However, education's role must not be overlooked as it may have aftermath effects on the quest for a sustainable environment in the country. Finally, we admit that promoting environmental sustainability is becoming increasingly challenging. However, policymakers must strategize to the safe the future of the environment we live in.

The findings have a number of implications for Nigeria and South Africa, which are discussed as follows. First, the bidirectional causality observed between ICT and environmental sustainability shows that Nigeria's present ICT infrastructure has a feedback effect on the environment. Consequently, the policy makers need to provide more intervention programs to mitigate the environmental impacts in the country. Second, the speed of convergence of the environmental sustainability indicator is relatively slow, indicating the urgent need to address multifaceted challenges associated with the nature of the technology used. Precisely, the country can invest in clean technology that is environmentally friendly to address the observed setbacks.

For South Africa, investment in ICT contributes to environmental sustainability and increasing the investment in clean technology can help close the gap among the environmental fundamentals further. Similarly, the indicator’s speed of convergence is high and attaining a greater environmental sustainability level will translate to inclusive growth and open an opportunity for human capital development in South Africa.

The findings obviously leave room for future research especially in terms of assessing how the findings are relevant for other African countries in particular and other developing countries in general. Accordingly, engaging such country-specific studies is relevant in providing more country-specific policy implications. Moreover, while the present study focuses on sustainable development related to environmental sustainability, other sustainable development goals can also be considered in the light of the United Nations' 2030 sustainable development agenda.

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References

Ahmed, Z., Nathaniel, S. P., & Shahbaz, M. (2020). The criticality of information and communication technology and human capital in environmental sustainability: Evidence from Latin American and Caribbean countries. *Journal of Cleaner Production*, 125529.

Ahmed, Z., Asghar, M. M., Malik, M. N., & Nawaz, K. (2020). Moving towards a sustainable environment: The dynamic linkage between natural resources, human capital, urbanization, economic growth, and ecological footprint in China. *Resources Policy*, *67*, 101677.

Aldy, J. E. (2006). Per capita carbon dioxide emissions: convergence or divergence? *Environmental and Resource Economics*, *33*(4), 533-555.

Amri, F., Zaied, Y. B., &Lahouel, B. B. (2019). ICT, total factor productivity, and carbon dioxide emissions in Tunisia. *Technological Forecasting and Social Change*, *146*, 212-217.

Asongu, S. A., le Roux, S., &Biekpe, N., (2017). Environmental Degradation, ICT and Inclusive Development in Sub-Saharan Africa. *Energy Policy*, 111(December), 353-361.

Asongu, S. A., Le Roux, S., &Biekpe, N., (2018). Enhancing ICT for environmental sustainability in sub-Saharan Africa. *Technological Forecasting and Social Change*, 127, 209-216.

Avom, D., Nkengfack, H., Fotio, H. K., &Totouom, A. (2020). ICT and environmental quality in Sub-Saharan Africa: Effects and transmission channels. *Technological Forecasting and Social Change*, *155*, 120028.

Brooks, C. (2019). *Introductory econometrics for finance*. Cambridge university press.

Cakiroglu, U., Kokoç, M., Gökoğlu, S., Öztürk, M., &Erdoğdu, F. (2019). An analysis of the journey of open and distance education: Major concepts and cutoff points in research trends. *International Review of Research in Open and Distributed Learning*, *20*(1).

Danish. (2019). Effects of information and communication technology and real income on CO2 emissions: The experience of countries along Belt and Road. *Telematics and Informatics, 45.*

Dietz, T., & Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. *Proceedings of the National Academy of Sciences*, *94*(1), 175-179.

Dong, K., Dong, X., & Ren, X. (2020). Can expanding natural gas infrastructure mitigate CO2 emissions? Analysis of heterogeneous and mediation effects for China. *Energy Economics, 90*, 104830.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, 424-438.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica: journal of the Econometric Society,* 1551-1580.

Khan, Z., Ali, S., Dong, K., & Li, R. Y. M. (2020). How does fiscal decentralization affect CO2 emissions? The roles of institutions and human capital. *Energy Economics*, 105060.

Kuriyama, N. (2016). Testing cointegration in quantile regressions with an application to the term structure of interest rates. *Studies in Nonlinear Dynamics & Econometrics, 20*(2), 107-121.

Lee, C. C., Chang, C. P., & Chen, P. F. (2008). Do CO2 emission levels converge among 21 OECD countries? New evidence from unit root structural break tests. *Applied Economics Letters*, *15*(7), 551-556.

Nykvist, B., & Whitmarsh, L. (2008). A multi-level analysis of sustainable mobility transitions: Niche development in the UK and Sweden. *Technological forecasting and social change*, *75*(9), 1373-1387.

Mills, T., & Patterson, K. (Eds.). (2009). *Palgrave Handbook of Econometrics: Volume 2: Applied Econometrics* (Vol. 2). Springer.

Ollo-López, A., &Aramendía-Muneta, M. E. (2012). ICT impact on competitiveness, innovation and environment. *Telematics and Informatics, 29*(2), 204-210.

Ren, X., Cheng, C., Wang, Z., & Yan, C. (2021). Spillover and dynamic effects of energy transition and economic growth on carbon dioxide emissions for the European Union: A dynamic spatial panel model. *Sustainable Development*, *29*(1), 228-242.

Ren, X., Li, Y., Wen, F., & Lu, Z. (2022). The interrelationship between the carbon market and the green bonds market: Evidence from wavelet quantile-on-quantile method. *Technological Forecasting and Social Change, 179*, 121611.

Riahi, K., Grübler, A., &Nakicenovic, N. (2007). Scenarios of long-term socio-economic and environmental development under climate stabilization. *Technological Forecasting and Social Change*, *74*(7), 887-935.

Shahbaz, M., Balsalobre, D., & Shahzad, S. J. H. (2019). The influencing factors of CO 2 emissions and the role of biomass energy consumption: statistical experience from G-7 countries. *Environmental Modeling& Assessment, 24*(2), 143-161.

Shahbaz, M., Shahzad, S. J. H., &Mahalik, M. K. (2018). Is globalization detrimental to CO 2 emissions in Japan? New threshold analysis. *Environmental Modeling& Assessment*, *23*(5), 557-568.

Shahbaz, M., Khraief, N., &Hammoudeh, S. (2018). How do carbon emissions respond to economic shocks? Evidence from low-, middle-, and high-income countries. *The Journal of Energy and Development*, *44*(1/2), 161-196.

Shobande, O. A. (2019). Effects of Energy Use on Socioeconomic Predictors in Africa: Synthesizing Evidence. *Studia Universitatis VasileGoldiş, Arad-SeriaŞtiinţeEconomice*, *29*(4), 21-40.

Shobande, O. A., &Shodipe, O. T. (2019). Carbon policy for the United States, China, and Nigeria: An estimated dynamic stochastic general equilibrium model. *Science of The Total Environment*, *697*, 134130.

Shobande, O. A., & Asongu, S. A. (2022). The Critical Role of Education and ICT in Promoting Environmental Sustainability in Eastern and Southern Africa: A Panel VAR Approach. *Technological Forecasting and Social Change*, *176*, 121480.

Shobande, O. A. (2020). Does electricity use Granger cause mortality? *The Journal of Energy and Development*, *46*(1/2), 265-291.

Sholihin, M., Sari, R. C., Yuniarti, N., &Ilyana, S. (2020). A new way of teaching business ethics: The evaluation of virtual reality-based learning media. *The International Journal of Management Education*, *18*(3), 100428.

Van, P. N. (2005). Distribution dynamics of CO 2 emissions. *Environmental and Resource Economics*, *32*(4), 495-508.

Strazicich, M. C., & List, J. A. (2003). Are CO 2 emission levels converging among industrial countries? *Environmental and Resource Economics*, *24*(3), 263-271.

Sinha, A., Shahbaz, M., & Sengupta, T. (2018). Renewable energy policies and contradictions in causality: A case of Next 11 countries. *Journal of cleaner production*, *197*, 73-84.

Sun, L., & Wang, M. (1996). Global warming and global dioxide emission: an empirical study. *Journal of Environmental Management*, *46*(4), 327-343.

Troster, V. (2018). Testing for Granger-causality in quantiles. *Econometric Reviews*, *37*(8), 850-866.

Troster, V., Shahbaz, M., & Uddin, G. S. (2018). Renewable energy, oil prices, and economic activity: A Granger-causality in quantiles analysis. *Energy Economics*, *70*, 440-452.

Wang, X., Wang, X., Ren, X., & Wen, F. (2022). Can digital financial inclusion affect CO2 emissions of China at the prefecture level? Evidence from a spatial econometric approach. *Energy Economics*, *109*, 105966.

Wang, J., Dong, X., & Dong, K. (2022). How does ICT agglomeration affect carbon emissions? The case of Yangtze River Delta urban agglomeration in China. *Energy Economics*, 106107
.

Zhang, Y. J., & Wei, Y. M. (2010). The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. *Resources Policy*, *35*(3), 168-177.