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Impact of energy intensity, renewable energy, and economic growth on CO_2 emissions: Evidence from Africa across regions and income levels

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ABSTRACT

Existing studies have widely examined the link between energy consumption, economic growth, and CO_2 emissions regionally and globally across development levels. Very few studies conducted at the African level overlooked the difference in regions and income levels of the countries involved in the research. This study empirically examined the long-run impact of energy intensity, renewable energy consumption, and economic growth on CO_2 emissions across regions and income levels over 50 African countries from 1980 to 2018. The most recent panel estimators, causality test, and impulse response and variance decomposition analysis were employed. The findings from panel estimators revealed that renewable energy consumption contributed to mitigating CO_2 emissions, while energy intensity promoted emissions across regions and income levels, and at the African level. Economic growth affected CO_2 emissions negatively at the African level but the effect was mixed across regions and income levels. The causality test confirmed bi-directional causations between CO_2 emissions and its determinants in African, and some regions and income levels. Again, unidirectional causation was highly supported across regions and income levels. Moreover, results of impulse response and variance decomposition analysis showed that both energy intensity and economic growth counted higher variations of CO_2 emissions, while renewable energy highly contributed to reducing emissions within 10 years. Our findings grasp new insight into country development, income levels, and regions for regional and government policy-makers related to effectively mitigate CO_2 emissions.

1. Introduction

To mitigate carbon dioxide (CO_2) emissions towards environmental sustainability, effective global CO_2 mitigation follow-ups have been established, such as The United Nations Framework Convention on Climate Change (UNFCCC) in 1992, the Tokyo protocol in 1997 [1,2], Copenhagen agreement in 2009 [3], the China and USA agreement in 2014, and Paris agreement proposed in 2015, have been led to reasonable achievements towards environmental sustainability [4,5]. These agreements rely on reducing emissions primitive determinants, such as fossil fuel combustion, and other nonrenewable energy use, human activities, and others. The green growth[1] economy coupled with green energy use has also initiated to reduce CO_2 emissions based on decoupling economic growth from resource use, however, the effective impact is promising [6,7].

The global emissions reached 35976.937 metric tons in 2016 due to a higher dependence on nonrenewable energy, and economic activities [8,9]. Existing literature intensively contributed to identifying the causal link between CO_2 emissions and their causes and proposed policy implications at the global and regional levels (see Ref. [10] and references therein). Specifically, economic growth and nonrenewable energy are among the leading causes of emissions. For instance, Kuznets [11] showed an inverted-U-shaped link between CO_2 and economic growth, and Dong et al. [12] argued that economic growth leads to CO_2

Abbreviationlist: UNFCCC, The United Nations Framework Convention on Climate Change; CCEMG, common correlated effect means group; CD-DL, cross-sectional augmented distributed lags; PMG, pooled means group; ARDL, Autoregressive distributed lags; VECM, vector error-corrected model; OPEC, Organization of Petroleum and Exporting countries; ECOWAS, Economic Community of West African States; WAPP, Western African power pool; SAPP, Southern African power pool; EAPP, Eastern African power pool; NAPP, Northern African power pool; EIA, U.S Energy Information Administration; CAPP, Central African power pool; EI, energy intensity; Y, CO_2 emission; REN, renewable energy consumption; GDP, gross domestic product/economic growth.

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[1] Green growth is defined differently by different institutions, such the World Bank [81] and OECD [82].

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emissions. On the other hand, several studies indicated that the more nonrenewable energy consumption, the higher CO_2 emissions, while the scenario varies across the income levels [10,13–16]. Responding to this emissions problem, renewable energy received reasonable concern. Sharif et al. [17] showed that renewable energy negatively affects CO_2 emissions and contributes to minimizing environmental hazards. Moreover, Dong et al. [18] noted environmental Kuznets hypothesis between CO_2 emissions and renewable energy consumption in upper-middle- and high-income levels. However, research can deeply examine relationships between emissions and their leading causes concerning variabilities and contribution of the individual cause, is of interest to global and regional policymakers for delivering the new insight towards environmental sustainability.

Previously, CO_2 emitted from the African continent was ignored due to insignificant development. Currently, an initiative for effectively mitigating CO_2 emissions is viable in all African countries under the five regions associated with regional renewable energy projects and eight economic communities [19], see (Fig. 1A). The North region counted among the top five global emissions producers, South Africa (single country) ranked 14th at the World ranks with 468 million metric tons of CO_2 emissions in 2018 [20]. This may be the consequence of the least attention from the global policymakers due to the lack of studies on the link between CO_2 emissions and its determinants covering the entire continent [21,22]. It is crucial to examine the historical impact of energy use and economic growth on CO_2 emissions and estimate to which extent these factors can affect CO_2 across regions and income levels in the African continent.

Recent literature considered some African countries and use various methods to investigate the links among energy intensity, renewable energy consumption, economic growth, and CO_2 emissions. Dabachi et al. [23] and Abubakar et al. [24] used Panel Autoregressive distributed lags (ARDL) to examine the energy intensity-growth-emissions nexus in OPEC[2] African countries. Shahbaz et al. [25] employed VECM Granger causality to examine the impact of energy intensity and CO_2 in some Sub-Sahara countries. Ozturk et al. [26] applied the common correlated effect and pooled means group (CCEMG and CCEP) to investigate relationships between renewable energy and financial development and CO_2 emissions in 30 African countries. However, to the best of our knowledge, very few studies considered some African counties, covering the global and regional levels to draw a general conclusion. The study on the impact of energy intensity, renewable energy consumption, and economic growth to mitigate CO_2 emissions that can cover all African countries across regions and development levels are of interest to the regions and government policymakers.

Most studies conducted in African countries on CO_2 emission and its driving forces, however, ignored differences across regional variations in the development levels of countries involved in the study. Again, the patterns and changes among emissions, renewable energy use, and economic growth are different across these subgroups of Africa. Responding to these scarcities, we noted that conducting this study across development and regional levels can grasp great impact for scientific support towards environmental sustainability. Classifying countries based on income and regional levels allows this study to deeply examine the impact of energy intensity, renewable energy consumption, and economic growth on CO_2 emissions in African.

Reasonable policy implications are available for research that merely on the impact of energy intensity, renewable energy use, and economic growth on CO_2 emissions in African. Sustainable development based on rapid urbanization and economic growth is a prior motive for all countries, although it leads to a higher extent of energy consumption and environmental issues. Thus, examining the effect of development levels, renewable energy, and energy intensity on emissions could bring new insight that may lead to environmental sustainability. In this respect, the aim is that if the economic growth promotes emissions concerning income levels, new policies will be directed to the main inputs of growth. Again, the side effect can be due to renewable energy and energy intensity on emissions. Related measures, including renewable energy projects, will be proposed for promoting environmental programs in all regions and countries. These measures will be attentionally taken regarding that some may negatively affect economic growth through labor, capital, and the well-being of the population.

From the overall view of existing studies, a better understanding of the relationships between CO_2 emissions and its determinants was presented for both policymakers and environmental quality at the global and regional levels. This achievement is not only mitigating CO_2 but also promoting the energy sector and global economy. However, three main features that differentiate this study from the existing studies were identified and contribute to adding input to the literature. First, this study examines the effect of renewable energy, energy intensity, and economic growth on CO_2 emissions across 5-regions (Northern, Western, Eastern, Central, and Southern, see Fig. 1A) and in development levels (low-, lower-middle-, upper-middle- and high-income) based on the World Bank classification (2018) [27], see (Fig. 1B). Second, except one global study showed to which extent of energy consumption and economic growth affect emissions across income levels [10], this study is the first to investigate to which extent energy intensity, renewable energy, and economic growth exert on CO_2 emissions across regions and income levels. Third, different from several studies that used previous approaches, which ignore the cross-sectional dependence, heterogeneity, and multicollinearity, the approaches have used in this study provide a more robust analysis for their potentiality to overcome these limitations. The novel empirical results of this are predominantly useful for regional and government policymakers to establish effective policies related to mitigating CO_2 emissions. The dataset of 50 African countries for 1980–2018 is used to obtain the findings, which do not only contribute to enlarge the current literature but also awaken up the policymakers.

The rest of this study is illustrated as follows. Section 2 provides an overview of the existing literature on the renewable energy-economic growth-CO_2 nexus in African. Data, empirical model, and estimators are discussed in section 3. Section 4 presents results and discussion. Conclusion and policy implications are presented in section 5.

2. Literature review

2.1. Overview of renewable energy and CO_2 emissions in African regions

African continent counted about 1.9% of global emissions in 1973. To ignore its negative effect led to significant environmental deterioration and increasing trends with more than a 3% increment rate [28,29]. Currently, reasonable attention has been taken to mitigate CO_2 emissions across regions and regional economic communities.[3] These regions have established renewable energy projects based on power pools (Central, West, Southern, and Eastern, see Fig. 1A) associated with cross-border power trades [30]. From these projects, regional energy systems, such as hydropower and Solar energy are the leading renewable energy resources and playing a significant role to reduce energy demand, energy poverty, and emissions in the continent. The contribution of regional power pools attracted the researchers to examine the nexus between renewable energy, economic growth, water, and CO_2 emissions. For instance, De Felice et al. [31] examined the water-renewable

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[2] Organization of Petroleum and Exporting countries (OPEC) in Africa includes Angola, Algeria, Congo, Gabon, Nigeria, Guinea, and Libya.

[3] The African Union recognizes eight regional economic communities (UMA, COMESA, CEN-SAD, EAC, ECCAS, ECOWAS, IGAD and SADC). They are closely integrated with the African Union's work and serve as its building blocks; ECOWAS is among the best-performing economic communities on the continent.

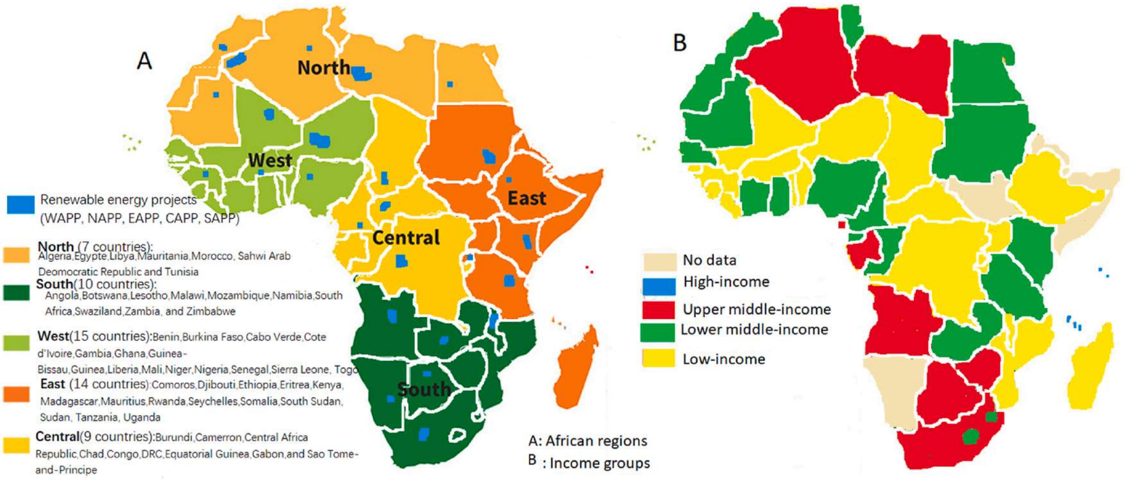

Fig. 1. The map of African regions, economic communities, and renewable energy projects (A) [19] and distribution of income levels across countries (B) [27].

energy nexus linked with the ecosystem. Results revealed that the amount of energy generated from the Western power pool (WAPP) was affected by water evaporation and reduced income generation across the linked countries. The cross-border trade among these countries reduced the unserved electricity demand and decrease generation cost at the country and regional levels, as argued by Adeoye et al. [32]. Moreover, through the initiative of the Economic Community of West African States (ECOWAS), renewable energy projects planning and generated electricity will get on 52% in 2030 in the region and reduce the emissions at a higher rate [33].

The Southern African power pool (SAPP) contributes to generating renewable energy, reduces emissions, and gaining income via the cross-border power trade among the connected countries [34,35]. Eastern African Power Pool (EAPP) coupled with hydropower plants created in Ethiopia, the Republic Democratic of Congo (DRC), and Tanzania as the Eastern regional renewable energy projects handled the preliminary reluctance in energy deliverance, emissions reduction, and economic growth via the cross-border power trade [30,36,37]. In the case of Central and North African power pools (CAPP and NAPP), Matija et al. [38] showed that climate changes affect energy production, energy use, income generation, and CO_2 emissions across the countries linked to these power pools. Again, the existence of CAPP and NAPP will reduce the higher amount of emissions within the regions, as argued by Pavicevic and Quoilin [39]. However, employing modeling tools to tackle environmental and socio-economic activities and bioenergy carbon capture and storage can lead to environmental sustainability in the entire continent [40,41].

2.2. *Existing studies on renewable energy, energy intensity, economic growth, and CO_2 emissions nexus in Africa*

There is a growing literature on CO_2 emissions-energy-growth nexus at the global level, regional levels, and country levels, see ([10] and brief reviews therein). In Africa, studies conducted on this topic in Sub-Sahara countries show that energy intensity promotes emissions, and an inverted-U sharp relationship was noted between economic growth and CO_2 [25,42]. Abubakar et al. [24] show that economic growth increases methane and CO_2 emissions, while energy consumption insignificantly affects greenhouse emissions (CO_2, N_2O, and CH_4) in OPEC countries. Apergis et al. [43] argue that renewable energy consumption reduces CO_2 emissions, while economic growth increases CO_2 emissions in 42-African countries. Ozturk et al. [26] illustrates that renewable energy and energy intensity contribute to reducing CO_2 emissions, while economic growth increases emissions in 34 African countries. Contrary, Adams et al. [44] indicates that both energy (renewable and nonrenewable) consumption and economic growth promote CO_2 in 28 countries. Benjamin et al. [45] shows that energy consumption (petroleum and natural gas) has an asymmetric (positive and negative) effect on CO_2 emissions in top-ten Oil producers' countries in Africa. Nathaniel et al. [46] confirm that in 19 African countries, nonrenewable energy increases CO_2 emissions, while renewable energy inhibits it. The impact of both renewable and nonrenewable vary across countries and economic growth neutrally affects CO_2 emissions. Ben Jebli et al. [47] argue that renewable energy positively increases CO_2 emissions across 22 Sub-Sahara countries. Beyond the African continent, several studies demonstrate contradicting results, whereas some argue that renewable energy and energy intensity contribute to mitigate CO_2 emissions, see Refs. [26,48–50] and others say that these two types of energy increase CO_2 emissions, see Refs. [25,47,51].

From the above background, a glowing beam of literature argued that renewable energy use reduces CO_2 emissions and leads to achieving Sustainable Development Goals related to environmental quality, as suggested by Bekun et al. [52]. Very few studies concluded that renewable energy consumption contributes to increasing CO_2 emissions in Africa and at the global level. Similarly, in the literature, we found contradictory results on how energy intensity and renewable energy affect emissions, and the environmental Kuznets hypothesis confirmed between economic growth and CO_2 emissions. However, to overcome the contradiction, this study uses 50 African countries to examine the effect of renewable energy consumption, energy intensity, and economic growth on CO_2 emissions.

2.3. *Review of existing estimators*

The nexus of CO_2 emissions, renewable energy, energy intensity, and economic growth examined by using various estimators. Some are from the first-generation estimators, such as Fully Modified Ordinary Least Square (FMOLS), Dynamic OLS (DOLS), Generalized Methods of Moment (GMM), and Autoregressive Distributed Lags (ARDL). Other estimators are from the second-generation estimators, such as Mean group (MG), Dynamic Fixed Effect (DFE), Pooled Mean Group (PMG), Common Corrected Effect Means Groups (CCEMG), and others.

The first-generation estimators are highly used, for example, Zoundi [53] used FMOLS and DOLS to investigate the impact of renewable energy on CO_2 emissions in 25 selected African countries. Al-Mulali et al. [54] and Sahb et al. [55] have used similar estimators to examine the relationship between CO_2 emissions, energy consumption, economic growth, and urbanization in MENA countries. Adams et al. [56] employed these approaches to examine the causal relationship of renewable and nonrenewable energy, and economic growth on CO_2

emissions in 28 African countries. On the other hand, Panel-ARDL and ARDL were intensively used to examine the effect of energy consumption, economic, and population growth on CO_2 emissions in country-specific studies, see ([57–59]). Although the first-generation estimators are both simple and able to show how renewable energy use, energy intensity, and economic growth affect CO_2 emissions, the estimators assume cross-sectional dependence that may exist among cross-national, ignore heterogeneity, and collinearities, which can provide inconsistent results or misleading information [60].

The second-generation estimators were proposed to overcome the weakness of the first-generation. Some of them are CCEMG proposed by Pesaran [61], advanced by Kapetania et al. [62], Augmented Mean Groups (AMG) was developed by Eberhardt and Bond [63], PMG estimator by Pesaran et al. [64], and others. Those estimators allow cross-sectional dependence across-national studies via estimating the effect of cross-sectional averaged variables and were used in some studies. For instance, Salim et al. [65] and Azam [65] used CCEMG and PMG to examine the effect of renewable energy on economic growth in OECD countries. Nathaniel [46] has used AMG to examine the causal relationship between energy use and CO_2 in 19-African countries. Ozturk et al. [26] used the CCEMG and CCEP to study the link between renewable energy and financial development on CO_2 in 30 African countries.

In this study, we use the most recent estimators, which are the panel cross-sectional augmented distributed lags (CS-DL) and CCEMG proposed by Chudik et al. (2015) [66,67]. These estimators allow the presence of lagged values of the endogenous and exogenous regressors in the model for estimating long-run relationships between variables. Moreover, these estimators are not only potential to detect cross-sectional dependence and heterogeneity among the selected variables, but also to estimate their effect on variables of interest. The section below briefly introduces econometric methodology and estimators.

3. Data and methodology

This section introduces data and econometric methods, such as cross-sectional dependence, unit root, and cointegration tests of the selected variables. In the estimation process, panel data estimators and causality tests are also introduced, see Fig. 2 for the methodological flowchart.

3.1. Data

The panel data mined from The World Bank database [8] and US Energy Information Administration database (EIA) [68] from 1980 to 2018, have employed. The energy intensity per capita and renewable energy (renewable and nuclear) consumption measured in Quadrillion Btu[4] and transferred into kg of oil equivalent per capita. GDP per capita (in constant 2010 US. dollars) used as economic growth, and CO_2 emissions in metric tons transferred into per capita by dividing the yearly total population. The selected variables have transformed into the natural logarithm to achieve a robust analysis and avoid possible heteroscedasticity. After all transformations, variables are noted as follow: CO_2 emissions is Y_{it}, energy intensity is EI_{it}, renewable energy consumption is REN_{it}, and economic growth is GDP_{it}. Descriptive statistics of all selected variables are presented in Table .1.

3.2. Mathematical model

This study aims to examine the impact of energy intensity, renewable energy use, and economic growth on CO_2 emissions across regional and income levels in African countries. To effectively achieve the aim of the study, existing contributors of GDP, such as labor and capital, and dependence between covariates are assumed to be invariant, and then for the country i at the time$t$, $Y_{it}$is given by the following mathematical function:

$$Y_{it} = f(EI_{it},\ GDP_{it}, REN_{it}) \tag{1}$$

For $i = 1, 2, \ldots N$represent the country, $t = 1, 2, \ldots T$time, $Y_{it}$is the CO_2 emission, $REN_{it}$is renewable energy consumption, EI_{it} is energy intensity, and GDP_{it} is economic growth. Therefore, the multivariate equation can be written as follow:

$$lnY_{it} = \alpha_{0i} + \alpha_{1i} lnEI_{it} + \alpha_{2i} lnGDP_{it} + \alpha_{3i} lnREN_{it} + u_{it} \tag{2}$$

For $\alpha_{0i}$is the unobserved country fixed effect, $\alpha_1 - \alpha_3$ are the long-run equilibrium coefficients, and u_{it} is the error term.

3.3. Econometric methodology

3.3.1. Cross-sectional dependence tests

The most crucial issue to be concerned with among the panel data is cross-sectional dependence, as suggested by Goldin [69]. To overlook this issue can lead to inconsistent estimates and misleading information. In this respect, Pesaran [70] proposed Pesaran CD and standardized Lagrange Multiplier (LM) tests, and Breusch and Pagan [71] proposed Breusch-Pagan LM test for detecting cross-sectional dependence. The cross-sectional tests proposed by Pasaran are potential for large panel data size N and time T, and can be computed as follows:

$$LM = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T_{ij} \mu_{ij}^2 - 1 \right) \rightarrow N(0, 1) \tag{3}$$

$$CD = \sqrt{{}^{2}/N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij} \mu_{ij}^2 \rightarrow N(0, 1) \tag{4}$$

The equation (3) used for large size and changeable time T, and equation (4) used for large N and fixed T, however, the Breusch-pagan LM test is efficient for small size and T, can be computed as follows:

$$LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij} \mu_{ij}^2 \rightarrow \chi^2 \left(N(N-1)/2 \right) \tag{5}$$

For $\mu_{ij}^2$is the correlation coefficients obtained from the residuals of the equation (3), can be estimated as follows:

$$\mu_{ij} = \mu_{ji} = \frac{\sum_{t-1}^{T} \varepsilon_{ij} \varepsilon_{ji}}{\left(\sum_{t-1}^{T} \varepsilon_{ij}^2 \right)^{\frac{1}{2}} \left(\sum_{t-1}^{T} \varepsilon_{jt}^2 \right)^{1/2}} \tag{6}$$

where ε_{ij} *and* $\varepsilon_{ji}$are standard errors.

3.3.2. Pesaran CIPS unit root test

The Pesaran CIPS panel unit root test proposed by Pesaran [72] is a potential unit root test for panel data, which allows the cross-sectional dependence by considering the averages of lagged levels and differences for each unit. This approach is denoted as cross-sectionally augmented Dickey-Fuller, and can be computed as follows:

$$\Delta y_{it} = \psi_i + \alpha_i y_{i,\ t-1} + \beta_i \overline{y}_{t-1} + \sum_{j=0}^{p} d_{ij} \Delta \overline{y}_{t-j} + \sum_{j=1}^{p} \xi_{ij} \Delta y_{i,t-j} + u_{it} \tag{7}$$

For $\overline{y}_{t-1}$ and $\Delta\overline{y}_{t-j}$ are the cross-sectional averages of lagged levels, and first difference with β and d coefficients, respectively, ψ and α are the intercept and trends and ξ lead coefficient, see Ref. [72]. The cross-sectionally augmented Dickey-Fuller (CADF) statistics used to compute the CIPS statistic in the following equation:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF_i \tag{8a}$$

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[4] British thermal Units.

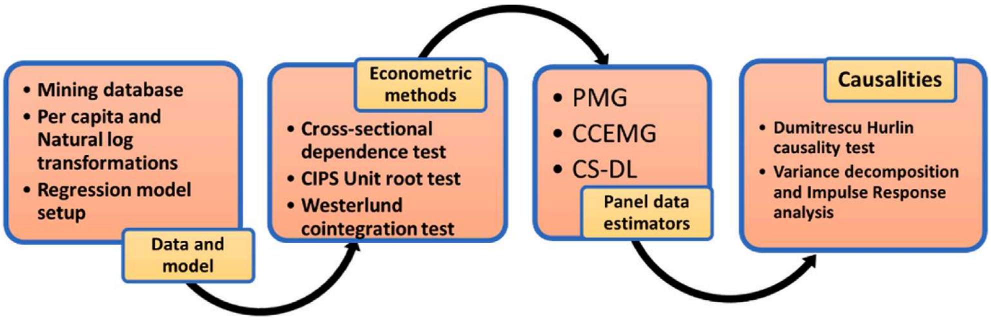

Fig. 2. Methodological flowchart.

Table 1
Descriptive statistics.

Region	Variable	Mean	Median	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis	Observations
Northern	lnY	1.41313	1.536582	2.374701	−0.28881	0.612068	−0.90013	3.297357	234
	lnEI	1.465828	1.455799	2.161781	0.606083	0.369293	0.007435	2.41567	234
	lnGDP	3.467283	3.421793	4.081519	3.042492	0.265746	0.672299	2.429748	234
	lnREN	0.811572	0.836975	1.775799	−0.53323	0.602819	−0.24381	2.107346	234
Western	lnY	0.142718	0.041393	2.005615	−1.27482	0.648766	0.6875	3.458578	585
	lnEI	0.548763	0.52871	1.443385	−0.2228	0.322241	0.11605	2.785537	585
	lnGDP	2.894721	2.851426	3.572872	2.436149	0.223151	0.741863	3.211582	585
	lnREN	0.600638	0.748189	2.0849	−1.37148	0.845851	−0.70232	2.926229	585
Eastern	lnY	0.126338	0.113734	1.272924	−1.44928	0.685934	−0.29364	2.20347	351
	lnEI	0.496502	0.312444	2.283537	−0.44182	0.636506	1.562274	4.782656	351
	lnGDP	2.895986	2.883446	4.158877	2.215734	0.454877	1.093763	3.872054	351
	lnREN	0.907053	0.934682	1.752485	−0.95727	0.437657	−0.80496	4.308265	351
Central	lnY	−0.13495	−0.04576	0.862145	−1.49404	0.651639	−0.31987	1.775404	312
	lnEI	0.678493	0.705772	1.910146	−0.47498	0.612309	0.056756	2.4429	312
	lnGDP	3.149375	2.970152	4.312451	2.440997	0.51554	0.749181	2.343143	312
	lnREN	0.880529	1.428987	2.322702	−2.75566	1.42928	−1.73203	4.888327	312
Southern	lnY	0.498546	0.399079	2.680506	−1.00000	0.780822	1.250071	4.845594	468
	lnEI	1.035048	1.122862	2.050679	−0.01385	0.546088	−0.09848	2.184	468
	lnGDP	3.221863	3.222572	4.02437	2.216073	0.465577	−0.21655	1.815871	468
	lnREN	−0.38603	−0.176	0.727143	−38.7064	1.85213	−18.9815	393.2424	468
Low-income	lnY	−0.02003	−0.01867	1.269819	−1.08071	0.463203	0.303759	2.841342	741
	lnEI	0.263674	0.251842	1.155873	−0.47498	0.293316	−0.11094	3.305007	741
	lnGDP	2.690658	2.699473	3.278775	2.215734	0.182345	−0.08145	3.472143	741
	lnREN	0.209553	0.624629	1.752485	−2.75566	1.070266	−1.05811	3.557365	741
Lower-middle	lnY	0.542694	0.618392	2.374701	−1.49404	0.894569	−0.28296	2.538585	858
	lnEI	0.933607	0.874424	1.775177	−0.01385	0.369272	0.043947	2.678008	858
	lnGDP	3.181498	3.142041	3.683824	2.67809	0.233327	0.237592	2.367037	858
	lnREN	0.780527	0.900423	2.0849	−1.04561	0.736638	−0.45189	2.4168	858
Upper-middle	lnY	0.836195	0.5172	2.680506	−1.25673	1.020978	0.265296	2.593559	234
	lnEI	1.595019	1.585474	2.161781	0.445063	0.429786	−0.94374	3.526008	234
	lnGDP	3.769111	3.824135	4.312451	2.695666	0.328126	−1.66073	6.018878	234
	lnREN	0.230792	0.064081	2.322702	−38.7064	2.740051	−12.2833	175.8199	234
High-income	lnY	0.106552	0.040841	0.82727	−0.69897	0.418066	0.072425	2.038262	78
	lnEI	1.811309	1.905868	2.283537	1.082824	0.341191	−0.58075	2.37923	78
	lnGDP	3.829902	3.875023	4.158877	3.366308	0.201798	−0.60375	2.620445	78
	lnREN	0.47742	0.400337	1.354905	−1.03292	0.818586	−0.26587	1.425805	78
Panel of all regions	lnY	0.333191	0.327005	2.680506	−1.49404	0.818236	0.498552	3.214835	1950
	lnEI	0.786869	0.735075	2.283537	−0.47498	0.596382	0.403789	2.516301	1950
	lnGDP	3.082915	2.995404	4.312451	2.215734	0.441445	0.563561	2.56148	1950
	lnREN	0.462346	0.649917	2.322702	−38.7064	1.308375	−14.0576	413.4098	1950

3.3.3. *Panel cointegration test*

We used the error correction panel cointegration test proposed by Westerlund [73]. This approach is effective for cross-sectional dependence by applying an error correction term (ECT) and test two different null hypotheses (no cointegration in some cross-sectional panels and no cointegration in all cross-sectional panels). It is computed as follows:

$$\Delta z_{it} = \alpha_i^{'} d_i + \vartheta_i \left(z_{i(t-1)} + \pi_i^{'} y_{i(t-1)} \right) + \sum_{j=1}^{m} \varphi_{ij} \Delta z_{i(t-1)} + \sum_{j=0}^{m} \phi_{ij} \Delta y_{i(t-1)} + \omega_{it} \tag{8b}$$

For ϑ_i is the adjustment term, d_i is a vector of deterministic components, including constant and linear time trends. $z_{it} = (x_{it}, y_{it})$is the k+1 dimensioned vector of integrated variables, while other parameters introduce the nuisance in the variable of interest. Thus, referred to the estimates of ϑ_i, the statistics of Westerlund ECT based panel cointegration tests can be determined as follows:

$$G_\tau = \frac{1}{N} \sum_{i=1}^{N} \frac{\vartheta_i}{SE(\vartheta_i^{'})} \tag{9}$$

$$G_\alpha = \frac{1}{N} \sum_{i=1}^{N} \frac{T\vartheta_i}{\vartheta_i^{'}(1)} \tag{10}$$

where G_τ and $G_\alpha$are group mean statistics, and test the null hypothesis, which states that there is no existence of cointegration in the cross-sectional panel. The rejection of this hypothesis implies the existence of cointegration for at least one cross-sectional unit in the panel. The group mean statistics, which tests the cross-sectional in all unit of panels can be computed as follows:

$$P_\tau = \frac{\widehat{\vartheta}_i}{SE\left(\widehat{\vartheta}_i\right)} \tag{11}$$

$$P_\alpha = T\widehat{\vartheta}_i \tag{12}$$

The rejection of the null hypothesis implies no cointegration for the whole panel.

3.3.4. Panel cross-sectional augmented distributed lags (CS-DL)

Due to this study uses panel data, which are mostly suspected to have cross-sectional dependence across countries, the panel CS-DL test proposed by Chudik et al. [66] has employed. This test allows and estimates the effect of the possible cross-sectional lags and cross-sectional average variables on the variable of interest. Thus, the CS-DL equation can be written as follows:

$$y_{it} = \alpha_i + \beta_i y_{it-1} + \delta_{0i} x_{it} + \delta_{1i} x_{it-1} + \sum_{l=0}^{PT} \sigma'_{il} \overline{z}_{it-l} + u_{it} \tag{13}$$

For $i = 1, 2, \ldots, N$, and $\overline{z}_t = N^{-1} \sum_{i=1}^{N} z_{it} = \left(\overline{y}_t, \overline{x}_t, \overline{f}_t\right)'$, where β_0 and δ_0 obtained by arithmetic averages of least squares estimators of β_i and δ_{0i} based on the Pesaran (2006) [61], and f_t is the unobserved common factor with heterogeneous factor, α_i and u_{it} are intercept and error term. The long-rung coefficients can be estimated in this equation:

$$\widehat{\theta}_{cs-DL} = \frac{\sum_{l=0}^{q} \widehat{\delta}_{il}}{1 - \sum_{l=1}^{p} \widehat{\beta}_{il}} \tag{14}$$

3.3.5. Common correlated effect means groups (CCEMG)

The panel CCEMG proposed by Pesaran (2006) [61] and extended by Chudik et al. (2015) [67] and Pooled means group proposed (PMG) by Pesaran et al. [74] have also used in this study. The CCEMG estimator estimates the effect of cross-sectional average regressors on the variables of interest. This is the unique feature that makes CCEMG better than the previous versions, which assume the cross-sectional effect. CCEMG can be estimated in the following equation.

$$y_{it} = \alpha_i + \sum_{l=0}^{p} \beta_{il} y_{it-l} + \sum_{l=0}^{q} \delta_{il} x_{it-l} + \sum_{l=0}^{Z} \mu_{il} \overline{z}_{it-l} + u_{it} \tag{15}$$

where $\overline{z}_t = \left(\overline{y}_t, \overline{x}_t\right)'$, $\overline{y}_t = n^{-1} \sum_{i}^{N} y_t$ and $\overline{x}_t = n^{-1} \sum_{i}^{N} x_t$, for (p, q, z) are the lags.

In this estimator, $\overline{z}_t$ is the combination of the cross-sectional averages of the variable of interest and regressors, which are the observed common effects employed with coefficients presented in Kapetania et al. [62]. α_i is the intercept, $\beta_{il}$is the effect of lagged variables, δ_{il} is the effect of regressors, μ_{il} is the effect of combined cross-sectional averaged variables at lag (l), and u_{it} error term. Therefore, PMG, CS-DL, and CCEMG provide similar conclusions based on the estimated confident interval of each regression coefficient. More importantly, CS-DL can detect the multi-collinearity between the cross-sectional averaged variables and drop them out in the estimation process, however, CS-DL can produce better results than those from CCEMG and PMG, see Ref. [75].

3.3.6. Causality test

This study used the causality test proposed by Dumitrescu Hurlin [76], determine the directional causal relationship between variables. This directional causal relation can be seen in three ways: Bi-directional causal or two-way directional causal relations, which runs from one variable to the other, and vice-versa; unidirectional causal or one-way directional, which runs from one variable to the other; and neutral causal relationship. Thus, the causality test expressed as follows:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \delta_i^k y_{i,t-k} + \sum_{k=1}^{k} \beta_i^k x_{i,t-k} + \varepsilon_{it} \tag{16}$$

where *y and x* are variables to be tested, α is the individual fixed effect, δ and β are the autoregressive parameter and regression coefficient, respectively, which are different across groups. k gives information about the optimal lag and identical for all cross-sectional units. The hull hypothesis of this test is based on the regression coefficient slop, and associates with the individual Wald statistics of Granger non-causality averaged across the cross-sectional units, which is written as follows:

$$W_{i,T} = \widehat{\theta}_i' R' \left[\widehat{\theta}_i^2 R \left(Z_i' Z_i\right)^{-1} R'\right]^{-1} R \widehat{\theta}_i \tag{17}$$

For more detail about parameters, see Ref. [76].

3.3.7. Variance decomposition and impulse response approach

To examine the current and future impact of a shock to explanatory variables on the variable of interest, impulse response, and variance decomposition analysis have been employed. This impact can be exerted between the variable itself or transmitted to the other variables by the dynamic structure of the model. The estimate of impulse response appeared in a stable companion matrix of vector autoregressive (VAR) model, as recently suggested by Lanne [77], this model can be written as follows:

$$y_t = \sum_{j=0}^{P} \Phi_i y_{t-i} + \varepsilon_t \tag{18}$$

where Φ_i is the simple impulse response function can be estimated by changing the equation (18) to an infinite vector moving-average, and it can be estimated from the following equation:

$$\Phi_i = \begin{cases} I_{k,} & i=0 \\ \sum_{j=1}^{i} \Phi_{t-j} A_j, & i = 1, 2, .. \end{cases} \tag{19}$$

For I_k is the identity element of the companion matrix, A_j is the coefficient matrix of the transformed VAR into infinity vector moving average form, P is the optimal lag, and ε_t is the error term. The h-step ahead forecast-error is obtained from the following expression:

$$y_{it+h} - E[y_{it+h}] = \sum_{i=0}^{h-1} \varepsilon_{i(t+h-1)} \Phi_i \tag{20}$$

where y_{it+h} is the vector of variables at time $t+h$ and $E[y_{it+h}]$ is the h-step ahead predicted vector in time t. The change of variables has been orthogonalized by using matrix p (cross product of $K \times K$) to identify the impact of the variable on the forecast-error variance. Thus, the contribution of a variable n to the h-step ahead forecast-error variance of variable m can be obtained from the following expression:

$$\sum_{i=0}^{h\ l} \theta_{nm}^2 = \sum_{i=0}^{h\ l} \left(i_m' P \Phi_{in}\right)^2 \tag{21}$$

For i_s is the sth column of I_k.

4. Results and discussion

4.1. Cross-sectional dependence and panel unit root tests results

The results presented in Table 2 were obtained using the cross-sectional dependence tests proposed by Pesaran [70] and Breusch [71]. Results reveal that the null hypothesis of no cross-sectional

Table 2
Cross-sectional dependence test results.

Region	Breusch LM				Pesaran CD			
	LnY	lnEI	lnGDP	lnREN	LnY	lnEI	lnGDP	lnREN
Northern	378.982*	121.890*	198.264*	82.997*	19.228*	6.477*	8.634*	2.818*
Western	2309.841*	1092.189*	1381.352*	1193.541*	43.167*	13.789*	10.399*	9.429*
Eastern	910.318*	538.164*	741.109*	253.464*	29.384*	11.912*	14.221*	1.404
Central	489.996*	229.306*	323.093*	253.051*	17.312*	2.036**	1.097	−0.262
Southern	1095.146*	825.060*	1284.856*	737.506*	26.883*	8.623*	19.421*	11.263*
Income groups								
Low-income	3252.064*	1720.198*	2529.487*	1614.988*	48.915*	11.329*	11.032*	21.709*
Lower-middle	5411.415*	2819.773*	3827.237*	2044.090*	67.273*	25.320*	38.265*	−1.746*
Upper-middle	272.216*	124.422*	227.243*	63.944*	15.634*	1.657*	1.366	0.639
High-income	36.395*	27.976*	37.449*	2.160	6.032*	5.289*	6.119*	−1.469
Africa level (Panel)	25651.880*	13948.130*	19796.850*	11319.450*	140.527*	42.051*	52.741*	15.719*

*, **, and *** indicate significant levels of 1%, 5%, and 10%, respectively, Y: CO_2 emissions, EI: energy intensity, REN: renewable energy consumption, GDP: gross domestic product used as economic growth.

independence is rejected at a 1% significance level at the African, regions, and income levels, implying the presence of cross-sectional dependence. In this respect, the Pesaran CIPS panel unit root test by Pesaran [72] was used to examine the stationarity and integration levels of all selected variables. Table 3 presents the results obtained from the unit root test shows that the null hypothesis of the unit root is rejected for some variables at the levels and others at the first difference. This indicates that the cointegration order of all selected variables is the optimal order of integration among all variables, and it is I (1). Thus, the appropriate test to examine the presence of the long-run equilibrium relationship among variables is the error-correction term-based panel cointegration test proposed by Westerlund [73].

Table 4
Westerlund panel cointegration test results.

Dependent: lnY				
Region	Gτ	Gα	Pτ	Pα
Northern	−2.529**	−13.320**	−6.618*	−15.197*
Western	−1.880	−6.552	−11.013*	−11.217*
Eastern	−0.970	−6.554	−6.033***	−12.521*
Central	−1.299	−1.761	−6.457*	−9.509*
Southern	−2.144***	−7.496	−6.535***	−10.499*
Income groups				
Low-income	−1.586	−5.536	−10.103*	−10.961*
Lower-middle	−2.070**	−8.515	−12.606*	−15.187*
Upper-middle	−1.448	−5.321	−4.938***	−8.058***
High-income	−1.240	0.055	−1.066	−1.314
Africa level (Panel)	−1.743	−6.495	−18.432*	−14.197*

*, **, and *** indicate significant levels of 1%, 5%, and 10%, respectively.

4.2. Panel cointegration test results

Table 4 presents findings from the Westerlund panel cointegration test [73] at the regional levels, income levels, and African level. The Westerlund test statistics reject the null hypothesis of no cointegration in favor of its alternative, which states that there is a cointegration in all panels. These results confirm the long-run cointegration relationships among the selected variables, imply the presence of long-run equilibrium causal relationships of renewable energy, energy intensity, and economic growth on CO_2 emissions across the regions, income levels, and panel of 50 African countries from 1980 to 2018. The presence of subpanels and panel cointegration causal link among selected variables assisted the prior aim of this study and allowed us to examine the effects of renewable energy consumption, energy intensity, and economic growth on CO_2 emissions across the African countries.

4.3. Results of estimators

The results of the PMG, CCEMG and CS-DL estimators are presented in Table 5. The findings of these three estimators show that the energy intensity has a significant positive effect, while renewable energy and economic growth have a significant negative effect on CO_2 emissions at the African level in the long term. Refer to our estimation procedures, a long-term effect from regressors to emissions obtained from CS-DL is better than those of other estimators, therefore, our main findings rely on CS-DL. This is supported by Ditzen (2018) [75], who argued that results obtained from CS-DL are more robust than those obtained from previous estimators. These findings are consistent with Shahbaz et al. [25], who showed that energy intensity contributes to increasing CO_2 emissions in 24-African countries. And similar to those obtained by Shahbaz et al. [25] for the environmental Kuznets curve in Sub-Sahara countries, and Abubakar et al. [24], and Ozturk et al. [26], who indicated that the increase in economic growth leads to an increase in CO_2 emissions at the African level. Our results contradict those obtained by

Table 3
CIPS panel unit root test results.

	Levels				1st difference			
Regions	LnY	lnEI	lnGDP	lnREN	LnY	lnEI	lnGDP	lnREN
Northern	−2.956**	−2.977**	−2.760***	−1.917	−5.736*	−5.615*	−5.131*	−6.190*
Western	−2.978*	−2.933*	−2.699***	−2.227	−6.087*	−5.840*	−5.508*	−5.746*
Eastern	−3.195*	−2.797**	−2.117	−1.438	−6.370*	−6.361*	−4.882*	−5.222*
Central	−2.928**	−3.003**	−1.637	−4.333*	−6.184*	−6.121*	−4.305*	−5.506*
Southern	−2.079***	−2.446	−1.809	−3.485*	−5.873*	−5.997*	−5.327*	−5.963*
Income groups								
Low-income	−2.880*	−3.000*	−3.103*	−2.454	−6.101*	−5.983*	−5.500*	−5.325*
Lower-middle	−2.834*	−2.858*	−2.404	−2.774**	−6.087*	−5.911*	−4.835*	−5.784*
Upper-middle	−1.749	−2.949**	−2.900**	−3.544*	−5.975*	−6.035*	−5.190*	−6.290*
High-income	−4.244*	−1.775	−2.523	−6.420*	−6.351*	−6.420*	−5.379*	−6.420*
Africa level (Panel)	−2.864*	−3.012*	−2.544	−3.032*	−6.106*	−5.999*	−5.182*	−5.632*

*, **, and *** indicate significant levels of 1%, 5%, and 10%, respectively.

Table 5
The long-run estimates.

Dependent: lnY									
Estimators	PMG			CCEMG			CS-DL		
Region	LnEI	LnGDP	lnREN	lnEI	lnGDP	lnREN	lnEI	lnGDP	lnREN
Northern	1.367*	0.152	−0.009*	0.886*	0.027	−0.051	0.764*	−0.227	−0.132
Western	1.048*	−0.040	−0.007*	0.659*	0.201	−0.069*	0.711*	0.613	−0.0638*
Eastern	0.808*	0.045	−0.048*	0.793*	−0.115	−0.181*	0.586*	−0.046	−0.218**
Central	1.168*	0.028	−0.208*	1.038*	−0.487	−0.171*	1.359*	−0.367	−0.292*
Southern	1.119*	0.179*	−0.031**	1.440*	0.252	−0.328**	1.122*	0.842	−0.226***
Income groups									
Low-income	0.887*	1.745*	−0.531*	0.929*	−0.234	−0.252*	0.928*	−0.123	−0.185**
Lower-middle	0.981*	−0.071**	−0.015	0.918*	−0.363**	−0.170	0.883*	−0.479	−0.270***
Upper-middle	1.078*	−0.103	−0.088*	1.035*	0.152	−0.050	0.874*	0.205**	−0.182
High-income	1.066*	0.271	−0.023	1.082*	0.231*	−0.040*	0.486	0.551*	−0.066**
Africa level (Panel)	1.134*	−0.078**	−0.042*	0.939*	−0.302**	−0.195*	0.888*	−0.228**	−0.187**

*, **, and *** indicate significant levels of 1%, 5%, and 10%, respectively.

Adams et al. [44], who argued that renewable energy use insignificantly contributes to increasing CO_2 emissions in 28 Sub-Sahara countries.

The novel empirical findings of this study are those from regional and income levels. In the case of regional levels, renewable energy consumption contributes to significantly reduce CO_2 emissions, while energy intensity significantly promotes emissions, except in the North region, where the effect is insignificant. On the other hand, economic growth has a mixed effect and mostly insignificant on emissions. In the case of income levels, renewable energy consumption significantly contributes to reducing emissions, except in the Upper-middle group, where the contribution is insignificant. The energy intensity significantly increases emissions in all income groups, while economic growth negatively and positively affects emissions.

More specifically, at the African level, the results reveal that a 1% increase in energy intensity leads to a 0.888% increase in CO_2, a 5% increase in GDP leads to a 0.228% decrease in CO_2, and a 1% increase in renewable energy use leads to 0.187% decrease in CO_2. The results are consistent with Zoundi [32], Dong et al. [1], and Shuai et al. [50], who suggested that renewable energy and GDP negatively and positively affect CO_2 emissions, respectively. These findings imply that renewable energy projects established in the African continent are significant to contribute to CO_2 emissions depletion and measures can be addressed to reduce energy intensity, especially, nonrenewable energy. In regions, a 1% increase in renewable energy leads to a 0.063% and 0.292% decrease in CO_2 in Western and Central regions, respectively. A 5% and 10% increase in renewable energy led to a 0.218% and 0.226% decrease in CO_2 in Eastern and Southern regions, respectively. A 1% increase in energy intensity leads to more than a 0.5% increase in CO_2 in all regions. In income levels, a 5% increase in renewable energy leads to a 0.1885% and 0.066% decrease in CO_2 in Low- and high-income groups and a 10% increase leads to a 0.270% decrease in CO_2 in Lower-income. On the other hand, a 1% increase in energy intensity leads to a more than 0.8% increase in CO_2 in income levels. Thus, our results reveal that increase in renewable energy use leads to significant emissions depletion across the regions and income levels, imply that a country-specific contribution to reducing emissions plays a vital role in the whole African continent.

Table 6
Results of causalities and hypotheses.

Regional/income groups	variables	Statistics	Hypotheses	Variables	Statistics	Hypothesis
Northern	Y→EI	1.735	neutral	EI→Y	3.333	neutral
	Y→GDP	2.809	neutral	GDP→Y	5.426*	growth
	Y →REN	4.284**	conservative	REN→Y	2.378	neutral
Western	Y →EI	4.313*	conservative	EI→Y	4.119	growth
	Y→GDP	3.732*	conservative	GDP→Y	3.122***	growth
	Y→REN	3.482**	conservative	REN→Y	3.071	neutral
Eastern	Y→EI	4.558*	conservative	EI→Y	2.518	neutral
	Y→GDP	4.869*	conservative	GDP→Y	3.214	neutral
	Y→REN	3.575***	conservative	REN→Y	3.444***	growth
Central	Y→EI	3.178	neutral	EI→Y	3.144	neutral
	Y→GDP	5.773*	conservative	GDP→Y	4.151**	growth
	Y→REN	10.908*	conservative	REN→Y	2.308	neutral
Southern	Y→EI	3.876*	conservative	EI→Y	3.850*	growth
	Y→GDP	3.877*	conservative	GDP→Y	7.003*	growth
	Y→REN	2.663	neutral	REN→Y	6.878*	growth
Low-income	Y→EI	3.017***	conservative	EI→Y	2.641	neutral
	Y→GDP	4.518*	conservative	GDP→Y	3.516*	growth
	Y→REN	3.306**	conservative	REN→Y	4.330*	growth
Lower-middle	Y→EI	4.309*	conservative	EI→Y	3.073***	growth
	Y→GDP	3.927*	conservative	GDP→Y	4.936*	growth
	Y→REN	5.323*	conservative	REN→Y	2.211	neutral
Upper-middle	Y→EI	3.086	neutral	EI→Y	2.390	neutral
	Y→GDP	2.692	neutral	GDP→Y	9.521*	growth
	Y→REN	6.667*	conservative	REN→Y	9.350*	growth
High-income	Y→EI	7.555*	conservative	EI→Y	11.185*	growth
	Y→GDP	3.891	neutral	GDP→Y	2.400	neutral
	Y→REN	2.939	neutral	REN→Y	2.428	neutral
Africa level (Regional panel)	Y→EI	3.761*	conservative	EI→Y	3.516*	growth
	Y→GDP	3.928*	conservative	GDP→Y	4.771*	growth
	Y→REN	4.539*	conservative	REN→Y	4.075*	growth

*, **, and *** indicate significant levels of 1%, 5%, and 10%, respectively.

4.4. Causalities and hypotheses results

Table 6 shows the causality results of the Dumitrescu Hurlin [76] causality test in form of hypothesized (two-way directional, one-way directional or growth and conservative, and neutral) tested for CO_2 emissions and its determinants in 50 African countries divided into five regions and four income levels. In regions, results show one-way directional causation that runs from CO_2 to renewable energy and from GDP to CO_2 in the North region. In the Western region, we noticed the two-way directional causation that runs from CO_2 to GDP and vice-versa and one-way directional causation that runs from CO_2 to energy intensity and renewable energy. One-way directional causation running from CO_2 to energy intensity and GDP, and bidirectional causation running from renewable energy to CO_2, and vise-versa are noted in the Eastern region. These results are consistent with those obtained in the study conducted at the eastern regional level [78]. On the other hand, two-way directional causation running from GDP to CO_2 and vice-versa, and one-way directional causation runs from CO_2 to renewable energy are both noted in the Central region. Bi-directional causation running from CO_2 to energy intensity, and GDP, vice-versa; and one-way directional causation that runs from renewable energy to CO_2 are noted in the South region. Therefore, these findings imply that GDP and energy intensity cause emissions. Furthermore, the emissions have a negative side effect on renewable energy resources, such as Solar energy and others, which reduces renewable energy generation.

In income levels, results show bi-directional causation runs from CO_2 to GDP, and renewable energy, vice-versa; and one-way directional causation that runs from CO_2 to energy intensity in low-income level. In lower and middle-income levels, a two-way directional causal link runs from CO_2 to energy intensity and GDP, vice-versa; and one-way directional causation runs from CO_2 to renewable energy are noted. Two-way directional causal link running from CO_2 to renewable energy and vice-versa, one-way directional causation that runs from GDP to CO_2 are noted in Upper middle-income levels. Bi-directional causation runs from CO_2 to energy intensity and vice-versa is noted in high-income level. The summary of hypotheses tested in region levels, income levels, and at the African level are presented in Fig. 3. Lastly, at the African level (panel of all countries), we noted the bi-directional causation runs from CO_2 to energy intensity, GDP, and renewable energy, and vice-versa. The results at the African level are consistent with those obtained by some researchers on CO_2 emissions and its determinants for sampled African countries, see Refs. [25,43,46].

4.5. Impulsive response and variance decomposition results

To estimate which extent to energy intensity, renewable energy, and economic growth can exert to CO_2 emissions across regional and income levels, the impulse response and variance decomposition method proposed by Lanne [77] has been employed. Table 7 presents the results from variance decomposition and impulse response analysis for 10 years forecast horizon. In the case of the African level, the findings show that 59.439% of the variation in CO_2 can be explained by innovative shocks in CO_2 itself, while energy intensity, GDP, and renewable energy contribute 9.294%, 23.308%, and 8.048%, respectively. Energy intensity will contribute to CO_2 more than GDP and renewable energy, whereas 29.161%, 10.804%, and 0.028% of the variation in CO_2 can be explained by the innovative shocks in the energy intensity, GDP, and renewable energy, respectively in the North region of Africa. These results are similar to those obtained in the West region, whereas 14.619%, 19.803%, and 1.131% of the variation in CO_2 can be explained by the innovative shocks in the energy intensity, GDP, and renewable energy, respectively. In the case of the Eastern region, renewable energy appeared to have the least contribution to CO_2 than energy intensity and GDP, whereas 1.155%, 26.537%, and 17.594% of the variation of CO_2 can be explained by innovative shocks in the renewable energy, energy intensity, and GDP. In the Central region, 11.758%, 18.723%, and 0.020% variation in CO_2 can be explained by innovative shocks in energy intensity, GDP, and renewable energy, respectively. In the case of the South region, 19.051%, 21.343%, and 0.314% variation in CO_2 can be explained by innovative shocks in the energy intensity, GDP, and renewable energy, respectively. The overall results reveal that renewable energy has a lower variation than those energy intensities and economic growth across regional levels, which implies that renewable energy consumption will continue to reduce CO_2 emissions within10 years.

Fig. 4 shows that at the first two years, the variation of CO_2 itself has

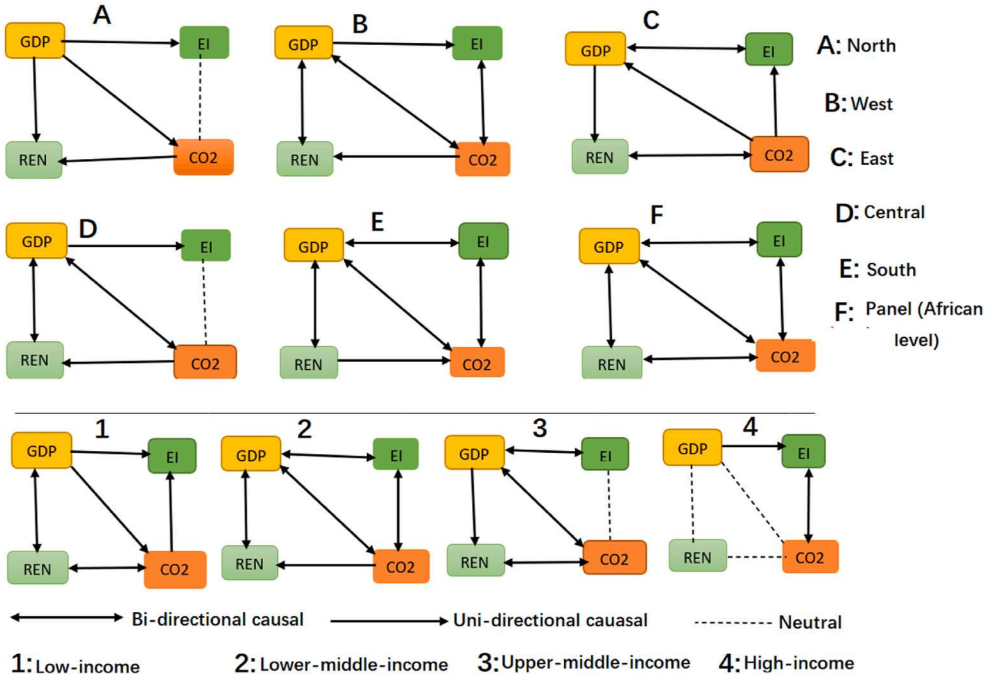

Fig. 3. Representation of directional causal link between CO_2 emissions and its determinants.

Table 7
Impulse response and variance decomposition results.

Regions	response variable	period	Impulse variable			
			CO_2	EI	GDP	REN
Northern	CO_2	10	60.043	29.161	10.804	0.028
	EI	10	56.328	36.834	6.304	0.532
	GDP	10	5.669	2.162	91.986	0.181
	REN	10	0.478	0.890	2.125	96.505
Western	CO_2	10	65.445	14.619	19.803	1.131
	EI	10	31.914	60.188	7.718	0.178
	GDP	10	0.758	1.410	97.437	0.393
	REN	10	0.206	0.121	2.219	97.452
Eastern	CO_2	10	55.713	26.594	17.155	1.537
	EI	10	19.107	78.719	1.742	0.431
	GDP	10	1.313	0.321	97.423	0.941
	REN	10	0.198	1.463	0.083	98.254
Central	CO_2	10	69.497	11.758	18.723	0.020
	EI	10	39.038	26.486	29.726	4.747
	GDP	10	0.455	4.483	93.723	1.338
	REN	10	7.373	4.546	5.811	82.268
Southern	CO_2	10	58.289	19.051	21.343	0.314
	EI	10	22.965	66.632	10.386	0.015
	GDP	10	0.466	3.671	93.639	2.222
	REN	10	0.025	31.633	1.066	67.274
Income levels						
Low-income	CO_2	10	59.297	19.048	21.112	0.541
	EI	10	22.625	70.691	1.766	4.916
	GDP	10	1.288	0.663	97.920	0.128
	REN	10	1.366	1.219	1.071	96.342
Lower-middle	CO_2	10	69.014	10.408	19.559	1.017
	EI	10	44.016	51.526	4.429	0.026
	GDP	10	2.351	2.179	94.989	0.479
	REN	10	0.114	1.664	3.486	94.734
Upper-middle	CO_2	10	59.192	6.786	29.440	4.580
	EI	10	48.060	16.566	38.643	0.729
	GDP	10	4.449	0.440	93.309	1.800
	REN	10	1.048	3.566	5.276	90.108
High-income	CO_2	10	55.619	30.070	13.468	0.842
	EI	10	4.461	64.231	27.723	3.583
	GDP	10	7.439	2.091	88.907	1.561
	REN	10	5.321	6.010	6.247	82.419
Panel (African level)	CO_2	10	59.437	9.204	23.308	8.048
	EI	10	38.986	54.964	6.022	0.026

reduced, and slightly increases at the third years, and the slight decrease up to 10th years in all regions. This implies the increment of its determinants, such as economic growth and energy intensity. GDP contribution has decreased in first two years, slightly increase in the next years in North region, steady decrease in West and South, highly increase in East, and neutral contribution in Central region. The variation of energy intensity on CO_2 emissions has seen to highly decreased in North, West, Central, and South, steady increase in East region. The renewable energy variation to CO_2 is very low compared to those from energy intensity and economic growth. This indicates that the rest share of renewable energy highly contributes to reducing CO_2 emissions across the regions.

From Table 7, in the case of income levels, except the contribution of CO_2 itself, 19.048%, 21.12%, and 0.541% variations of CO_2 can be explained by innovative shocks in the energy intensity, GDP, and renewable energy, respectively, at the low-income level. These results are similar to those obtained in lower-middle-income, whereas renewable energy is the least to contribute to CO_2 variations. More interestingly, the contribution of GPD in Upper-middle-income is higher than those for energy intensity and renewable energy. This is different from the high-income level, whereas 30.070%, 13.468%, and 0.842% variations in CO_2 can be explained by innovative shocks in the energy intensity, GDP, and renewable energy, respectively. The findings show that the variation of CO_2 that can be explained by innovative shock in the GDP is higher than those from energy intensity and renewable energy in low-, lower-middle-, and upper-middle-income levels, indicates that renewable energy has a higher contribution to CO_2 emissions depletion within 10 years.

Fig. 5 indicates that the variation of CO_2 emissions itself has been highly reduced in all income levels, which implies that some of its driving forces highly contributed to the rest variations. The contribution of economic growth has highly increased in Low- and Lower and middle-, and high-income groups, and highly decrease in Upper-middle-income. The energy intensity has rapidly reduced in Low- and Lower-middle-income groups, but remain higher, while it was declined up to zero in Upper-middle- and high-income levels. Moreover, at the African level, there was a sharp decrease in the CO_2 emissions itself and energy intensity and renewable energy, while economic growth steadily increased within 10 years.

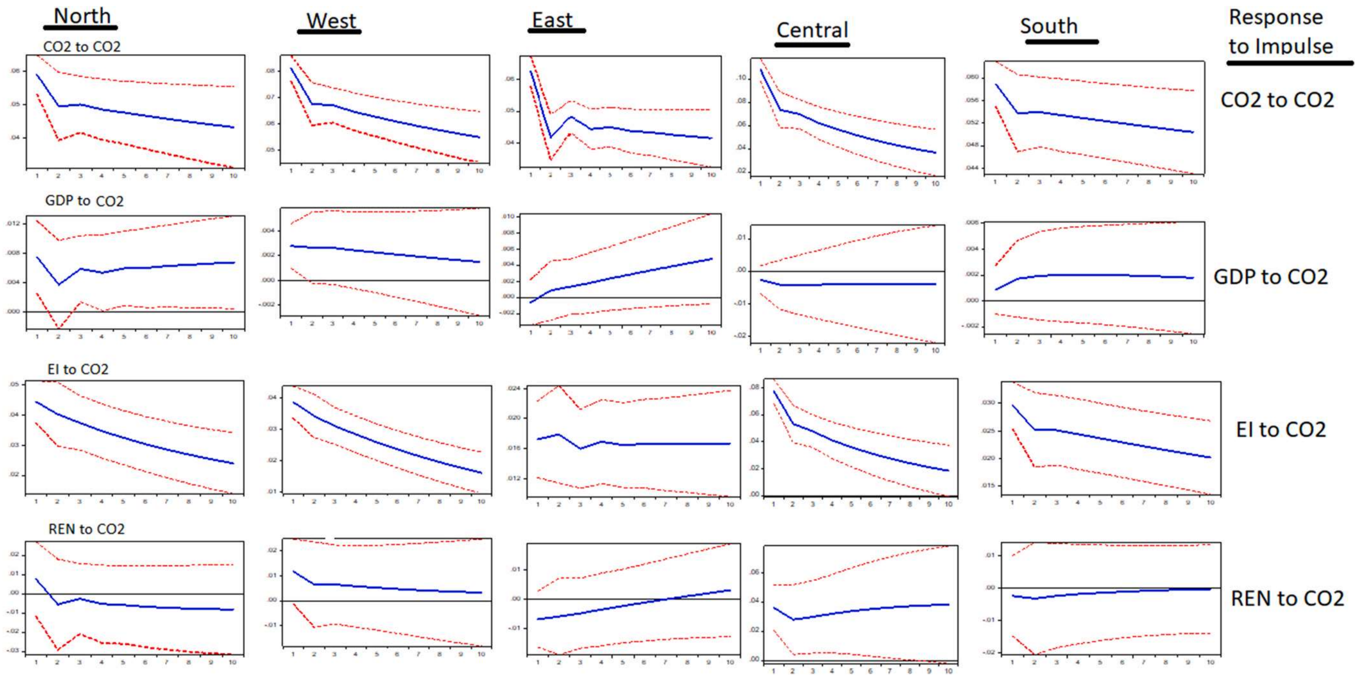

Fig. 4. Impulse response of African regions of CO_2, EI, GDP, and REN for prediction of 10 years (blue color) with 95% of confidence interval (red color).

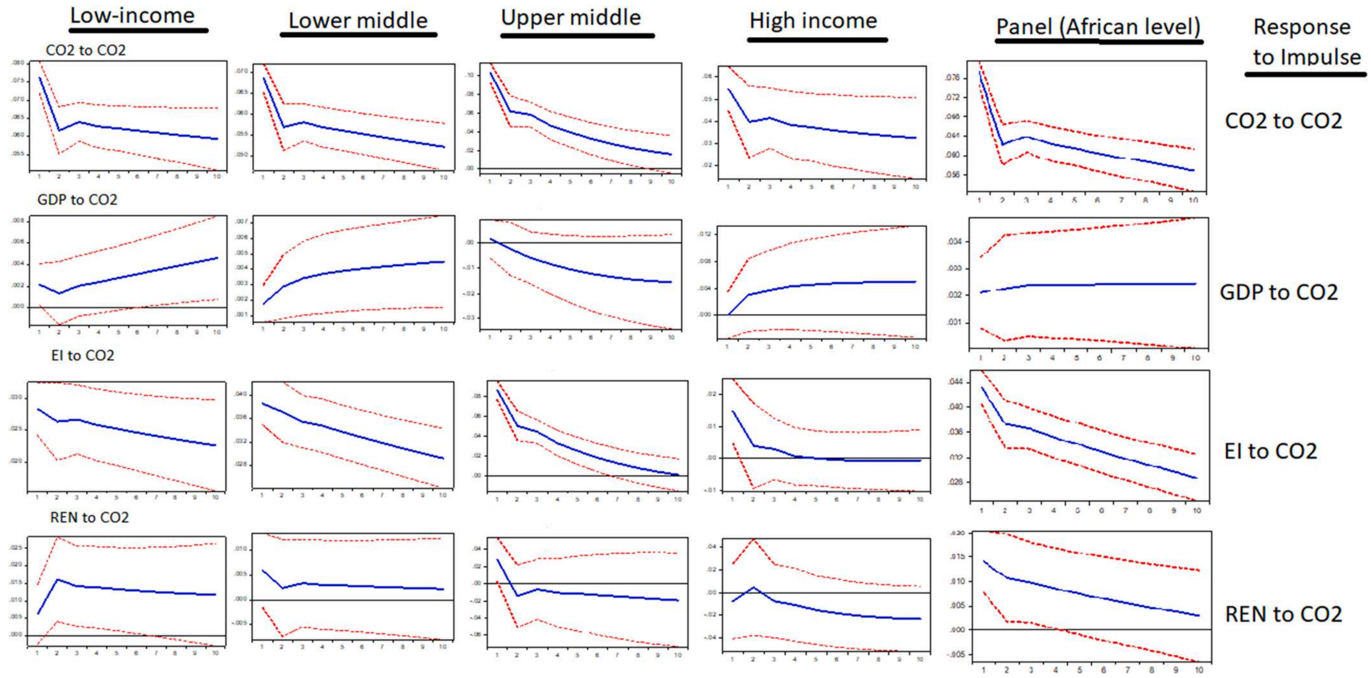

Fig. 5. Impulse response of income levels of CO_2, EI, GDP, and REN for prediction of 10 years (blue color) with 95% of confidence interval (red color).

The overall results reveal that the variation of CO_2 that can be explained by innovative shocks in the CO_2 itself is higher than those of its determinants in the regional levels, income levels, and at the African level, while the variation of CO_2 that can be explained by innovative in renewable energy consumption is the least in all regions and income levels. This implies that renewable energy use in a favor of reducing CO_2 emissions is at the standard level in the African countries. This shows the inequality of economic growth, renewable energy generation, and energy intensity, and utilization to reduce emissions among the regions. The nonrenewable energy resources and the way of exploration are different, which leads to variation in energy intensity and renewable energy among the regions and income levels. Therefore, regional policymakers should co-cooperate to validate and establish several energy projects and monitor economic growth in the favor of environmental sustainability. This study has limitations on some variables, such as urbanization, agriculture, globalization, industrialization, and others due to unavailable data/various missing values, although some studies argued that those variables have a significant influence on CO_2 emissions [79,80].

5. Conclusion and policy implications

Existing studies have intensively examined the energy intensity, renewable energy, economic growth, and CO_2 emissions nexus at global and income levels. Most cross-country studies at the African level ignored the difference in the regions, and income levels regard to CO_2 emissions. Again, patterns and variations in energy intensity, renewable energy, and growth to affect CO_2 emissions as control policy or causation are rarely discussed. Research considers various subgroups grasp a reasonable impact for scientific discovery towards the environmental sustainability at the African continent. In this respect, this study aims to examine the long-term impact of energy intensity, renewable energy consumption, and economic growth on CO_2 emissions across the regional and income levels in the African continent using various panel data estimators. We investigated the causation relationships between variables using the Dumitrescu Hurlin causality test. Furthermore, impulse response and variance decomposition analysis were employed to estimate the extent to which energy intensity, renewable energy, and economic growth can exert CO_2 emissions within 10 years. The dataset for the panel of 50 countries that vary in their income levels and are grouped into five regions was analyzed from 1980 to 2018.

The main results of this study were initiated by the testing framework (cross-sectional dependence, unit root, and cointegration tests). These tests testified the existence of cross-sectional dependence, unit roots, and long-run cointegration relationships among the selected variables across regions and income level, and at the panel of African countries. The panel data estimator (CS-DL) showed the long-term impact of energy intensity, renewable energy, and economic growth on CO_2 emissions. We found that renewable energy consumption significantly contributes to mitigating CO_2 emissions across regions and income levels, and the African level. Economic growth negatively affects CO_2 emissions at the panel of 50 African countries, while the effect is mixed across regions and income levels. Furthermore, the energy intensity significantly promotes CO_2 across regional and income levels, and at the African level.

We also found the directional causal relationships among the selected variables. The bi-directional causal link was noted between CO_2 and GDP in West, Central, and South regions, in lower-middle- and upper-middle-income levels, and at the African level. This relationship was also noted between CO_2 and energy intensity in West and South regions, in lower-middle- and high-income levels, and at the panel of all countries. A bidirectional causal link was also noted between CO_2 and renewable energy in the East region, in low- and upper-middle-income levels, and the African level. On the other hand, one-way directional causation was noted between renewable energy and CO_2 in North, West, and Central regions and Lower-middle-income level. It was noted also GDP and CO_2 in the North region and Low-income level. Furthermore, we estimated to which extend the energy intensity, renewable energy, and economic growth can exert on CO_2 within 10 years. The results revealed that a very low variation in CO_2 emissions can be explained by innovative shocks in renewable energy consumption in all regions, income levels, and at the African level. This implies that renewable energy has a reasonable impact to reduce CO_2 on the continent. The overall results showed that the impact of energy intensity, renewable energy use, and economic growth on CO_2 emissions in all countries could be influenced by either unobserved features or structural economic changes, although renewable energy consumption has a significant impact to deplete CO_2 emissions.

Based on our findings, policy implications are addresses to regional and government policymakers as follows. Firstly, our findings suggest that energy intensity and economic growth led to CO_2 emissions, while renewable energy reduces it across the regions and income levels; long-run relationships between variables supported the results. We suggest that intensive investment in existing and planned renewable energy projects coupled with economic activity management can lead to significant CO_2 emissions reduction in the African continent. Secondly, a bidirectional and unidirectional causal link between variables suggested that energy intensity is the CO_2 emissions causal, therefore, new policies that can reduce energy intensity by dropping nonrenewable energy are needed in all countries to meet the UNFCCC targets-based CO_2 mitigation. Thirdly, results obtained from variance decomposition analysis show that renewable energy is the most contributing factor for CO_2 reduction due to its low variations, economic growth, and energy intensity positively influence emissions for their higher variations. Thus, a green growth policy can be implemented to mitigate CO_2 emissions towards environmental sustainability in all countries. Lastly, further studies can be conducted in country-specific and regional studies by employing all possible factors that lead to CO_2 emissions, such as Urbanization, deforestation, and others.

Data availability statement

The dataset used is available from the World Bank database [8] and EIA [68].

Credit author statement

J.P. Namahoro: Conceptualization, Data curation, Formal analysis interpretation of data, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. Q. Wu: Funding acquisition, Project administration, Supervision. N. Zhou: Validation, Visualization, Writing – review & editing. S. Xue: Validation, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that there is no conflict of interest and approve the submission to your reverence journal.

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