Fossil fuel energy consumption, economic growth, urbanization, and carbon dioxide emissions in Kenya

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Abstract

We investigate the relationship between fossil fuel energy consumption, economic growth, urbanization, and carbon dioxide emissions in Kenya from 1971 to 2014. The study employs lin-log and log-lin models and uses the autoregressive distributed lag bounds cointegration test, the Johansen-Juselius cointegration test, and the Gregory-Hansen structural breaks test for cointegration to determine the presence of a long-run causal relationship between variables. Except for urbanization, the empirical results of fossil fuel consumption and economic growth show a positive relationship with carbon dioxide emissions. Besides, the study investigates the relationship between the variables by employing a Granger causality test based on a vector error correction model. Short-run Granger causality results show unidirectional causality running from fossil fuel energy consumption to economic growth, urbanization to carbon dioxide emissions, and economic growth to carbon dioxide emissions. These findings can assist policymakers in Kenya and other developing countries in developing conservation and efficiency policies for sustainable urbanization and production that reduce carbon dioxide emissions.

Keywords: Cointegration, Carbon dioxide emissions, Urbanization, Fossil fuel energy consumption, Economic growth, Kenya.

JEL Classification: K32, P18, Q35, Q43, Q44

1 Introduction

Carbon dioxide (CO_2) emissions from the combustion of fossil fuels are one of the most serious environmental threats of our time, contributing to global warming and eventual climate change (Zhang et al. 2018). The Kyoto Protocol was signed by 192 parties in 1997 as a component of the United Nations Framework Convention on Climate Change (UNFCCC) to significantly reduce the impact of greenhouse gas emissions (Maamoun 2019; Torrey 2007). Total global greenhouse emissions increased by 1.1 % in 2019, with the combustion of fossil fuels accounting for 0.9% of total global CO_2 emissions (Olivier & Peters 2020). Kenya like many other developing countries is experiencing increased economic growth and transformation, which is leading to urbanization as a new development trend. Urbanization and economic growth increase the demand for energy to power industries, homes, and automobiles used to transport people to cities (Bakirtas & Akpolat 2018). Urbanization entails the movement of labour from rural areas with zero marginal product to urban areas, where labour has a positive marginal product. This is a precursor to economic growth in developing countries due to the rise of modern service and industrial economies (Timmer & Akkus 2008). The effects of economic growth and urbanization on CO_2 emissions, on the other hand, remain inconclusive and contentious.

Kenya has one of the strongest economies in Sub-Saharan Africa, with consistent and robust economic growth, and it strives to increase its economic potential. Before COVID-19, the average annual economic growth rate was 5.6% (KIPPRA 2020). Due to the intermittent nature of hydropower, economic growth in Kenya is associated with 32.5% of fossil fuel as an input in the production energy mix (Government of Kenya 2018). Further, Kenya heavily relies on imported liquid petroleum for the transportation of people and goods to and from urban and rural areas, although fossil fuel consumption is not environmentally sustainable. As a result, Kenya's desire to achieve sustainable economic growth necessitates climate mitigation measures aimed at reducing CO_2 emissions by 30 % (Munene 2019). However, total GHG emissions were projected to rise by 100 million tons of carbon emission equivalent (MtCO2e) by the end of 2020 and 143 MtCO2e by 2030, with the energy sector emitting the most (Government of Kenya 2018). Several studies in Sub-Saharan Africa (Acheampong et al. 2019; Otim et al. 2022) and Kenya (Kongo & Box 2018; Munene, 2019) on the drivers of CO_2 emissions gave less attention to the influence of urbanization on CO_2 emissions. Besides, there is still no agreement on the impact of urbanization and Gross Domestic Product (GDP) on CO_2 emissions. According to some studies, urbanization reduces CO_2 emissions (Ali et al. 2017) while others show that urbanization has a positive effect on CO_2 emissions (Shahbaz et al. 2016; Wang et al. 2014). Since Kenya is a developing country with growing cities, the investigation of the cause-effect relationship between urbanization and CO_2 emissions is critical.

In Kenya, the increase in CO_2 emissions due to the high use of fossil fuels is likely to continue in the face of economic growth, urbanization, and intermittent hydroelectricity supply (Sarkodie & Adom 2018). In Kenya, for example, the transportation sector accounts for 83.3% of the consumption of liquid fossil fuels and has the potential to increase CO_2 emissions due to the combustion of fossil fuels during transportation (Government of Kenya 2018). The empirical paper by Sarkodie and Ozturk (2020) tests the Environmental Kuznets Curve (EKC) hypothesis in Kenya using data from 1971 to 2013 and their estimation procedures such as Autoregressive Distribution Lag (ARDL) and Utest are the most comprehensive and detailed in the analysis of Kenya's environmental quality. The use EKC hypothesis, which was first used in the 1990s (Grossman & Krueger 1995) in testing for environmental quality suffers from multicollinearity due to the estimation's squared term of GDP. In this study, we estimate CO_2 emissions in Kenya using the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model as an environmental indicator. The STIRPAT model has the advantage of taking a linear form that is easy to estimate and interpret. Besides, it connects human activities in the form of driving forces to their environmental impacts, with the impact of each factor shown in terms of elasticities (Wang et al. 2017). Reliable estimation is critical for funding and achieving the carbon neutrality goal.

Given that association is not the same as causation, several studies have looked for a causal link between fossil fuel consumption, urbanization, economic growth, and CO_2 emissions around the world. The summary of some results are provided in Table 1. The study on the causality between GDP and CO_2 emissions (Appiah 2018; Hongxing et al. 2021; Islam et al. 2022) and energy consumption and economic growth (Beşe & Kalayci 2019; Mehdi & Slim, 2017; Rehman et al. 2019) and urbanization and CO_2 emissions (Hanif 2018; Shahbaz et al. 2016; Wang et al. 2014) remain mixed and inconclusive. Understanding the drivers of CO_2 emissions is critical for developing effective and appropriate energy conservation programs. This is because reducing carbon intensity, promoting energy efficiency, and improving energy conservation policies will go a long way towards reducing the demand for fossil fuels, primarily for powering transportation and industrial sectors. It also reduces demand for hydrocarbons, which is associated with import inflation, as well as investment in additional energy generation plants as a result of energy efficiency. Despite the importance of carbon emission reduction strategies derived from a better understanding of the drivers of CO_2 emissions, empirical studies in Kenya are still lacking. The current study is motivated by two objectives. First, it investigates the effects of fossil fuel consumption, urbanization, and GDP on Kenya's carbon dioxide emissions. Second, it evaluates the causality between the variables under consideration in the context of Kenya.

The novelty of the study is based on the ground that most previous studies on the energy-growth-environmental nexus used the Engle-Granger cointegration approach, which is often inappropriate when the sample size is small (Odhiambo 2009). To ensure the health of the estimate of the long-run cointegrating relationship through triangulation, the current study employs the Autoregressive Distributed Lag (ARDL) bounds cointegration test, Johnsen and Juselius cointegration tests, and Gregory-Hansen cointegration tests. Specifically, Gregory-Hansen structural tests for cointegration are very helpful in testing for cointegration in case the structural breaks exist in the data where the conventional cointegration tests become inappropriate. Some existing studies such as the empirical work of Altinay and Karagol (2005) and Narayan and Narayan (2010) used bivariate analysis which makes their models suffer from the omitted variable bias (Alkhathlan & Javid 2013). We used a multivariate framework to address the issue of omitted variable bias. The empirical findings of this study are expected to contribute to the existing body of knowledge on Kenya and other developing countries and are relevant for their long-term growth trajectory.

The remaining sections of the paper are structured as follows: Section 2 describes the data and theoretical framework, Section 3 includes data and estimation strategy, Section 4 shows results and discussion, and Section 5 provides conclusion and policy implications.

Table 1 The global summary of causality tests, along with previous studies related to them.

Authors	Country	Period	Methodology	Conclusion
Islam et al. (2022)	Bangladesh	1976-2014	VAR's innovative accounting approach and ARDL bounds test	$GDP \leftrightarrow CO_2$ $CO_2 \rightarrow CTI$
Hongxing et al. (2021)	Belt Road Initiative economies	1990-2018	Westerlund cointegration test and Pooled Mean Group-ARDL (PMG-ARDL)	$CO_2 \rightarrow GDP$ $EC \leftrightarrow GDP$
Beşe & Kalayci, (2019)	Kenya	1971-2014	VAR Granger causality; JJ cointegration	$EC \neq GDP$ $EC \rightarrow CO_2$
Rehman et al. (2019)	Pakistan	1990-2017	ARDL bounds cointegration approach	$GDP \leftrightarrow CO_2$ $FF \leftrightarrow GDP$
Appiah (2018)	Ghana	1960-2015	Toda-Yamamoto causality test and ARDL bound testing technique	$EC \rightarrow GDP$ $GDP \neq EC$ $EC \leftrightarrow CO_2$
Hanif (2018)	Sub-Saharan Africa	1990-2015	Generalized methods of moments (GMM)	$FF \rightarrow CO_2$ $URB \rightarrow CO_2$ $GDP \rightarrow CO_2$
Mehdi & Slim (2017)	North African countries	1980-2011	Panel cointegration techniques and Granger Causality	$GDP \rightarrow CO_2$ $NRE \rightarrow GDP$ $RE \rightarrow CO_2$
Shahbaz et al. (2015)	Portugal	1971-2008	ARDL bounds cointegration approach	$URB \rightarrow CO_2$ $EC \rightarrow CO_2$
Wang et al. (2014)	China	1995-2011	Panel Granger causality, vector error correction model and Pedroni cointegration test	$URB \rightarrow CO_2$ $EC \rightarrow CO_2$ $URB \rightarrow EC$
Soytas et al. (2007)	USA	1960-2004	Toda –Yamamoto procedure and VAR model.	$GDP \neq CO_2$ $EC \rightarrow CO_2$

Notes: Abbreviations are defined as follows: ARDL: autoregressive distributed lag, VAR: vector autoregressive, CTI: composite trading intensity, EC: energy consumption, FF: fossil fuel, urbanization, NRE: non-renewable energy, CO_2: carbon dioxide emissions, GDP: gross domestic product. $\neq, \rightarrow$ and $\leftrightarrow$ no causality, unidirectional, and bidirectional respectively. $\rightarrow$ and $\leftrightarrow$ show only positive causal direction.

2. Theoretical framework

The growing demand for energy to promote economic growth in developing countries raises the environmental policy concerns (Kaika & Zervas 2013). Therefore, suitable models should be used to study the drivers of environmental pollution. The study adopts the STIRPAT model (York et al. 2003; Dietz & Rosa 1997) which extends the empirical work of Ehrlich and Holdren (1972) which assumes a unit elasticity (Rosa & Dietz 2012). The STIRPAT model has been used by environmental scientists and economists to study the effect of anthropogenic emissions on the environment (Wu et al. 2021; Xu et al. 2020; Yang et al. 2021). The model starts with the IPAT identity which describes the driving factors that lead to environmental changes. The IPAT model demonstrates how population, affluence, and technology impact the environment. The identity is expressed:

$$I = P.A.T \tag{1}$$

Where I, denotes the impact of pollution on the environment and CO_2 is measured as a proxy of environmental pollution as in Eq. (1). Besides other environmental indicators or pollutants that can be used (Selden and Song 1994; Grossman and Krueger 1995; Stern 2004; Murakami et al. 2020; Ali et al. 2021). P denotes population, A: denotes Affluence or wealth, and T is the technology index. The modified IPAT model termed STIRPAT using the time series model framework is expressed as follows:

$$I_t = aP_t^bA_t^cT_t^de_t \tag{2}$$

Where t denotes the time in years, a is a constant and b, c and d are the index elasticities for estimation and e is the stochastic disturbance term. Eq. (2) can be transformed as follows:

$$\ln I_t = \ln a + b\ln P_t + c\ln A_t + d\ln T_t + e_t \tag{3}$$

The population (P) is used in STIRPAT due to its ability to exert pressure on the environment (Adams et al. 2020; Usman & Hammar 2021). Its effect is more felt through urbanization especially in Africa due to its growing population. The relationship between CO_2 emissions and urbanization has been studied for some time, but empirical results have been mixed. Affluence in the STIRPAT model is measured in terms of economic growth is necessary for welfare improvement and propels energy consumption. What is striking about economic growth is that it increases pollution levels (Khan et al. 2020; Rao & Yan 2020) because people become unsatisfied with the same bundle of consumption goods. There is no consensus in the IPAT and STIRPAT models on which proxy of T to employ in the empirical model since it is left to the discretion of researchers because the STIRPAT model contains the residual factor that affects emissions other than P and A (Dietz & Rosa1997; York et al. 2003). As a result, we employed fossil fuels as a proxy for technology in this study. The CO_2 emissions result from the consumption of fossil fuels in the manufacturing process, which contribute to climate change (Omri 2014). Coal, crude oil, natural gas, and shale oil are examples of fossil fuels whose primary supplies derive from a finite and non-renewable stock of resources (Bhattacharyya 2019). Nonrenewable energy resources have two major drawbacks: they are depletable in a finite amount of time and they contaminate the environment. Shafiei and Salim (2014) use the STIRPAT model to analyze the impact of non-renewable energy on emissions using a panel of 29 OECD nations from 1980 to 2011. Their research reveals that consumption of nonrenewable energy has a significant and a positive effect on CO_2 emissions. Empirical publications from both rich and developing countries back up the findings of their investigation (Anwar et al. 2021; Awodumi & Adewuyi 2020; Erdogan et al. 2020; Koengkan et al. 2020; Sahoo & Sahoo 2020).

Most empirical studies involving environmental pollution growth nexus are conducted based on the bivariate analysis which suffers from the omitted variable bias problem (Ozturk & Acaravi 2010). A multivariate framework is employed in this study to overcome such a problem. To examine the effect of fossil fuels, urbanization and GDP on carbon dioxide emissions in Kenya, we estimated Eq. (4) as follows:

$$CO_{2t} = \vartheta + \varphi LURB_t + \mu LGDP_t + \omega LFF + \varepsilon_t \tag{4}$$

Where CO_2 is carbon dioxide emissions, LURB: denotes the log of urbanization, LGDP: represents the log of the gross domestic product as a measure of a country's wealth or economic growth, and LFF: denotes the log of fossil fuel energy consumption. However, little attention is made to examining the role of fossil fuel consumption in Kenya's emissions, which would allow the country to make an informed decision about how to decrease its carbon emissions based on facts.

3 Data and estimation strategy

3.1 Data

The annual data, variables, references, and a priori expectations used in the study are in Table 2. The data spans a period of 44 years starting from 1971 to 2014. The period is used because the data is available for all the variables under investigation.

Table 2 Data and variable description

Variable	Expected Sign	Proxy	Data source
Carbon dioxide emissions	N/A	Environment	World Bank
Urbanization	+/-	Population	World Bank
Gross Domestic Product	+	Affluence	World Bank
Fossil fuel consumption	+	Technology (There is no clear effect of technological development on fossil fuel consumption)	World Bank

3.2 Empirical framework

3.2.1 Unit root tests

Macroeconomic time-series data always have a non-stationary component (Nelson & Plosser 1982). As a result, the data generation process (DGP) is predicated on whether or not a unit roots exist. A stationary time series has data that varies and centers on a constant mean, as well as a finite variance that is not time-dependent with a unit root. On the other hand, a time series with a unit root deviates from its long-run deterministic trend with no propensity to return to it. Such series follow a random walk process. Considering a simple AR (1) process following Augmented Dickey-Fuller (ADF) test (Dickey & Fuller 1979) is given as follows:

$$y_t = \alpha + \rho y_{t-1} + \omega_t \tag{5}$$

Where $\omega_t \sim \mathrm{iid}(o, \sigma_t^2)$ and t the time trend. Adding autoregressive lags to control for serial correlations in the errors and a trend gives the test equation.

$$\Delta y_t = \alpha + \delta t + \theta y_{t-1} + \sum_{i=1}^{k} \varrho_i \Delta y_{t-i} + \omega_t \tag{6}$$

Where t denotes the index of time, α is an intercept representing a drift: shows the time trend's coefficient, and θ represents the coefficient for testing the presence of a unit root. The choice of the lag length k depends on the frequency of the data. The null hypothesis is $|\rho| = 1$: for homogeneous non-stationary. The hypothesis is $|\rho| < 1$ and where $\theta = (\rho - 1)$ therefore $\theta < 0$ (Wooldridge 2012). In summary $H_o: \theta \geq 0$ against $H_1: \theta < 0$. The conclusion is that the test statistic is larger in values than the critical values, we reject the null and conclude that the process in question is stationary.

Estimating a regression equation with data containing a non-stationary series without testing for a unit root or taking the first difference in the series may lead to spurious regression coefficient estimates. Such coefficients are inconsistent and biased and should not be used as a basis for policy. Some scholars have claimed, however, that due to their small power and size, unit root tests such as ADF do not provide accurate conclusions in the face of structural discontinuities (Glynn et al. 2007; Nelson & Plosser 1982). The study uses Zivot and Andrews's structural break unit root test to determine the breakpoints in the intercept, trend and/or both (Zivot & Andrews 1992) for the robustness purpose.

3.2.2 Cointegration test

The study investigates whether there is a long-run relationship between fossil fuel consumption, GDP, urbanization, and CO_2 emissions in Kenya using three cointegration methodologies. the Johansen & Juselius (1990) cointegration strategy, ARDL bounds cointegration, and the Gregory-Hansen structural break cointegration approach were all used in the study. A method proposed by Pesaran et al. (2001) was used to check for long-run cointegration. The method is based on comparing the null hypothesis of no cointegration to the alternative hypothesis of cointegration's existence. If the estimated F-statistic is greater than the critical value for the upper bound I(1), we conclude that there is a long-run integrating relationship, reject the null hypothesis, and estimate the long-run association, which is the long-run error correction model. We estimate the short-run ARDL model if the null hypothesis is not rejected. The following are some of the advantages of employing the ARDL technique: (i) It can be used with a mixture of I(0) and I(1) as well as just I(0) or I(1), but not with the I(2) series. (ii) When the regressors are endogenous, it allows a small sample size, (iii) when proper lag orders are chosen, it eliminates the concerns of endogeneity and serial correlation. (iv) It uses a single reduced equation form, and (v) the findings are more reliable than other standard cointegration methods. The ARDL $(p, q, \ldots, q)$ model estimation is as follows:

$$\Delta CO_{2t} = \zeta_1 + \sum_{i=1}^{P1} \phi_{1i} \Delta CO_{2t-i} + \sum_{j=0}^{q1} \xi_{1j} \Delta LURB_{t-j} + \sum_{m=0}^{q2} \theta_{1m} \Delta LGDP_{t-m} + \sum_{k=0}^{q3} \gamma_{1k} \Delta LFF_{t-k} + \mu_1 CO_{2t-1}$$

$$+ \mu_2 LURB_{t-1} + \mu_3 GDP_{t-1} + \mu_4 LFF_{t-1} + \varepsilon_{1t} \tag{7}$$

Where Δ denotes the first difference operator and ε_{1t} is a white noise component. The ideal lag orders p and q are found by minimizing model selection criteria based on the Akaike Information Criterion (AIC) and Bayesian

Information Criterion (BIC) in most circumstances (BIC). We estimate a long-run and a short-run model as in equations (8) and (9) respectively in the presence of a long-run link between fossil fuels, urbanization, GDP, and CO_2 emissions in Kenya:

$$\mathrm{CO}_{2\mathrm{t}} = \zeta_2 + \sum_{i=1}^{p1} \phi_{2i}\mathrm{CO}_{2\mathrm{t}-i} + \sum_{j=0}^{q1} \xi_{2j}\mathrm{LURB}_{t-j} + \sum_{m=0}^{q2} \theta_{2m}\mathrm{LGDP}_{t-m} + \sum_{k=0}^{q3} \gamma_{2k}\mathrm{LFF}_{t-k} + \varepsilon_{2t} \tag{8}$$

$$\Delta\mathrm{CO}_{2\mathrm{t}} = \zeta_3 + \sum_{i=1}^{p1} \phi_{3i}\Delta\mathrm{CO}_{2\mathrm{t}-i} + \sum_{j=0}^{q1} \xi_{3j}\Delta\mathrm{LURB}_{t-j} + \sum_{m=0}^{q2} \theta_{3m}\Delta\mathrm{LGDP}_{t-m} + \sum_{k=0}^{q3} \gamma_{3k}\Delta\mathrm{LFF}_{t-k} + \lambda ECT_{t-1} + \varepsilon_{3t} \tag{9}$$

Where λ is the rate of adjustment toward long-run equilibrium, as well as the Error Correction Term's coefficient (hereafter ECT). ECT is defined as follows:

$$ECT_{t-1} = \mathrm{CO}_{2\mathrm{t}} - \zeta_2 - \sum_{i=1}^{p1} \phi_{2i}CO_{2t-i} - \sum_{j=0}^{q1} \xi_{2j}\mathrm{LURB}_{t-j} - \sum_{m=0}^{q2} \theta_{2m}\mathrm{LGDP}_{t-m} - \sum_{k=0}^{q3} \gamma_{2k}\mathrm{LFF}_{t-k} \tag{10}$$

In the next forecasting period, ECT illustrates how rapidly the disequilibrium will vanish. In other words, it refers to the notion that the last period of divergence from the long-run equilibrium has an impact on the dependent variable's short-run dynamics. The ECT coefficient, λ, should have a negative sign, be statistically significant, and be less than one for the properly described model. In our model, λ measures the speed at which CO_2 returns to equilibrium after a change in fossil fuel consumption, urbanization and GDP. Besides ECT is important for showing bi-directional and unidirectional causality between variables.

Johansen and Juselius's (1990) test for cointegration is used to triangulate the existence of cointegration among the variables. Two test statistics (λ_{trace} and λ_{max}) were developed by Johansen and Juselius (JJ) to validate the presence of a long-term association. The test statistics are expressed as follows:

$$\lambda_{\mathrm{trace}} = -\mathrm{T}\sum_{\mathrm{i=r+1}}^{\mathrm{n}} \ln(1-\hat{\lambda}_{\mathrm{i}}) \tag{11}$$

$$\lambda_{\mathrm{max}}(\mathrm{r}+\mathrm{r}+1) = -\mathrm{T}\ln\left(1-\hat{\lambda}_{\mathrm{i}}\right) \tag{12}$$

Where $\hat{\lambda}_i$ denotes the expected eigenvalue of the characteristic roots and T is the sample size. The null hypothesis for JJ cointegration assumes that no long-run cointegrating relationship between or among variables exists. The decision criterion is set up in such a way that the null hypothesis is rejected when the test statistic exceeds the critical value; otherwise, we fail to reject the null and conclude that there is no cointegration. In the absence of cointegration, the error correction model should not be estimated.

Common cointegration tests, such as the ARDL bound test and JJ cointegration tests, are based on the null hypothesis of no cointegration. These tests are appropriate for the standard cointegration model with a trend but no structural change. Gregory and Hansen (1996) in their empirical paper demonstrate that the conventional cointegration test may not hold when there are structural breaks or regime shifts because of the distributional theory which evaluates the residual-based tests vary. To cope with the challenge of potential structural breaks in our data, we employed Gregory-Hansen's (1996) test for structural breaks.

3.3.3 Causality analysis

The JJ cointegration, ARDL cointegration, and Gregory-Hansen cointegration methods examine whether a long-run relationship exists between fossil fuels, urbanization, economic growth, and CO_2 emissions. They do not, however, test for the existence of causality between variables. The Granger causality is based on the view that the past can cause the future but not the future causing the past, implying that the cause occurs before the effect (Granger 1988; Odhiambo

2009). The causality is therefore defined as follows when X_t Granger causes Y_t where X_t and Y_t are both time series, which means that Y_t can be predicted well with a small variance of forecast error using its lagged values than by not doing so. In other words, if the lagged values of X_t significantly contribute to predicting Y_t, then it is said to Granger causes Y_t . This applies to the causality running from Y_t to X_t. With this definition, two types of causality emerged: (i) when $X_t \rightarrow Y_t$ only, or $Y_t \rightarrow X_t$ only is termed as a unidirectional causality or a one-way causality. (ii) When $X_t \rightarrow Y_t$ and also $X_t \rightarrow Y_t$ denoted as $X_t \leftrightarrow Y_t$ is termed as feedback causality or bidirectional causality. The vector error correction model formulation is expressed in Eq. (13) as follows:

$$\begin{aligned}
\begin{bmatrix} \Delta CO_{2t} \\ \Delta LURB_t \\ \Delta LGDP_t \\ \Delta LFF_t \end{bmatrix} = \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \end{bmatrix} + \begin{bmatrix} \omega_{11.1} & \omega_{12.1} & \omega_{13.1} & \omega_{14.1} \\ \omega_{21.1} & \omega_{22.1} & \omega_{23.1} & \omega_{24.1} \\ \omega_{31.1} & \omega_{31.1} & \omega_{33.1} & \omega_{34.1} \\ \omega_{41.1} & \omega_{42.1} & \omega_{43.1} & \omega_{44.1} \end{bmatrix} \begin{bmatrix} \Delta CO_{2t-1} \\ \Delta LURB_{t-1} \\ \Delta LGDP_{t-1} \\ \Delta LFF_{t-1} \end{bmatrix} \\
+ \cdots \\
+ \begin{bmatrix} \omega_{11.k} & \omega_{12.k} & \omega_{13.k} & \omega_{14.k} \\ \omega_{21.k} & \omega_{22.k} & \omega_{23.k} & \omega_{24.k} \\ \omega_{31.k} & \omega_{31.k} & \omega_{33.k} & \omega_{34.k} \\ \omega_{41.k} & \omega_{42.k} & \omega_{43.k} & \omega_{44.k} \end{bmatrix} \begin{bmatrix} \Delta CO_{2t-k} \\ \Delta LURB_{t-k} \\ \Delta LGDP_{t-k} \\ \Delta LFF_{t-k} \end{bmatrix} \\
+ \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{bmatrix} ECT_{t-1} \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \end{bmatrix} \qquad (13)
\end{aligned}$$

The disturbance terms, $\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t}$ and ϵ_{4t} are independent and identically distributed with zero mean and constant variance. The selection of optimal lag structure is based on AIC and BIC. For the short-run analysis, the formulation in Eq. (13) is first estimated using VECM, and then Granger causalities are tested using the Wald test with χ^2 distribution. The long-run causalities were examined at a 5% significance level for the coefficient of error correction representation term. Table 3 depicts the null hypothesis for Granger causality in both the short and long run. The Granger causality technique applied in the study is more appropriate in both small and large samples than other alternative techniques for testing for causality between variables (Odhiambo 2009).

Table 3 The null hypothesis for Granger causality in the short and long run.

Variable	Short-run				Long-run
	ΔCO_{2t}	$\Delta LURB_t$	$\Delta LGDP_t$	ΔFF_t	λ_i
ΔCO_{2t}	-	$\omega_{12.1} = \cdots = \omega_{12.k} = 0$	$\omega_{13.1} = \cdots = \omega_{13.k} = 0$	$\omega_{14.1} = \cdots = \omega_{14.k} = 0$	$\lambda_1 = 0$
$\Delta LURB_t$	$\omega_{21.1} = \cdots = \omega_{21.k} = 0$	-	$\omega_{23.1} = \cdots = \omega_{23.k} = 0$	$\omega_{21.1} = \cdots = \omega_{21.k} = 0$	$\lambda_2 = 0$
$\Delta LGDP_t$	$\omega_{31.1} = \cdots = \omega_{31.k} = 0$	$\omega_{32.1} = \cdots = \omega_{32.k} = 0$	-	$\omega_{31.1} = \cdots = \omega_{31.k} = 0$	$\lambda_3 = 0$
ΔFF_t	$\omega_{41.1} = \cdots = \omega_{41.k} = 0$	$\omega_{42.1} = \cdots = \omega_{42.k} = 0$	$\omega_{43.1} = \cdots = \omega_{43.k} = 0$	-	$\lambda_4 = 0$

4 Results and discussion

4.1 Descriptive statistics

Table 4 shows the descriptive statistics for all of the study's variables. CO_2 emissions have a mean of 0.269 and a maximum of 0.383 metric tons per capita, with a standard deviation (SD) of 0.054 metric tons per capita. In log form, the mean value of urbanization is 2.872, with a minimum of 2.378, a maximum of 3.228, and a standard deviation of 0.219. The mean GDP is 24.116, with a standard deviation of 0.462, a minimum value of 23.17, and a maximum value of 24.925 in log form. The log of fossil fuel energy consumption has a mean of 2.87, a standard deviation of 0.119, a minimum of 2.565, and a maximum of 3.078. All of the variables' data reveal no significant departure from their mean values. The correlation between the variables was investigated, with the results shown in Table 5. In Kenya, there is a 98.6 % positive correlation between GDP and urbanization. Furthermore, 75.6 % of CO_2 emissions are linked to the use of fossil fuels. Other variables have moderate relationships with each other.

Table 4 Variable Description

Variables	Obs	Mean	SD	Min	Max
CO_2 emissions (metric tons per capita)	44	0.269	0.054	0.188	0.383
Urban population (% of the total population) log	44	2.872	0.219	2.378	3.228
Gross Domestic Product (constant 2015 US$)log	44	24.116	0.461	23.170	24.925
Fossil fuel (% share of total energy consumption) log	44	2.879	0.119	2.565	3.078

Table 5 Matrix of correlations

Variables	(1)	(2)	(3)	(4)
(1) CO_2	1.000			
(2) LURB	-0.391	1.000		
(3) LGDP	-0.410	0.986	1.000	
(4) LFF	0.756	-0.586	-0.569	1.000

4.2 Unit root test results

When non-stationary time series variables are estimated, the parameter estimates are frequently misleading. We use ADF and Zivot-Andrew unit root tests to ensure that the variables are stationary. The validity of the test results, on the other hand, is dependent on the careful selection of the best lag structure. Based on AIC and HQIC, three lags were chosen as appropriate for the empirical estimation used in this research. Table 6 shows the outcomes of the lag selection criteria. The ADF test's null hypothesis is that the series has a unit root, and the test results are shown in Table 7. All variables were non-stationary and integrated of order one, I(1) except for urbanization, I(0). Before running the cointegration tests, the Zivot-Andrews unit root structural break tests are run as a robustness check to ensure that each series is stationary. The Zivot-Andrews structural break test findings based on BIC are shown in Table 8. The cointegration order that results is mixed, with I(0) and I(1). Table 8 shows that structural changes began in Kenya in the 1980s, as evidenced by the Zivot-Andrews test findings. Kenya's government secured a structural adjustment loan with the World Bank, resulting in significant changes in trade policy. The government replaced import substitution policies with an export promotional programme (Gertz 2008). Trade liberalization did not result from incredible policies but was always subject to policy reversals. Kenya’s export performance as a percentage of GDP has been declining with ever-increasing imports (Kimenyi et al. 2016). Shifts in the policy regime could have an impact on the variables under our investigation. The ADF unit root tests were confirmed by the Zivot-Andrews unit root tests. Cointegration tests can now be run because all variables are stationary at either at level or at their levels of first difference.

Table 6 Optimal lag selection criteria

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	180.128		1.8e-09	-8.80642	-8.74536	-8.63753
1	389.383	418.51	1.1e-13	-18.4692	-18.1638	-17.6247
2	429.843	80.919	3.4e-14	-19.6922	-19.1426	-18.1722*
3	454.035	48.384*	2.4e-14*	-20.1018*	-19.3079*	-17.9062
4	466.449	24.827	3.3e-14	-19.9225	-18.8844	-17.0514

*lag order selected by criterion at 5% level of significance. The unit root is conducted based on intercept and trend

Table 7 Unit root test results

Variable	Augmented Dickey-Fuller test statistics				Order of integration
	In levels	P-value	In first difference	P-value	I(d)
CO_2	-1.717	0.7433	-3.791	0.017**	I(1)
LURB	-4.520	0.001***			I(0)
LGDP	-2.131	0.529	-3.971	0.010**	I(1)
LFF	-2.567	0.295	-4.810	0.000***	I(1)

***, ** Significance at 1 % and 5% levels respectively

Table 8 Zivot-Andrews structural break unit root test based on BIC

Variable	At levels				At first difference			I(d)
	Model	T-statistic	Critical value at 5%	Time break	T-statistic	Critical value at 5%	Time break	
CO_2	c	-5.676	-4.80	1982				I(0)
	t	-3.50	-4.42	1987	-6.893	-4.42	1983	I(1)
	c &t	-5.625	-5.08	1982				I(0)
LURB	c	-4.530	-4.80	1980	-11.027	-4.80	1980	I(1)
	t	-4.488	-4.42	1994				I(0)
	c & t	-7.326	-5.08	1980				I(0)
LGDP	c	-2.963	-4.80	1992	-6.433	-4.80	1991	I(1)
	t	-2.935	-4.42	1979	-5.866	-4.42	2000	I(1)
	c &t	-3.131	-5.08	1997	-6.286	-5.08	1991	I(1)
LFF	c	-6.490	-4.80	2004				I(0)
	t	-4.837	-4.42	1982				I(0)
	c &t	-3.315	-5.08	2006	-5.287	-5.08	2005	I(1)

Note: c, t, and c&t are models that allow for breaks in intercept, trend, and both intercept and trend respectively.

4.3 Cointegration test results

The cointegration tests determine whether a long-run relationship exists, and if it does, ECT can be calculated using either the ARDL or the Vector Error Correction Model (VECM). It also enables the testing of both short- and long-run Granger causality. Because the F-test statistic of 19.457 is considerably greater than the I(1) of 5.61 at a 1% critical value bound, the ARDL bound test utilizing the F-statistic in Table 9 reveals the existence of cointegration. The JJ cointegration determines whether the variables under examination have a cointegrating equation. In Kenya, at least one cointegrating rank exists between fossil fuel energy consumption, GDP, urbanization, and CO_2 emissions, as shown in Table 10. When there are structural breaks in the data, bound and the JJ cointegration test results can be doubtful and even misleading. In the event of a regime shift or structural change, the Gregory-Hansen structural break cointegration is used as a robustness check for cointegration. Table 11 displays the results of the Gregory-Hansen cointegration tests, which show that the variables have a long-run relationship and thus estimating the long-run model is safe.

Table 9 Bound tests for cointegration

Variables	Test statistic	value	k
$(\mathrm{LCO2}\mid\mathrm{LURB},\mathrm{LGDP},\mathrm{LFF})$	F	19.457	3
	Critical value bounds	I(0) lower bound	I(1) upper bound
	10%	2.72	3.77
	5%	3.23	4.35
	1%	4.29	5.61

Table 10 JJ cointegration test results

Maximum Rank	Trace Statistic	5% critical value	Max-Eigen Value	5% critical value
0	87.55	47.21	59.84	27.07
1	27.70*	29.68	19.23	20.97
2	8.47	15.48	8.55	14.07

Table 11 Gregory-Hasen structural break cointegration test

Model	Procedure	Test statistic	Breakpoint	Asymptotic critical values		
				1%	5%	10%
C	ADF	-6.91	1982	-5.77	-5.28	-5.02
	Zt	-6.99	1982	-5.77	-5.77	-5.02
	Za	-47.92	1982	-63.64	-53.58	-48.65
C &T	ADF	-7.02	1982	-6.05	-5.75	-5.33
	Zt	-7.11	1982	-6.05	-5.75	-5.33
	Za	-48.62	1982	-70.27	-59.76	-54.94
R	ADF	-6.23	1982	-6.51	-6.00	-5.75
	Zt	-6.30	1982	-6.51	-6.00	-5.75
	Za	-43.32	1982	-80.94	-68.94	-6.42

Note: C is the change in Level, C &T denotes a change in level and trend and R refers to the change in Regime.

4.4 ARDL estimation results

Table 12 shows the long-run and short-run ARDL models with error correction representation. In Kenya, the long-run model demonstrates that fossil fuel energy consumption increases CO_2 emissions. At a 1% level of significance, a 1% increase in fossil fuel energy consumption results in a 0.297 percentage point rise in CO2 emissions, ceteris paribus. The positive effect of fossil fuel consumption on CO_2 emissions is supported by Munir & Khan (2014). The long-run and short-run ARDL models with error correction representation are shown in Table 12. The long-run model shows that fossil fuel energy consumption has a positive impact on CO_2 emissions in Kenya. Munir and Khan (2014), who studied the effects of fossil fuel energy use in Pakistan, found that it has a positive influence on CO_2 emissions. Besides, urbanization reduces CO_2 emissions in the long run, with a 1% increase in urbanization resulting in a 0.978 percentage point reduction in CO_2 emissions, ceteris paribus, at a 1% level of significance. Many empirical studies in both rich and developing countries contradict this conclusion. GDP also has an impact on CO_2 emissions. At a 1% level of significance, the data demonstrates that a 1% increase in GDP is associated with a 0.535 percentage point increase in CO_2 emissions. Furthermore, GDP has a positive effect on CO_2 emissions. The result shows that a 1% increase in GDP is associated with about a 0.535 percentage point increase in CO_2 emissions, at a 1% level of significance, ceteris paribus. The result supports the study of Ardakani and Seyedaliakbar (2019) in the Middle East and North Africa (MENA) countries.

The short-run model depicts how CO_2 emissions in Kenya are affected by fossil fuel energy consumption, urbanization, and GDP. The coefficient of the lagged ECT, which is the speed of adjustment towards long-run equilibrium, is negative, statistically significant at 5%, and lies between 0 and 1, which satisfies the model's requirements to converge or return to a stable long-run equilibrium per year after a short-run shock or innovation, as shown in Table 12. Using equation (8), the estimated coefficient is -0.479. According to the ECT, any deviation from the long-run equilibrium between the variables under investigation is corrected at a rate of around 48 % for each period, and it takes about two periods to return to the long-run stable equilibrium following a shock. Further, the result shows that the past values of CO_2 emissions negatively affect CO_2 emissions because it shrinks its growth by 0.299 and 0.329 percentage points yearly for the first and second lagged values respectively. Additionally, the present value of urbanization has a strong influence on CO_2 emissions since it lessens CO_2 emissions by 1.027 percentage points. By contrast, the first and second past lag values of urbanization in the short run have incremental effects of 0.337 and 3.005 percentage points respectively. The mixed effects of urbanization on CO_2 emissions confirm a study by Zhang

(2021) in China. Generally, the estimated model has a strong explanatory power in examining contributing factors of emissions in Kenya as seen by its high adjusted R^2 and low root means squared errors (RMSE).

The diagnostic tests are used to check the robustness of the estimated model, and the results are shown in Table 12. To check for serial correlation, the LM test for autocorrelation is utilized (Breusch & Pagan 1980). The calculated residual errors are not serially associated, according to the results. The model residuals are homoskedastic, according to the white and ARCH tests for heteroskedasticity. We also examined the model Cumulative Sum of Squares of Recursive Residual (CUSUMSQ) test established by Brown et al. (1975) for any potential instability. When the regressors are endogenous in a cointegrated or stationary environment (Caporale & Pittis 2004), this is a fairly robust test. Because CUSUMSQ plots lie under the critical bound of the 5% level of significance. Fig. 1 reveals that the regression error variance is stable. As a result, the model is fairly stable.

Table 12 ARDL results for the short-run and long-run dynamics

D.CO2	Coefficient	Standard error	t-statistic	P-value
ADJ				
CO2				
L1.	-0.479	0.074	-6.440	0.000***
LR				
LURB	-0.978	0.283	-3.450	0.002***
LGDP	0.535	0.144	3.720	0.001***
LFF	0.297	0.057	5.220	0.000***
SR				
CO2				
LD.	-0.299	0.090	-3.310	0.002***
L2D.	-0.329	0.081	-4.050	0.000**
LURB				
D1.	-1.027	0.474	-2.170	0.038**
LD.	0.337	0.698	0.480	0.632
L2D.	3.005	0.560	5.360	0.000***
Constant	-5.172	0.807	-6.410	0.000***
R^2	0.8482			
$Adj. R^2$	0.8041	Diagnostics	χ^2	
Log likelihood	123.001	LM	0.093	0.7605
RMSE	0.0139	HET	40.00	0.4260
ARDL	(3, 3, 0, 0)	ARCH	1.049	0.7893

Notes: ***, ** Significance at 1 % and 5% levels respectively. LM is the Lagrange Multiplier test with χ^2 distribution. HET is the White Heteroskedasticity test with χ^2 distribution. ARCH is the LM test for autoregressive conditional heteroscedasticity with χ^2 distribution.

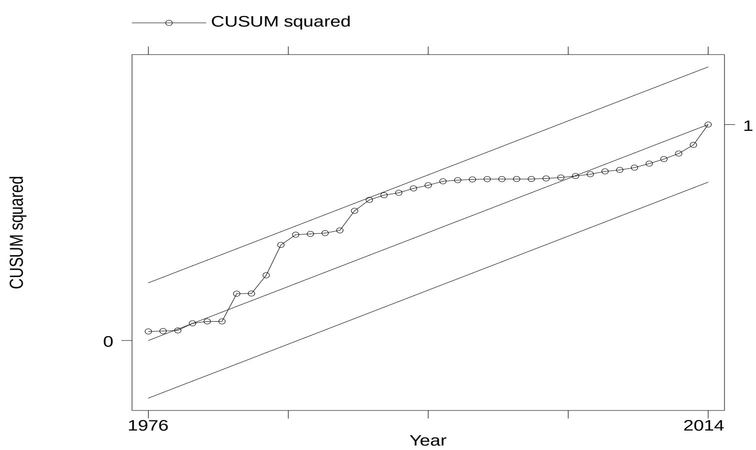

Fig. 1. The plot of CUSUM squares of recursive residual fitted at a 5% level of significance

4.5 Granger causality

Using a vector error correction Granger causality model, the study establishes an intriguing causal relationship between the variables under investigation. For both short-run (weak) and long-run Granger causalities, it deduces causality. The results for both the short-run and long-run models are presented in Table 13. The Granger causality results are summarized in Fig. 2 and briefly explained as follows:

(i) GDP is caused by fossil fuel energy consumption, and it is a one-way causality. The findings suggest that using fossil fuels has a favourable impact on Kenya's GDP.

(ii) GDP Granger causes CO_2 emissions in Kenya and it is a one-way causality implying that GDP has a positive effect on increasing the level of CO_2 emission.

(iii) Urbanization Granger causes CO_2 emissions and also shows one-way causation. However, urbanization has a positive effect on CO_2 emissions in Kenya.

(iv) There exist a strong long-run causal effect running from fossil fuel energy consumption, urbanization, and GDP on CO_2 emissions in Kenya. Therefore, the long-run equation exists for only the CO_2 equation.

(v) Interestingly, there is no direct relationship between fossil fuel energy consumption and CO_2 emissions, although numerous empirical articles claim that fossil fuel consumption is the primary source of CO_2 emissions and climate change.

(vi) In Kenya, there is little evidence of a link between urbanization and the consumption of fossil fuels.

(vii) There is no evidence of a causal association between urbanization and GDP, according to the study.

Table 13 Granger causality test results

Variables	Short-run (or weak) Granger causality				Long-run Granger causality
	ΔCO2	ΔURB	ΔLGDP	ΔLFF	$\lambda_i = 1,2.3.4$
ΔCO2	-	35.00 (0.0000)***	5.44(0.066)*	2.21(0.332)	-0.404(0.000)***
ΔURB	2.29 (0.334)	-	2.60(0.272)	1.04 (0.595)	-0.010(0.537)
ΔLGDP	2.78 (0.249)	0.79 (0.673)	-	7.39 (0.025)**	-0.020(0.754)
ΔLFF	0.79 (0.6743)	0.55(0.7604)	0.48(0.7856)	-	-0.099(0.666)

Notes: The null hypothesis is that there is no Granger causality between variables. Variables in parenthesis are p-values for the Wald test with a χ^2 distribution in the short run and coefficient of ECT in the long run.
***, **, * indicate 1%, 5% and 10% significant levels respectively.

The empirical results of our study are controversial, although they agree with some earlier empirical papers. It is consistent with the work of Hanif (2018) on the causal effect of GDP on CO_2 emissions as being unidirectional. However, it disagrees with the role of fossil fuels in CO_2 emissions as being neutral. However, fossil fuel consumption causes an increase in GDP, which in turn causes CO_2 emissions. This implies that fossil fuels may not directly CO_2 emissions in Kenya as we think. Nevertheless, the CO_2 emissions may be coming from other human activities such as poor farming methods, bush burning, methane emissions from animals, or energy inefficiency during the production process. This makes the result inconclusive. The study mostly disagrees with Wang et al. (2014) in their empirical work for China. We found urbanization to cause a reduction in CO_2 emissions in Kenya, which is supported by Ali et al. (2017) who found that despite the 100% urbanization rate in Singapore, urbanization shrinks CO_2 emissions. Generally, our results support energy conservation and efficiency policies such as developing fuel efficiency yardsticks for heavy and light-duty vehicles, using solar lighting systems in public squares and using programmed motion sensors in offices and street lighting. Such measures reduce carbon emissions, energy waste, and energy efficiency, and are more likely to have no negative impact on Kenya's economic growth.

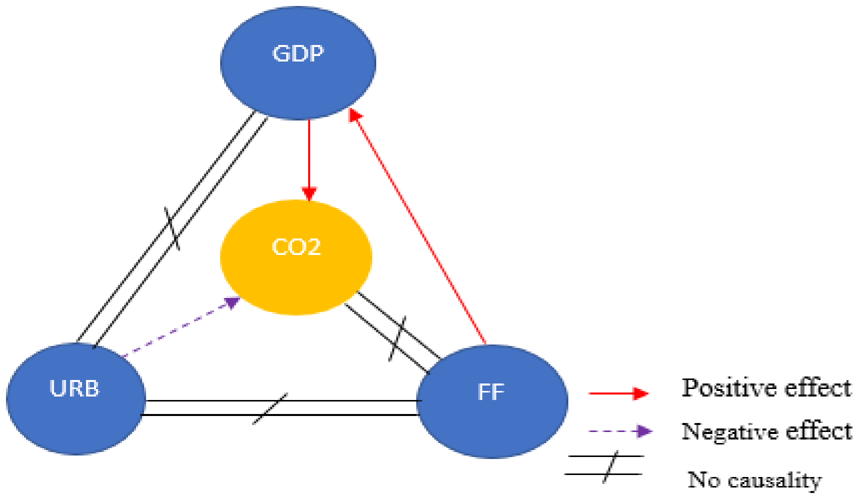

Fig. 2. Granger based causality test results

5 Conclusion and policy implications

Using data from 1971 to 2014, this research investigates the effects of fossil fuel energy consumption, GDP, and urbanization on CO_2 emissions in Kenya. Using the ARDL bounds cointegration test, the JJ cointegration test, and the Gregory-Hansen structural breaks test for cointegration, we evaluate the presence of a long-run link between the variables under examination. A Granger-based causality test anchored on a vector error correction model framework is also used to investigate the relationship between the variables. Based on the negative coefficient of ECT of 0.479, which is statistically significant at 5%, long-run causation was detected, indicating that fossil fuel consumption, GDP, and urbanization cause CO_2 emissions. The result of short-run Granger causality reveals that GDP is caused by fossil fuel consumption. As a result, fossil energy consumption is a major input in Kenya's output function. Even though many empirical articles support the assumption that fossil fuel consumption increases CO_2 emissions, no causality between the two has been discovered. In the short-run, our findings reveal a positive relationship between CO_2 emissions and fossil use, but no causality. However, we found GDP to cause CO_2 emissions. We conclude that any policy that reduces the consumption of fossil fuels in Kenya without increasing energy efficiency may hurt the country's economic growth. Further, urbanization was found to reduce CO_2 emissions in Kenya, implying that encouraging urbanization will go a long way in reducing the amount of CO_2 emissions the country generates. However, caution should be taken when encouraging urbanization since our ARDL model shows that our first lag value has a negative sign but the second and third have positive signs, but the lag values do not cause CO_2 emissions. As a result, metropolitan areas should be designed to reduce fuel traffic congestion, which is linked to significant CO_2 emissions. It is important to promote the use of energy-efficient transportation and public transit and the use of clean energy in residential buildings.

Kenya ratified the United Nations Framework Convention on Climate Change (UNFCCC) in 1994 as a member of the Common Market for Eastern and Southern Africa (COMESA). As part of her mandate, the government decided to adopt the clean development mechanism to reduce CO_2 emissions from fossil fuel combustion and deforestation (The Republic of Kenya 2001). In addition, the government of Kenya can reduce CO_2 emissions by increasing the production and uptake of renewable energy consumption, phasing out subsidies for conventional energy supply, accelerating the development of clean energy technologies, promoting energy efficiency and building strong institutions and human capacity to handle the challenges that come with adopting renewable technologies such as solar, hydropower and wind energy, reduce its overreliance on fossil fuel by encouraging the use of biofuels, geothermal, wind power and other green energies. The government should create public awareness of the importance of environmental protection and internalize externalities. The proposed measures can be adopted by other countries to promote sustainable growth and environmental protection.

The study findings of our empirical investigation not only add to the literature but also provide policy implications that are expected to guide Kenyan and other neighbouring countries' policymakers. Furthermore, the research strengthens and expands our understanding of the relationship between fossil fuel energy consumption, economic growth, urbanization, and carbon dioxide emissions in Kenya. This research can be expanded by incorporating other environmental degradation proxies such as methane, nitrous oxide and fluorinated pollutants. In the future, a similar study could be undertaken at the regional level. The variability of connections may also be revealed by regional outcomes. These findings could lead to locally-focused varied policy recommendations, and considering regional realities would allow for bigger samples, ensuring the robustness of empirical results and delivering more credible conclusions.

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