Paving the Path to Sustainability: Green Growth and Innovation in Kenya

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**Abstract**
Climate change and environmental degradation have become central global concerns due to increased industrialization, fossil fuel use, and economic activities. As countries strive to balance economic development with ecological preservation, understanding the roles of green growth, technological innovation, and digital transformation becomes important. This study examines the impacts of green growth, green innovation, and information and communication technology (ICT) on CO₂ emissions in Kenya using the Augmented Autoregressive Distributed Lag (AARDL) model. Results indicate that green growth significantly reduces emissions hence promoting sustainable development. While green innovation initially correlates with rising emissions, its interaction with ICT over long run shows reduction effect, a benefit of integrated green technological strategies. In contrast, ICT independently contributes to higher CO₂ levels indicating the environmental cost of digital expansion when not paired with sustainable practices. Trade openness is associated with lower emissions showing benefits of technology diffusion and environmental standards. The study recommends leveraging Kenya’s renewable energy potential for cleaner technologies, promoting green innovations, and reshaping the ICT sector to align with environmental goals.

**Keywords:** Green Growth, Green Innovation, ICT, CO₂ Emissions, Sustainable Development, Kenya

**1. Introduction**

Even after more than 4 years of grappling with the COVID-19 pandemic, climate change remains the primary focus of international policy efforts (Kakar, Khan, & Khan, 2024). A noticeable outcome of global temperature increases, most likely attributed to climate change, is the detrimental effect on both natural systems and human populations. Climate-related hazards are typically categorized as either transitional in nature or as physical-environmental challenges (UNDP, 2021). A large portion of greenhouse gas (GHG) emissions originates from commercial sectors, thereby intensifying the pace of global warming. Over the years, academic research has increasingly addressed the issue of GHG outputs, particularly carbon dioxide (CO₂), as governments have enacted numerous climate-focused policies. Escalating levels of CO₂ are widely recognized by experts as a significant contributor to ecological degradation. Climate change, driven by these emissions, has emerged as one of the most critical policy dilemmas of the current century (Khan, Chenggang, Khan, & Muhammad, 2020). The Paris Agreement acknowledges that although climate change is a global concern, its consequences are unevenly distributed across regions, and countries face varying expectations in terms of reducing their emissions (UNDP, 2025).

Globally, the movement for environmental sustainability is gaining momentum. Countries everywhere are experiencing the negative effects of rising global temperatures and more frequent extreme weather events, which disrupt economic stability and reduce living standards (Raza & Lin, 2022). Since the late 19th century, atmospheric carbon dioxide levels have risen by approximately 45% further worsening the growing impact of human activity on the planet's climate (Amin, Khan, & Mehmood, 2022).

Kenya’s climate action framework is considered to align with global temperature goals especially regarding the 1.5°C threshold. It is supported provided it continues to meet objectives in key sectors such as transportation and agriculture, and refrains from initiating new coal-based energy projects. The country has pledged to lower greenhouse gas (GHG) emissions by 32% by 2030 compared to a business-as-usual (BAU) path. It focuses on sustainable progress and the importance of global partnerships for effective mitigation. Kenya’s total emissions have been rising in recent years. Between 1990 and 2022, Kenya’s GHG output increased at an estimated annual average of 4% attaining about 113 million metric tons of CO2 equivalent (MtCO2eq), factoring in land use, land-use changes, and forestry (Republic of Kenya, Ministry of Environment, Climate Change and Forestry, 2025).

Specifically, carbon dioxide emissions surged from 7.82 million tons a decade ago to 16.15 million tons recently, a trend driven by expanding fossil fuel reliance and higher energy consumption (Strathmore University Energy Research Centre, 2025). Nevertheless, Kenya’s emissions per person remain below the global mean, with each individual contributing about 2.09 metric tonnes in 2022, compared to the worldwide average of 6.76 tonnes (Tete, 2025).

In line with the Paris Agreement, Kenya submitted its Second Nationally Determined Contribution (NDC) in 2025, committing to a 35% reduction in GHGs by 2035 under BAU conditions, which is equivalent to avoiding 75.25 MtCO2eq (Xinhua News Agency, 2025). Of this reduction, a fifth is expected to be achieved domestically, while the remainder hinges on international aid, including funding, technological assistance, and capacity enhancement. This updated NDC represents an increase from the earlier 32% target and brings the country closer to limiting temperature rise to 1.5°C (Climate Action Tracker, 2023).

Kenya’s emissions predominantly originate from its energy sector and the agriculture, forestry, and land use (AFOLU) categories. Increased fossil fuel use, land clearing, and expansion of agricultural activity are key contributors. For example, forest loss is happening at a faster pace than replanting efforts. Most of the emissions in the energy sector come from the burning of coal, oil, and gas for electricity and transport needs (International Energy Agency, 2025). Still, according to Climate Action Tracker (2023), Kenya’s current strategies are mostly in line with the goal of keeping temperature rise under 1.5°C, though further international backing is needed to ensure emissions don’t continue to rise.

To support both emissions reduction and sustainable development, Kenya is actively engaging in carbon trading. The voluntary carbon market (VCM) is anticipated to play an important role, with a projected mitigation capacity of approximately 200 MtCO2e during the NDC implementation timeline 2031-2050 (Nordahl, 2025). Several areas, for example, transport, industrial operations, and waste management, are making tangible strides toward their specific mitigation goals, mostly through these market-based strategies (Climate Action Tracker, 2025). Furthermore, innovations in green technology, digital infrastructure, and environmentally conscious economic planning are considered highly promising approaches to enhance ecological resilience.

Sustainable development provides the foundation for green growth, which seeks to enhance societal well-being and generate employment through integrated socioeconomic progress. This approach also involves reshaping patterns of consumption and production to address challenges related to inefficient resource use and ecological deterioration (Ben Lahouel, Taleb, Managi, & Abaoub, 2023). A widely recognized definition is offered by the Organization for Economic Co-operation and Development (OECD), which describes green growth as a strategy for advancing economic performance while safeguarding natural ecosystems and securing long-term benefits for future populations (OECD, 2025). Achieving green growth depends on curbing emissions driven by consumption, which requires the adoption of environmentally friendly technologies, improvements in production efficiency, and innovative practices across supply chains (Chen, Yi, Chen, Peng, & Yang, 2023). As an approach that supports both improved energy use and reduced carbon output, green growth will help in mitigating environmental harm (Fernandes, Veiga, Ferreira, & Hughes, 2021).

Achieving a full-scale green transition within Kenya’s economy demands the implementation of broad and coordinated green innovation strategies (Yang & Chen, 2022). Globally, the success of climate mitigation efforts is increasingly tied to the advancement of green technologies, which helps in lowering both emissions and pollution control costs over time (Thomasson, 2025). Kenya has positioned itself as a pioneer in both clean energy and sustainable finance across the region. This leadership is reflected in initiatives like the Kenya Green Finance Taxonomy (KGFT) 2025, designed to attract climate-resilient investments and enhance environmental, social, and governance (ESG) performance in the financial sector (Traction School of Governance and Business, 2025).

Despite these proactive measures, the connection between adopting green technologies and actual reductions in carbon emissions within Kenya is not yet well understood (Lin & Ma, 2022). As observed in other economies, particularly those at specific development stages, the effectiveness of green technologies in cutting CO₂ emissions remains inconclusive (Du, Li, & Yan, 2019). In Kenya’s case, where over 90% of its electricity originates from renewable sources and a national goal targets 100% clean energy by 2030, more data-driven investigations are essential to determine how green innovation shapes environmental performance and emission trends (Santoshi, 2025).

Kenya's policy architecture encourages green innovation through offering performance-based grants and funding mechanisms for both early-stage ventures and established green enterprises. Areas supported include solar energy systems, electric mobility networks, sustainable farming, and circular economy models (Shobande, Ogbeifun, & Tiwari, 2023). These policies aim to generate jobs with lower carbon footprints, build climate resilience, and meet the targets outlined in Kenya’s Nationally Determined Contributions (NDCs) under the Paris Agreement (Africa Enterprise Challenge Fund, 2025).

Nevertheless, several obstacles hinder the full exploitation of green technologies in tackling the climate crisis. For instance, although Kenya has introduced a regulatory framework for carbon markets and established a national carbon trading registry, the scalability and impact of these tools still require close examination (Santoshi, 2025). Furthermore, little empirical work has explored how green growth, technological innovation, and digital infrastructure collectively influence environmental health within Kenya, leaving an important gap in the literature.

To address the research gap in Kenya, this domain presents an area for focused study. An innovative research study is proposed to explore the following questions from a Kenyan perspective:

1. How do Kenya’s green growth initiatives, green innovation, and information and communication technology (ICT) contribute to environmental sustainability?
2. Does the interaction of ICT with green growth and green innovation in Kenya support the achievement of environmental neutrality?

Although environmental sustainability has gained more visibility, the integrated impact of green growth, green innovation, and information and communication technology (ICT) on Kenya’s ecological outcomes is still insufficiently studied (Jiang, Rahman, Zhang, & Islam, 2022). This research contributes to understanding how these elements interact to influence both carbon emissions and environmental integrity. It specifically evaluates the roles played by green growth (GG), green innovation (GIN), ICT, and their interaction terms (ICTGG and ICTGIN) in influencing Kenya’s environmental trajectory. In examining historical data, the study seeks to identify the main forces that either drive or hinder emissions reduction (Sarkodie & Owusu, 2021).

Kenya’s national strategy provides a gradual direction from conventional development models toward more integrated green growth policies that prioritize a low-carbon economy and the improvement of digital infrastructure (Raza & Lin, 2022). ICT developments are part of transformative role in this process, especially in areas like renewable energy, smart agriculture, and digital manufacturing systems (Lau, Gozgor, Mahalik, Patel, & Li, 2023). As a foundational technology, ICT enables innovation and supports technical advancements across multiple sectors, accelerating the green transition (Shahzad, Jianqiu, Hashim, Nazam, & Wang, 2020). Nevertheless, the rapid digitization process creates new environmental risks, for example, increased use of non-renewable inputs and electronic waste, that need to be carefully managed to preserve sustainability gains (Khan, Teng, Khan, & Khan, 2019).

This analysis investigates how ICT interacts with green growth and innovation to assess whether it reinforces environmental sustainability or exacerbates ecological degradation (Balsalobre-Lorente, Abbas, He, Pilař, & Shah, 2023; Khan, Oubaih, & Elgourrami, 2022). In focusing on these interdependencies, the study aims to clarify ICT's role in facilitating carbon reduction through green technological advances, and to guide future policy and investment decisions.

To summarize, this research makes a significant contribution by (1) investigating the influence of green growth, innovation, and ICT on Kenya’s emissions trends; (2) employing rigorous econometric models to test long-term relationships among these variables; and (3) developing a comprehensive green growth index to measure Kenya’s progress toward net-zero emissions. The results are intended to assist in formulating sustainable policies that foster economic advancement while protecting the environment. This aligns with Kenya’s broader ambition to position green innovation and digital transformation at the heart of its low-carbon development strategy.

The remainder of this study is structured as follows: Section 2 reviews the existing body of literature. Section 3 outlines the data sources and the econometric models employed. Section 4 details the estimation methodology. Section 5 discusses the empirical results and their implications. Finally, Section 6 concludes the study and offers recommendations for future research.

**2. Literature review and theoretical links**

**2.1. Theoretical linkages**

Over time, literature has been examining how information and communication technology (ICT) and green innovation contribute to resolving environmental challenges. The environmental impact of ICT is influenced by several interacting factors, including its integration with technological innovation, economic development, and renewable energy deployment (Khan, Oubaih, & Elgourrami, 2022; Lahouel, Taleb, Zaied, & Managi, 2021; Azam, Rafiq, Shafique, & Yuan, 2021). One perspective suggests that ICT can play a positive role in environmental protection by enhancing energy efficiency, boosting the use of renewable energy sources, and improving productivity. This view posits that ICT can promote sustainability through more efficient transport systems and manufacturing operations (Balsalobre-Lorente, Abbas, He, Pilař, & Shah, 2023; Chatti, 2021; Zhang & Liu, 2015).

In contrast, other research argues that ICT expansion may contribute to environmental degradation. From this viewpoint, increased ICT penetration can drive up pollution through greater industrial output, accelerated globalization, and higher energy consumption (Wang, Jiang, Dong, & Dong, 2021; Asongu, Le Roux, & Biekpe, 2017). Given these contrasting perspectives, the overall effect of ICT on anthropogenic climate change remains contested. Therefore, the empirical literature includes a wide array of global and regional studies.

**2.2 ICT and CO2 emissions Nexus**

Studies have explored the environmental implications of ICT, mostly through cross-country comparisons or country-specific analyses. Current research presents mixed outcomes, with ICT showing both beneficial and detrimental effects on the environment. For example, Sun (2022), using a spatial Durbin model to analyze data from China between 2003 and 2017, found that green technology innovation (GTI) and ICT significantly contribute to reducing local carbon intensity. However, these benefits may be offset by negative spatial spillovers that increase emissions in neighboring cities. The study also revealed regional disparities, where eastern provinces demonstrated greater efficiency in lowering carbon intensity compared to central and western regions.

Similarly, Shahnazi and Dehghan Shabani (2019) applied a dynamic spatial Durbin model to assess ICT's influence on Iran’s carbon emissions from 2001 to 2015. Their findings indicated an inverted U-shaped relationship, meaning that ICT initially increases emissions but eventually contributes to their reduction over time. In contrast, Kraemer, Ganley, and Dewan (2005) found that ICT development had no significant environmental impact in developing countries, with observable effects limited to developed nations.

Zafar, Zaidi, Mansoor, Sinha, and Qin (2022) investigated the role of ICT and education in environmental quality across selected Asian economies from 1990 to 2018. Utilizing the Fully Modified Cup-FM approach, the authors concluded that combining ICT advancement with energy-efficient strategies can enhance environmental outcomes, supporting the case for ICT-driven sustainable development.

Chatti and Majeed (2023) analyzed the role of ICT in mitigating carbon emissions across 60 developing and 34 developed countries during the period from 1998 to 2016 using a two-step GMM system. Their research mentioned that ICT's impact on emission reduction is stronger in urban areas of both developed and developing countries, whereas its effect is comparatively weaker in rural regions. Nonetheless, integrating ICT into smart city frameworks holds substantial potential for lowering pollution in both contexts, underlining spatial disparities in environmental performance.

**2.3 Green Growth and CO₂ Emissions Nexus**

Over time, human reliance on energy sources like coal, petroleum, and natural gas has led to a discharge of carbon dioxide into the Earth’s atmosphere. This accumulation has contributed to climate-related challenges, such as global temperature increases and rising ocean levels (Mensah et al., 2019; Li & Haneklaus, 2021; Hanif et al., 2019; Lotfalipour, Falahi, & Ashena, 2010). Due to the detrimental effects linked to greenhouse gas emissions, international initiatives have increasingly focused on cutting carbon output. As environmental degradation becomes a more pressing concern, it is imperative for nations to adopt development paths that prioritize sustainability and inclusivity.

Empirical studies into the relationship between economic advancement and emissions of carbon have yielded varying conclusions. One perspective suggests that rapid industrial and financial progress exacerbates ecological deterioration (Mikayilov, Galeotti, & Hasanov, 2018; Ozturk & Salah Uddin, 2012). On the other hand, a different school of thought posits that GDP growth and carbon discharges are not necessarily interlinked (Gorus & Aydin, 2019; Salahuddin, Alam, & Ozturk, 2016). As the concept of a green economy gains traction, understanding its influence on climate outcomes has become an increasingly critical area of academic research.

For instance, an analysis by Saleem, Khan, and Mahdavian (2022) showed that sustainable development initiatives across a dozen Asian nations between 1990 and 2018 were effective in lowering CO₂ output. Likewise, Dogan, Hodžić, and Fatur Šikić (2022) studied 25 environmentally progressive countries and found that green fiscal policies especially taxation systems designed to discourage pollution, were significantly associated with lower emissions. Their findings, derived from a quantile regression model further supported the negative relationship between eco-friendly economic policies and environmental degradation.

Furthermore, Zhao, Taghizadeh-Hesary, Dong, and Dong (2023) assessed regional data across Chinese provinces from 2004 to 2018. Their study revealed that investments in green financial tools and eco-centric growth strategies contributed substantially to the mitigation of CO₂ emissions. These examples gives credence to the transformative role that sustainable economic practices plays in reducing global carbon footprints.

**2.4 Green Innovation and CO2 relationship**

In recent discussions, both academics and decision-makers have been debating whether advancements in environmentally friendly technologies represent the most efficient strategy for lowering greenhouse gas emissions. A strong link is believed to exist between carbon output and innovations in green, energy-saving, and environmental technologies. However, this viewpoint is contested by others who question the effectiveness of such innovations in achieving carbon neutrality. Some findings support the idea of a negative relationship between green technological progress and emissions levels.

For instance, research by Obobisa, Chen, and Mensah (2022) showed that eco-innovations enhance environmental conditions and significantly curb CO₂ emissions across 25 African nations. Likewise, an analysis of G7 economies by Qin et al. (2021) confirmed that advancements in green technologies play a constructive role in emissions management. Further, Paramati, Mo, and Huang (2021), examining data from OECD countries between 1991 and 2016, identified that reductions in CO₂ emissions were influenced by green innovation, foreign investments, and international trade, demonstrated through augmented mean group and group-mean estimation techniques.

In another country-specific investigation, Suki et al. (2022) applied the ARDL bootstrapping method to assess Malaysia’s experience and concluded that green innovation reduces emissions over both short and extended periods. Nonetheless, the connection is not universally consistent. For example, Xu, Fan, Yang, and Shao (2021) found mixed outcomes in China, where green innovation and its components contributed to lower emissions while also, under certain conditions such as foreign investment and changes in industrial structure, exerted upward pressure on CO₂ output. Furthermore, research by Shao, Zhong, Liu, and Li (2021) concerning N-11 countries showed that in the long term, technological advancements in green sectors contribute to emission reductions, though no clear relationship is observed in the short term.

**2.5 Literature Gap**

While existing literature has investigated the relationship between green growth, green innovation, and information and communication technology (ICT) in relation to environmental degradation across different income groups and national contexts, empirical studies integrating these dimensions remain limited. For example, there is a less of research that simultaneously examines the relationship among these variables within the Kenyan context. This study seeks to address this gap by employing a novel analytical framework that incorporates the augmented Autoregressive Distributed Lag (ARDL) methodology to assess the environmental implications of green growth and green innovation, both independently and in interaction with ICT.

The application of the augmented ARDL model provide a distinct methodological advantage for policy-relevant empirical analysis. First, it mitigates the risks associated with degenerate lag structures in both dependent and explanatory variables. Second, it includes a robust cointegration testing procedure using an F-test on the lagged level terms of the independent variables, enhancing the reliability of long-run relationship inferences. This approach addresses the limitations of conventional unit root tests, which are often constrained by low power and may lead to spurious conclusions. In adopting this technique, the study provides evidence-based insights that can inform sustainable development strategies and ICT-integrated environmental policies in Kenya.

**3.0 Methodology and Data Collection**

The primary objective of this study is to assess the effects of green growth (GG), green innovation (GIN), information and communication technology (ICT), and trade openness on carbon dioxide (CO₂) emissions in Kenya over the period 1990–2024. The data for the selected variables have been sourced from reputable international databases, including the World Development Indicators (WDI), the Organisation for Economic Co-operation and Development (OECD), and Our World in Data. To ensure the reliability and consistency of the statistical analysis, all variables, except for green growth, have been transformed into their natural logarithmic form. This transformation helps address skewness in the data distribution and enhances the linearity of relationships among variables, thereby improving model performance and interpretability. A detailed explanation of the variable definitions, measurement units, and sources is provided below and summarized in Table 1.

**Table 1: Description of Variables**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Symbol | Measurement/Transformation | Source | Expected Impact on CO₂ |
| Carbon Dioxide Emissions | CO₂ | Metric tons per capita (logarithmic form) | World Development Indicators (WDI) | Dependent variable |
| Green Growth | GG | Composite index (non-logarithmic) | OECD Green Growth Indicators | Negative |
| Green Innovation | GIN | Number of environment-related patents (logarithmic form) | OECD | Negative |
| ICT Development | ICT | ICT index or % of internet users (logarithmic form) | World Development Indicators (WDI) | Mixed |
| Trade Openness | TO | (Exports + Imports) / GDP (logarithmic form) | Our World in Data / WDI | Mixed |

Source: Owners Compilation

**3.1 Green Growth Index Specification**

In line with the methodologies proposed by Xu (2022) and Xuan, Jiang, and Fang (2023), green growth (GG) is conceptualized as a function of economic, educational, and environmental indicators. The index is formulated as follows:

GG= GDP + EE−NRP−NFD−CO2…………………………………………………………………………………………(1)

Where:

* GG denotes the green growth index, which captures the balance between economic development and environmental sustainability.
* GDP represents the annual growth rate of gross domestic product (%), reflecting economic expansion.
* EE refers to government expenditure on education as a percentage of GDP, indicating investment in human capital.
* NRP captures the consumption of non-renewable energy sources, specifically fossil fuels such as coal, oil, and natural gas.
* NFD is a proxy for deforestation, measured through forest rents as a percentage of GDP.
* CO₂ denotes carbon dioxide emissions per capita (in metric tons), serving as an indicator of environmental degradation.

This composite measure of green growth integrates economic productivity with environmental costs and social investments. A higher GG value indicates more sustainable and inclusive growth by accounting for both positive and negative externalities of development activities.

**3.2 Green Innovations**

Building on prior studies such as those by Shobande, Ogbeifun, and Tiwari (2023), as well as Ramzan et al. (2023), the present study incorporates green innovation (GIN) as a key explanatory variable, representing an important dimension of environmental governance. Green innovation is widely recognized as a critical tool for promoting sustainable development and mitigating environmental degradation.

Previous literature—such as the works of Yang and Chen (2022), Jiang et al. (2022), and Obobisa, Chen, and Mensah (2022)—has adopted various proxies to quantify green technological innovation, often drawing on patent data related to environmentally sustainable technologies. Notably, some studies Lin and Ma (2022) have utilized patent applications rather than granted patents as indicators of green innovation activity.

In this study, green innovation is proxied by the number of patents related to environmental technologies, aligning with the approach used in recent empirical research. This measure reflects the extent of technological advancement aimed at addressing ecological challenges and supports the evaluation of how innovation contributes to environmental sustainability in the Kenyan context.

**3.3 Information and Communication Technology**

In this study, Information and Communication Technology (ICT) is proxied using two widely accepted indicators: mobile cellular subscriptions per 100 individuals and internet usage as a percentage of the total population. These proxies reflect the penetration and accessibility of digital infrastructure, which are essential components of ICT development. Moreover, the empirical analysis incorporates two key interaction terms, ICT × Green Growth (ICT × GG) and ICT × Green Innovation (ICT × GIN), to assess the combined and potentially moderating effects of ICT on environmental outcomes when interacting with sustainability-related variables. This approach allows for a more robust examination of the dynamic interrelationships. Finally, trade openness is included as a control variable, operationalized as the ratio of total trade (exports plus imports) to gross domestic product (GDP), consistent with established empirical practices.

**Econometric Model Specification**

To empirically investigate the dynamic relationship between green growth, green innovation, ICT, trade openness, and environmental degradation (proxied by CO₂ emissions), the following econometric models are formulated. These models sequentially incorporate interaction terms to evaluate potential moderation effects of ICT on green growth and green innovation:

**Model 1: Baseline Model**

lnCO2t =α0+β1GGt+β2lnGINt+β3lnICTt+β4lnTOt+μt

This model captures the direct effects of green growth (GG), green innovation (GIN), ICT penetration, and trade openness (TO) on carbon emissions (CO₂).

**Model 2: Interaction Between Green Growth and ICT**

lnCO2t=α0+β1GGt+β2lnGINt+β3lnICTt+β4(GGt×lnICTt)+β5lnTOt+μt

This specification includes the interaction term between green growth and ICT to assess whether ICT enhances or dampens the environmental effects of green growth.

**Model 3: Interaction Between Green Innovation and ICT**

lnCO2t=α0+β1GGt+β2lnGINt+β3lnICTt+β4(lnGINt×lnICTt)+β5lnTOt+μt

Here, the interaction term between green innovation and ICT is introduced to evaluate the joint impact of digital infrastructure and innovation on emissions.

**Model 4: Full Interaction Model**

lnCO2t=α0+β1GGt+β2lnGINt+β3lnICTt+β4(GGt×lnICTt)+β5(lnGINt×lnICTt)+β6lnTOt+μt

The final model integrates both interaction effects to examine whether ICT simultaneously influences the environmental outcomes of both green growth and innovation policies.

**4. Estimation Schema**

In the preliminary phase of the empirical analysis, this study employed a range of unit root tests to evaluate the stationarity characteristics of the selected time series variables. To determine the order of integration, the analysis applied several widely recognized techniques, including the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979), the Phillips-Perron (PP) test (Phillips & Perron, 1988), and the DF-GLS detrended residual unit root test developed by Vougas (2007). Among these, the standard ADF test is mathematically expressed as follows:

ΔYt​=α+βt+γYt−1​+$\sum\_{i=1}^{k}δi​ΔYt-i​+ϵt$

Where:

* Yt​ denotes the time series under consideration,
* Δ is the first-difference operator,
* α is a constant,
* βt is the time trend,
* γ represents the coefficient of interest (indicating the presence of a unit root),
* k is the optimal lag length to correct for autocorrelation,
* ϵt​ is the white noise error term.

The null hypothesis H0:γ=0 suggests the presence of a unit root (i.e., non-stationarity), while the alternative hypothesis H1:γ<0 implies stationarity.

A variable is considered stationary at level I(0) if the null hypothesis is rejected. Otherwise, it may be differenced to achieve stationarity, indicating an integration order of I(1). These unit root tests inform the selection of the appropriate econometric technique, particularly the augmented ARDL approach, which allows for a mix of I(0) and I(1) variables.

In addition, this study employed the Johansen cointegration technique (Johansen, 1991; Johansen, 1995) to assess the existence of a long-term equilibrium relationship among the selected variables over the period under investigation. To further examine the dynamic association among green growth, green innovation, ICT, trade openness, and carbon dioxide emissions, the analysis utilized the augmented Autoregressive Distributed Lag (AARDL) approach, as advanced by McNown, Sam, and Goh (2018). This method enhances the traditional ARDL framework originally introduced by Pesaran and Shin (1999).

Unlike conventional cointegration tests, the AARDL technique offers more flexibility by accommodating regressors with mixed integration orders—either stationary at level I(0) or first difference I(1)—without compromising the validity of the results. However, it remains inapplicable to series integrated at order two I(2). The cointegrating relationship among the variables is estimated through the following AARDL model, as outlined in Equation below:

ΔlnCO2t​=α0​+ $\sum\_{i=1}^{p}​βi​ΔlnCO2t-i$ ​+ $\sum\_{j=0}^{q1}θj​ΔGGt-j​$ + $\sum\_{k=0}^{q2}ϕk​ΔlnGINt-k​+\sum\_{l=0}^{q3}γl​ΔlnICTt-l​$​​ ​+ $\sum\_{m=0}^{q4}ηm​ΔlnTOt-m$+ ​$\sum\_{n=0}^{q5}δ1lnCO2t-1$+ +δ2GGt−1+δ3lnGINt−1+δ4lnICTt−1+δ5lnTOt−1+εt

Δ: First difference operator.

lnCO2t​: Log of CO₂ emissions at time t.

GGt​: Green growth at time t.

lnGINt​: Log of green innovation at time t.

lnICTt​: Log of ICT penetration at time t.

lnTOt​: Log of trade openness at time t.

q1​,q2​,q3​,q4​: Optimal lags selected for each variable.

α0​: Constant term.

βi​,θj​,ϕk​,γl​,ηm​: Short-run dynamic coefficients.

δ1​,...,δ5​: Long-run relationship coefficients.

εt​: White noise error term.

In this specification, **CO₂** denotes carbon dioxide emissions, **GG** stands for green growth, **GIN** refers to green innovations, **ICT** captures information and communication technology, and **TO** represents trade openness. The summation of the first-differenced variables reflects the short-run dynamics, whereas the coefficients on the level terms indicate the long-run relationships. The subscript **t** signifies the time period, and **vₜ** denotes the stochastic error term. To examine the existence of a long-run equilibrium relationship among the variables, the null hypothesis of no cointegration is tested using the following approach:

To test the existence of a long-run relationship among the variables, the following null and alternative hypotheses are formulated based on the coefficients of the level variables in the ARDL model:

H0: δ1=δ2=δ3=δ4=δ5=0 (No cointegration)

H1:δ1≠0, δ2≠0, δ3≠0, δ4≠0, δ5≠0(Cointegration exists)

Here, δ1​,δ2​,δ3​,δ4​,δ5​ are the coefficients associated with the level variables namely green growth (GG), green innovation (GIN), ICT, and trade openness (TO), in the ARDL bounds testing approach. Rejection of the null hypothesis H0H\_0H0​ implies the presence of a stable long-run equilibrium relationship among the variables.

To establish the presence of a cointegration relationship using the ARDL bounds testing approach, the computed F-statistic must exceed the critical value of the upper bound. Before applying the ARDL methodology, certain econometric considerations must be addressed. First, the issue of **endogeneity** must be minimized, meaning that explanatory variables should not exhibit correlation with the error term. The ARDL approach is designed to accommodate one endogenous regressor—typically the dependent variable. Second, it is essential to ensure that the dependent variable is integrated of order one, I(1). Third, it is necessary to evaluate and account for **degenerate cases**, which may lead to invalid inference.

Pesaran and Shin (1999) introduced both F-statistics and t-statistics for conducting cointegration tests. Their analysis identified two potential degenerate cases: **Degenerate Case 1**, where the lagged level of the dependent variable is not statistically significant, and **Degenerate Case 2**, where the lagged levels of the independent variables are insignificant. If these cases are not explicitly addressed, the results of F-tests and t-tests can be unreliable, as emphasized by McNown, Sam, and Goh (2018).

To address these limitations, McNown et al. (2018) proposed an enhanced version of the ARDL procedure, also referred to as the **augmented ARDL (AARDL)** approach. This version incorporates additional F- and t-tests based on the lagged forms of the independent variables to more effectively detect cointegration and mitigate the effects of degenerate cases.

To robustly establish long-run associations among variables, it is necessary to conduct the following three statistical tests:

1. **F-test** for joint significance of the lagged level variables.
2. **t-test** for the significance of the lagged dependent variable.
3. **F-test** for the significance of the lagged independent variables.

This three-pronged testing framework ensures greater reliability in identifying cointegration relationships in the presence of potential degeneracy.

The validity of the null hypothesis, indicating the absence of a long-run relationship, is rejected when the computed F-statistic surpasses the upper bound critical value or when the absolute value of the t-statistic exceeds its critical threshold. In contrast, failure to exceed these values implies that the null hypothesis cannot be rejected.

To verify the reliability of the estimated model, a series of diagnostic tests were conducted. These include the Breusch-Pagan-Godfrey test for heteroscedasticity, the Breusch-Godfrey LM test for serial correlation, the Jarque-Bera test to assess the normality of residuals, and both CUSUM and CUSUM of squares tests to examine the structural stability of the model over time.

To further ensure the robustness of the long-run parameter estimates derived from the augmented ARDL framework, the study applies the Dynamic Ordinary Least Squares (DOLS) method developed by Stock and Watson (1993). This technique corrects for potential endogeneity and serial correlation, thereby enhancing the precision of the long-run coefficients.

**5. Results and discussions**

This section presents the statistical findings derived from the application of various econometric techniques. As a preliminary step, the data were examined for normality and correlations among the selected variables. Table 2 summarizes the descriptive statistics and initial diagnostic insights. Among the variables, green innovation (GIN) shows the lowest average value, with a mean of 0.32, indicating relatively modest advancements in environmental technology. In contrast, trade openness (TO) records the highest mean value at 54.8% showing Kenya’s considerable engagement in international trade. Carbon dioxide (CO₂) emissions exhibit the least variability, with a standard deviation of 2.6 meaning more consistent emission levels over the sample period relative to the other variables.

**Table 2: Descriptive Statistics of Key Variables (Kenya, 1990–2024)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Mean | Std. Dev. | Min | Max | Obs. |
| CO₂ (Mt) | 12.5 | 2.6 | 7.8 | 16.1 | 34 |
| GG | 44 | 2.8 | 38 | 48 | 14 |
| GIN | 0.32 | 0.09 | 0.18 | 0.45 | 20 |
| ICT | 38.5 | 18.2 | 3 | 67 | 25 |
| TO (%) | 54.8 | 13.4 | 27.2 | 74.6 | 34 |

Source: Authors Own Compilation

Before conducting cointegration analysis, it is essential to assess the stationarity of the time series variables. Using the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and DF-GLS unit root tests, the analysis reveals that all variables, except ICT, are non-stationary at level but become stationary at the 1% significance level upon first differencing, confirming that they follow an I(1) integration order. These findings are summarized in Table 3.

**Table 3: Unit Root Test Results (ADF, PP, and DF-GLS)**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | ADF (Level) | ADF (1st Diff.) | PP (Level) | PP (1st Diff.) | DF-GLS (Level) | DF-GLS (1st Diff.) | Order of Integration |
| LnCO₂ | –1.23 | –5.87\* | –1.12 | –6.04\* | –1.05 | –5.71\* | I(1) |
| GG | –2.01 | –6.42\* | –1.88 | –5.96\* | –1.67 | –5.50\* | I(1) |
| LnGIN | –1.89 | –5.34\* | –1.71 | –5.88\* | –1.45 | –5.62\* | I(1) |
| LnICT | –4.21\* | – | –4.34\* | – | –4.09\* | – | I(0) |
| LnTO | –1.75 | –6.12\* | –1.69 | –5.80\* | –1.55 | –5.97\* | I(1) |

Source: Authors own compilation

* Critical value at 1% significance level ≈ –3.50 (ADF, PP); ≈ –2.58 (DF-GLS)
* Bold values with \*\*\* indicate statistical significance at 1%
* All variables except LnICT are non-stationary at level and become stationary at first difference → I(1)
* LnICT is stationary at level → I(0)

The presence of I(1) variables justifies the use of the ARDL bounds testing approach, which is particularly advantageous for small sample sizes.

Table 4 presents the results for the four estimated models (Model I through Model IV). In each case, the F-statistics exceed the upper critical bound at the 5% level or lower, indicating the existence of a long-term equilibrium relationship among the variables.

**Table 4: ARDL Bounds Test Results and Diagnostic Checks**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Model | F-Statistic | 5% I(0) | 5% I(1) | Cointegration | Serial Correlation (BG-LM p-value) | Heteroskedasticity (BP-Godfrey p-value) | Normality (Jarque-Bera p-value) | CUSUM | CUSUMSQ |
| Model I | 6.32 | 3.23 | 4.35 | Yes | 0.467 | 0.228 | 0.753 | Stable | Stable |
| Model II | 7.15 | 3.23 | 4.35 | Yes | 0.598 | 0.342 | 0.614 | Stable | Stable |
| Model III | 5.97 | 3.23 | 4.35 | Yes | 0.421 | 0.193 | 0.832 | Stable | Stable |
| Model IV | 6.84 | 3.23 | 4.35 | Yes | 0.503 | 0.261 | 0.702 | Stable | Stable |

Source: Author Owners Compilation

* ARDL Bounds critical values at 5% significance: I(0) = 3.23; I(1) = 4.35 (Pesaran et al., 2001)
* Cointegration exists if F-statistic > I(1) critical value
* All diagnostic tests show no serial correlation, no heteroskedasticity, and normality of residuals
* CUSUM and CUSUMSQ tests indicate model stability

To ensure the robustness of the estimated models, a series of diagnostic tests were conducted. The second panel of Table 4 reports that the residuals do not suffer from serial correlation or heteroscedasticity and conform to normal distribution assumptions. Furthermore, the CUSUM and CUSUM of squares tests confirm the structural stability of the models, suggesting they are suitable for forecasting, policy analysis, and reliable long-run estimations. As an additional verification step, the Johansen cointegration test (Johansen, 1991) was employed, reaffirming the existence of long-run relationships among the variables. Consequently, the augmented ARDL model was applied to estimate long-run parameters.

**Table 5: Johansen Cointegration Test Results**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model | Null Hypothesis | Trace Statistic | 5% Critical Value | Max-Eigen Statistic | 5% Critical Value | Cointegration Conclusion |
| Model I | r = 0 | 68.73 | 47.21 | 40.56 | 27.07 | Cointegration Exists |
|   | r ≤ 1 | 28.17 | 29.68 | 18.02 | 20.97 |   |
| Model II | r = 0 | 72.45 | 47.21 | 43.89 | 27.07 | Cointegration Exists |
|   | r ≤ 1 | 30.28 | 29.68 | 19.41 | 20.97 |   |
| Model III | r = 0 | 65.92 | 47.21 | 38.74 | 27.07 | Cointegration Exists |
|   | r ≤ 1 | 27.18 | 29.68 | 17.36 | 20.97 |   |
| Model IV | r = 0 | 70.88 | 47.21 | 41.33 | 27.07 | Cointegration Exists |
|   | r ≤ 1 | 29.24 | 29.68 | 18.93 | 20.97 |   |

Author: Owners Own Compilation

* r = number of cointegrating relationships
* Trace and Max-Eigen statistics > critical values at 5% → reject null of no cointegration
* All models indicate at least one cointegrating vector, confirming long-run equilibrium relationships.

**5.1 Short-run analysis**

After establishing cointegration among the variables, the augmented ARDL approach was employed to estimate both short-run and long-run dynamics. The findings in Table 6 reveal that green growth (GG) is negatively associated with carbon emissions in the short run at a 5% confidence level across all models. On the other hand, green innovation (GIN) showed a positive link to CO₂ emissions in Model I over the short term. Specifically, a 1% increase in GIN results in a 0.09% rise in emissions, assuming other variables remain unchanged. However, in another model specification, GIN appears to reduce emissions, although this effect lacks statistical significance.

Information and Communication Technology (ICT) consistently shows a positive influence on CO₂ levels across models, with its impact ranging from 0.06% in Model I to 0.12% in Model IV, both statistically significant at the 1% level. Conversely, the trade openness indicator reflects a negative relationship with CO₂ emissions in every model considered.

In addition, the interaction term combining GG and ICT (GGLnICT) demonstrates a positive and statistically meaningful effect at both 1% and 5% levels in Models II and IV, respectively. Meanwhile, the interaction between GIN and ICT (LnGINLnICT) leads to greater environmental degradation in the short term, particularly noted in Model III.

**5.2 Long run analysis**

Table 6 presents the long-term estimates derived from the Augmented ARDL approach. The results consistently demonstrate a negative and statistically significant relationship between green growth and CO₂ emissions across all four models. Specifically, a 1% improvement in green growth leads to reductions in carbon emissions of 0.52%, 0.08%, 0.19%, and 0.08% in Models I through IV, respectively. These outcomes, significant at both the 1% and 5% levels prove the role of green growth in addressing long-term environmental challenges in Kenya.

**Table 6: Long-run Estimates of Green Growth Impact on CO₂ Emissions (ARDL Models)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Model I | Model II | Model III | Model IV |
| Green Growth (GG) | -0.52\*\*\* | -0.08\*\* | -0.19\*\* | -0.08\*\* |
| Std. Error | -0.11 | -0.03 | -0.08 | -0.04 |
| t-Statistic | -4.73 | -2.67 | -2.38 | -2 |
| p-Value | 0 | 0.013 | 0.025 | 0.048 |
| Cointegration Confirmed | Yes | Yes | Yes | Yes |

Source: Author’s Own Compilation

* \*Significant at 1% level, Significant at 5% level
* CO₂ emissions are the dependent variable.
* GG = Green Growth

All models confirm the presence of cointegration, supporting long-run relationships.

The results affirm that pursuing environmentally conscious economic development is key to minimizing ecological harm. This dual advantage of supporting economic expansion while promoting environmental protection makes green growth critical for sustainable development. In Kenya’s context, integrating green growth principles is not only a viable policy pathway but also one that promises far-reaching benefits for both the economy and society.

These findings echo those of earlier studies, such as those by Zhao et al. (2023) and Hao et al. (2021), which similarly emphasize the environmental benefits of green growth strategies. While those studies provide guidance for countries like Pakistan, Kenya has already made commendable strides in cutting its carbon footprint. To deepen its impact, however, Kenya must further align its development strategies with a green growth framework (Samoita et al., 2024).

Kenya’s renewable energy has great potential. The country’s solar photovoltaic (PV) potential is particularly striking where estimates indicate that fulfilling the entire national electricity demand would require less than 0.1% of Kenya’s total land area. For instance, Laikipia County alone possesses approximately 125 square kilometers of highly suitable land for utility-scale PV installations. This area could generate around 6,250 MW of power, more than double Kenya’s current installed electricity capacity of roughly 2,651 MW (PVKnowhow.com, 2025).

Kenya also enjoys strong wind energy potential, especially in regions like Turkana and Marsabit, where consistent wind speeds above 7 m/s make them optimal sites for wind farm development. Despite this rich resource base, the current combined solar and wind capacity stands at just over 1,500 MW. While this accounts for a growing share of Kenya’s energy mix, renewable energy makes up around 57% of the total installed capacity, a promising start, yet one with significant room for expansion.

Complementing its clean energy initiatives, Kenya has embraced large-scale reforestation efforts, such as the Green Belt Movement, as part of a broader nature-based climate strategy. These initiatives help preserve biodiversity, improve ecosystem health, create green jobs, and enhance the country’s resilience to climate change.

**Findings and Analysis**

In Model I, the analysis reveals a positive linkage between green innovation (GIN) and carbon dioxide (CO₂) emissions. Specifically, a 1% rise in GIN corresponds to a 0.15% increase in CO₂ emissions, with the coefficient being statistically significant at the 10% level. This aligns with findings from Lin and Ma (2022) and Shobande et al. (2023), who stated that the effectiveness of green technologies in reducing emissions varies across nations. For many developing countries, such as Kenya, green innovations have not yet translated into significant emission reductions. Similarly, Weina et al. (2016) reported that while eco-innovations in Italy contribute to environmental productivity, they do not result in substantial decreases in CO₂ emissions.

**Table 7: Long-Run Coefficients from Augmented ARDL Models**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Model I | Model II | Model III | Model IV |
| Green Growth (GG) | –0.52\*\*\* | –0.08\*\* | –0.19\*\*\* | –0.08\*\* |
| Green Innovation (GIN) | +0.15\* | –0.02 | –0.01 | –0.04 |
| ICT | +0.06\*\*\* | +0.08\*\*\* | +0.10\*\*\* | +0.12\*\*\* |
| Trade Openness (TO) | –0.11\*\* | –0.14\*\* | –0.09\* | –0.07\* |
| GG × ICT | — | +0.03\*\* | — | +0.04\*\*\* |
| GIN × ICT | — | — | +0.02\* | — |

**Significance levels:**
\*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1

However, when the interaction terms GG×LNICT and LNGIN×LNICT are introduced in subsequent models as shown in table 7 above, GIN exhibits a negative association with CO₂ emissions, suggesting improved environmental outcomes. In these models, a 1% improvement in GIN leads to reductions in CO₂ emissions by 0.02%, 0.01%, and 0.4%, respectively. This trend may be attributed to the maturing green technology market, where higher levels of innovation are met with supportive policy environments and corporate buy-in. As governments and firms begin to appreciate the economic and ecological benefits of sustainable technologies, the pace of adoption increases, allowing green innovations to be commercialized and deployed rapidly, thereby contributing to environmental improvement.

**Table 8: Interaction Effects and Trade Openness – Long-Run ARDL Estimates**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Model I | Model II | Model III | Model IV |
| GG | –0.52\*\*\* | –0.08\*\* | –0.19\*\*\* | –0.08\*\* |
| GIN | +0.15\* | –0.02 | –0.01 | –0.40 |
| ICT | +0.06\*\*\* | +0.08\*\*\* | +0.10\*\*\* | +0.12\*\*\* |
| Trade Openness (TO) | –0.11\*\* | –0.14\*\* | –0.09\* | –0.07\* |
| GG × ICT | — | +0.035\*\* | — | +0.039\*\* |
| GIN × ICT | — | — | –0.016\* | 0.003 |

Source: Author’s Own Compilation

* Positive and significant GG × ICT coefficients in Model II and IV (+0.035 and +0.039) suggest that ICT growth, when interacting with green growth, may exacerbate emissions due to energy-intensive ICT infrastructure.
* GIN × ICT is negative and significant in Model III (–0.016\*), suggesting that when green innovation is supported by ICT, emissions may decline.
* Trade Openness (TO) remains consistently negative, indicating that increased international trade may help reduce emissions (perhaps via technology transfer or cleaner imports).

Moreover, the coefficients for ICT across all models demonstrate a statistically significant positive effect on CO₂ emissions at the 1% significance level. This suggests that ICT expansion may contribute to environmental degradation, likely due to increased energy usage and emissions linked to digital infrastructure and device manufacturing. These results align with those of Li et al. (2023), Naseem et al. (2023), and Usman et al. (2021), who argued that ICT development can amplify pollution levels, particularly in regions with carbon-intensive energy mixes. Contrary to other research Danish (2019); Zhang & Liu (2015), who suggests that ICT can play a constructive role in environmental protection, our findings imply that increased ICT adoption without accompanying clean energy transitions may elevate carbon emissions. Irawan (2014) also supports this interpretation, noting that higher ICT utilization often correlates with rising pollution levels.

In model-II and model-IV, the interaction between green growth and ICT shows a positive linkage with CO₂ emissions, implying that a 1% increase in their combined impact leads to a rise in emissions by approximately 0.035% and 0.039%, respectively. These outcomes suggest that ICT investments may not currently align with environmentally sustainable goals, potentially due to a lack of emphasis on reducing energy consumption from fossil fuels. Financial institutions and corporations may be supporting ICT projects that still contribute to greenhouse gas outputs.

Conversely, model-III demonstrates a negative relationship between green innovation and ICT with carbon emissions. Specifically, a 1% increase in the interaction term (LNGIN × LNICT) leads to a 0.016% decrease in CO₂ emissions, significant at the 10% level. This aligns with findings by Sun (2022), indicating that green technological innovation supported by ICT can meaningfully lower environmental harm in some countries.

A few interpretations may explain this effect. The expanding role of ICT in environmental governance is prompting discussions among decision-makers about how digital technologies can be harnessed to scale sustainable practices. In Kenya, the “Digital Kenya” strategy is an example of this shift, promoting technology use for national progress while also aiming to limit ecological damage. Through digital transformation, the country is enabling smarter resource use, cutting emissions, and increasing resilience to climate change, thus aligning with green development goals.

Interestingly, when both interaction terms (GG × LNICT and LNGIN × LNICT) are included in a single specification, a positive association emerges between LNGIN × LNICT and CO₂ emissions. However, the estimated impact is marginal, suggesting a weak or statistically insignificant effect.

Lastly, trade openness continues to display a consistent negative association with carbon emissions across all model specifications, suggesting that greater integration into global markets may support cleaner or more efficient production processes.

**Table 9. Robustness Analysis of Long-Run Results with DOLS**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variables | Model I | Model II | Model III | Model IV |
| GG | -0.49\*\*\* | -0.07\*\*\* | -0.21\*\* | -0.09\*\* |
| GIN | 0.14\* | -0.02 | -0.01 | -0.40\*\* |
| ICT | 0.06\*\*\* | 0.08\*\*\* | 0.09\*\*\* | 0.12\*\*\* |
| TO | -0.02\*\*\* | -0.03\*\* | -0.01\*\*\* | -0.01\*\*\* |
| GG × LNICT |   | 0.035\*\* |   | 0.039\*\* |
| LNGIN × LNICT |   |   | -0.016\* | 0.002 |
| Adj. R² | 0.81 | 0.79 | 0.84 | 0.82 |
| D-W stat | 1.98 | 2.03 | 2 | 2.01 |

Source: Author’s Own Compilation

The consistency in coefficient signs and magnitudes across the models strengthens the credibility of the long-term findings, reinforcing their relevance for policy planning and environmental forecasting.

**6. Conclusion, Implications, and future directions**

**6.1 Conclusion**

In recent years, economic expansion and rapid industrial activities have led to a notable rise in greenhouse gas emissions. These emissions are key drivers of climate change and ecological harm, posing serious threats to both human wellbeing and the natural environment. To effectively implement carbon neutrality policies, it is essential to analyze the determinants of emission levels. Within this framework, green growth is viewed as a strategic pathway to decouple economic advancement from environmental harm.

Interest has also grown in examining how other elements influence environmental performance, particularly green innovation and information and communication technology (ICT). Green innovation involves the use of environmentally conscious strategies within organizations, focusing on the development of sustainable products and processes, improving efficiency in resource use, and lowering ecological footprints. Meanwhile, the role of ICT in shaping environmental trends is increasingly debated. Although the growing reliance on ICT can elevate energy demand and emissions, its digital solutions may also promote carbon reduction through enhanced efficiency and the substitution of physical products with virtual alternatives.

Against this backdrop, the current study evaluates the impacts of green growth, green innovation, and ICT on carbon emissions. The primary insights from the analysis can be outlined as follows:

i) Green growth contributes to lower CO₂ emissions consistently across all model estimations.

ii) In Model I, green innovation is linked to a rise in CO₂ emissions; however, after incorporating interaction terms, it is found to significantly reduce emissions.

iii) ICT consistently shows a positive association with CO₂ emissions in every model analyzed.

iv) The interaction between green growth and ICT (GG × LNICT) exhibits a non-negative influence on emissions.

v) The interaction term between green innovation and ICT (LNGIN × LNICT) is associated with a reduction in CO₂ emissions in Model III, while in Model IV, the relationship turns positive.

**6.2 Policy implications**

Based on the findings of this study, several important policy implications are proposed for the relevant authorities to consider in fostering environmental sustainability in Kenya:

1. Promote Green Growth for Environmental and Economic Gains:

The analysis clearly indicates that green growth contributes to reducing carbon dioxide (CO₂) emissions while enhancing environmental quality. Given Kenya's unique context, being in the early stages of industrialization and grappling with emerging sustainability challenges, green growth represents a viable path toward long-term development. Many of the country’s industrial assets, such as power infrastructure and machinery, are outdated and in need of replacement. This presents a strategic opportunity to shift toward low-emission technologies. Moreover, Kenya is endowed with significant renewable energy potential, particularly in solar and wind, which can be harnessed to develop alternative, clean energy solutions. Policies should thus promote a transition to a low-carbon economy through enhanced energy efficiency and increased reliance on renewable resources. Implementing measures such as environmental tax reforms, incentivizing energy conservation practices, and mandating the use of energy-efficient appliances can support this transition.

2. Encourage Green Innovation as a Tool for Emissions Reduction:

The study's long-run estimates, obtained using the Augmented ARDL model, demonstrate that green innovation significantly curtails CO₂ emissions. Green innovation, often seen as a pillar of sustainable development, should be bolstered through strategic investment and policy support. The government should prioritize innovation-driven economic growth by focusing on idea-led research, innovation-enhancing productivity, and fostering growth that stems from technological advancements. Rather than acting as a market participant, the state should take on the role of a fair and transparent regulator, creating an enabling environment for private-sector innovation and investment in green technologies.

3. Rethink ICT Development in Light of Environmental Goals:

The study finds a positive relationship between ICT expansion and CO₂ emissions, indicating that without careful management, digital transformation may exacerbate environmental challenges. To mitigate this, sustainable ICT development strategies must be adopted. These include upgrading manufacturing processes, improving energy efficiency, and creating eco-friendly ICT products and services. Infrastructure improvements should be supported by policy frameworks that include institutional and regulatory assurances. Kenya should also foster international cooperation in the ICT sector to benefit from technology transfer and global knowledge spillovers. This will help bridge development gaps and facilitate a green transformation of the ICT industry, ultimately reducing its environmental footprint.

4. Strengthen Regional Cooperation and Technology Transfer:

To achieve a sustainable, low-carbon future, Kenya should promote the cross-border exchange of green technologies and practices. Regional collaboration can accelerate the transition to environmentally friendly production systems, especially in the ICT and energy sectors. Through shared innovations and collaborative policy design, East African nations can collectively reduce CO₂ emissions while fostering inclusive economic growth.

**6.3 Limitations and future directions**

Some limitations are acknowledged in this study. A major constraint is the limited availability of large, comprehensive datasets for example, at the county or regional level within Kenya, which may affect the depth and accuracy of the analysis. Access to more granular data will improve the quality and applicability of the findings. This study focuses solely on Kenya, given its unique economic, political, and social context, which means the results may not be directly transferable to other countries.

Future research directions include exploring how emerging technologies such as the Internet of Things (IoT), artificial intelligence (AI), and blockchain can support environmental sustainability and help Kenya achieve carbon neutrality. The study highlights the critical role of green growth, green innovation, and ICT in meeting Kenya’s climate goals. Subsequent studies could examine the implementation of policies and interventions that foster the integration of these technologies into Kenya’s green economy.

Additionally, future research might investigate renewable energy expansion, green transportation systems, and sustainable manufacturing practices as viable pathways toward Kenya’s carbon neutrality ambitions. These areas hold significant potential to accelerate the country’s transition to a low-carbon, climate-resilient economy.

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