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# Modelling the marginal effects of energy consumption, ICT, industrialization, and urbanization on environmental sustainability in Somalia: dynamic ARDL and KRLS approaches

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**Abstract**
As environmental degradation increasingly threatens ecosystems and economies, understanding the factors shaping ecological sustainability is more urgent than ever. Economic development, technological progress, industrial expansion, and urbanization play a crucial role in determining environmental outcomes, particularly in fragile regions. In Somalia's vulnerable economy, the balance between fostering economic growth and minimizing ecological footprints remains underexplored. This study addresses this gap by analyzing the effects of economic growth, energy consumption, adoption of information and communication technologies (ICT), industrialization, and urbanization on ecological footprints in Somalia using time-series data from 1990 to 2020. Through a dynamic autoregressive distributed lag (ARDL) model, the study captures both short- and long-term impacts, as well as the shocks of the regressors on ecological footprints. The results indicate that while economic growth reduces ecological footprints in the long-run, energy consumption exacerbates environmental degradation. Strikingly, ICT adoption consistently mitigates ecological footprints by improving resource efficiency and optimizing processes. Conversely, industrialization and urbanization impose significant ecological strain. Employing the Kernel-Based Regularized Least Squares (KRLS) method ensures robust estimates by accounting for the heterogeneity of the pointwise marginal effects of the explanatory variables. According to the findings, Somalia should prioritize promoting renewable energy to reduce dependence on fossil fuels, adopt sustainableindustrial practices, enforce comprehensive urban planning focusing on green infrastructure, leverage ICT for resource optimization, and integrate climate change adaptation into economic strategies.

**Keywords** Ecological footprints · Energy consumption · ICT adoption · Industrialization · Urbanization · Economic growth

## 1 Introduction

The accelerating pace of urbanization and industrialization has drastically increased carbon dioxide ($CO_2$) emissions, disrupting the natural carbon cycle and intensifying global climate change [1]. This escalation in greenhouse gas (GHG) emissions, primarily fueled by technological advancements and growing energy consumption, is reshaping the global carbon footprint, posing both challenges and prospects for sustainability [2]. Projections from the World Meteorological Organization indicate that, if current trends persist, global temperatures may increase by three to five degrees Celsius by

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2100 [3]. Carbon emissions, which account for 60% of global warming, have been a key driver of climate change over the past two decades [4]. Information and communication technology (ICT) has emerged as a vital instrument in combating these challenges by enhancing energy efficiency, advancing smart grid technologies, and fostering low-carbon solutions [5]. Additionally, industrialization has propelled urban expansion, resulting in over half of the global population currently living in urban areas [6]. There is a growing global consensus that environmental pollution and climate change represent the most pressing threats to economies, natural resources, air quality, biodiversity, the ozone layer, and human health [7]. Consequently, scholars and policymakers are increasingly examining the factors driving environmental degradation to formulate effective regulations and policies aimed at reducing emissions and mitigating environmental harm [8].

ICT plays a significant role in reducing environmental pollution by optimizing energy consumption and enhancing efficiency across various sectors. For instance, ICT has the potential to reduce $CO_2$ emissions in industries and urban areas by streamlining processes and minimizing energy waste, potentially cutting emissions by up to 20% by 2030 [9]. Digital technologies, such as the Internet of Things (IoT) and big data analytics, are also crucial in monitoring and managing environmental impacts, thereby contributing to global efforts to combat climate change [10]. However, the environmental impact of ICT is multifaceted. While it offers substantial benefits in reducing carbon emissions and enhancing productivity [11], the production, use, and disposal of ICT equipment can also harm the environment, primarily due to increased environmental pollution from power generation [12]. The influence of ICT on environmental outcomes varies across different regions, with its effectiveness in reducing emissions is more pronounced in some areas than others [8]. As ICT continues to evolve, integrating energy and environmental data within these technologies becomes increasingly important to maximize their positive effects and mitigate their negative impacts [13].

Economic growth and urbanization are fundamental drivers of modern development, each exerting a profound influence on environmental quality. The Environmental Kuznets Curve (EKC) hypothesis, which posits an inverted U-shaped relationship between economic growth and $CO_2$ emissions, has been extensively studied [5, 14]. In the early stages of economic transition, as countries shift from agriculture to industry and populations migrate from rural to urban areas, $CO_2$ emissions tend to rise due to increased energy consumption and industrial expansion [15]. While this transformation enhances living standards, it also significantly contributes to GHG emissions [16]. Urbanization, a defining feature of modernization, plays a crucial role in this process. Although essential for economic and societal progress, urbanization exhibits a complex relationship with $CO_2$ emissions [17]. Studies indicate that this relationship may also follow an inverted U-shaped trajectory, where initial urbanization phases lead to lower emissions, but as cities grow, emissions eventually escalate [18]. Empirical studies further support a positive correlation between urbanization and rising carbon emissions across various countries, which reflect the mounting environmental pressures linked to urban expansion [19]. The association between economic growth, urbanization, and environmental impact remains a critical area of study, with the EKC framework offering significant insights into the evolution of these dynamics over time [20].

Energy consumption and industrialization are major contributors to $CO_2$ emissions, driving environmental degradation and climate change. The Industrial Revolution marked a pivotal shift, triggering a sharp rise in GHG concentrations as $CO_2$ emissions escalated alongside economic growth [21]. By 2019, atmospheric $CO_2$ levels had surged to 409.8 ppm, the highest recorded in 800,000 years. Industrialized nations, primarily responsible for environmental harm, exacerbate climate change through fuel combustion, chemical waste emissions, and the release of microscopic particles into the atmosphere [20]. Beyond industrialized economies, developing nations are increasingly experiencing the adverse effects of rapid industrialization and urbanization, including air pollution, water contamination, and land degradation [22]. Addressing these challenges is crucial for achieving sustainable development [23]. Both industrialized and developing countries must navigate the delicate balance between economic expansion and environmental sustainability. Industrial activities not only accelerate resource depletion but also intensify pressure on ecosystems and human health, particularly in urbanized areas [24]. Without effective management of energy consumption and $CO_2$ emissions, industrialization will continue to pose significant environmental and public health risks [25]. The persistent rise in emissions stresses the necessity for stricter regulations and policies to mitigate the environmental externalities of energy consumption, which, if left unchecked, will further intensify the climate crisis [13].

As one of the least industrialized nations globally, Somalia faces significant energy consumption and sustainability challenges. The country's energy system remains heavily dependent on traditional biomass sources, such as wood and charcoal, which constitute over 90% of total energy consumption [26]. This reliance has led to widespread deforestation, accelerated land degradation, and increased susceptibility to climate change, mainly through more frequent and severe droughts. Access to modern energy remains critically low, with less than half of the population having electricity, leaving the majority, especially in rural areas, without reliable power [27]. Despite these energy challenges, Somalia's contribution to global $CO_2$ emissions remains minimal, with per capita emissions recorded at just 0.04 metric tons in 2020—one of the lowest worldwide [28]. Meanwhile, the expansion of Somalia's ICT sector presents both opportunities and challenges for environmental sustainability. Despite fragile infrastructure and ongoing political instability, ICT penetration has grown rapidly, particularly in urban areas, where approximately 28% of the population now has internet access [29]. However, the energy demands of ICT infrastructure, including data centers and mobile networks, often depend on non-renewable energy sources, exacerbating environmental stress. Nevertheless, integrating ICT across various sectors offers the potential to enhance energy efficiency, optimize resource management, and minimize the ecological footprint of industries.

The primary objective of this study is to examine the role of energy consumption, ICT, industrialization, and urbanization on environmental sustainability in Somalia, using ecological footprints as the dependent variable. This approach provides a more comprehensive assessment of environmental impact compared to traditional indicators such as carbon emissions or deforestation. By utilizing time-series data from 1990 to 2020, the study addresses a critical gap in the literature on the intersection of technological growth, energy use, and environmental performance in fragile, low-income states like Somalia. While previous research has often focused on broader regional dynamics [17, 19] or specific sectors such as agriculture [14, 30], the influence of industrialization and ICT adoption on Somalia's unique environmental challenges remains underexplored. This study contributes to the existing body of knowledge in several keyways. Firstly, it provides the first empirical analysis of how ICT, energy consumption, and industrialization collectively influence Somalia's ecological footprint. Previous studies have largely examined energy consumption and deforestation, overlooking the dual role of ICT as both a driver of environmental efficiency and a source of increased energy demand. Secondly, by incorporating urbanization and industrialization as determinants of environmental sustainability, this study addresses the rapidly growing urban population in Somalia and its interaction with technological expansion and industrial activities. Thirdly, advanced econometric techniques, including the Kernel-based Regularized Least Squares (KRLS) machine learning method and the dynamic autoregressive distributed lag (ARDL) model, are employed to produce precise and reliable results. These methodologies capture the marginal and heterogeneous effects of ICT and industrialization on Somalia's ecological footprint. Ultimately, this research informs policymakers on strategies to balance industrial and technological growth with environmental sustainability, providing critical recommendations for shaping Somalia's future development pathways.

The remainder of this paper is organized as follows. Section two reviews the relevant literature. Section three outlines the variables and econometric methods employed in the analysis. Section four presents the findings and discusses their implications. Finally, section five concludes the study and offers policy recommendations based on the results.

## 2 Literature review

### 2.1 Economic growth and ecological sustainability

The relationship between economic growth and environmental sustainability has been extensively studied, with particular attention to the EKC hypothesis. This hypothesis suggests that environmental degradation initially increases with economic growth but eventually decreases after reaching a certain income level. Armeanu et al. [31] confirmed the EKC hypothesis in the EU-28 countries, where pollutants such as ammonia, nitrogen oxides, and sulfur oxides initially rose with economic growth but declined beyond a certain income threshold. Similarly, Han et al. [32] found an inverted U-shaped curve between $CO_2$ emissions and economic growth in Shandong province, China. In contrast, Aung et al. [33] found a consistently positive relationship between GDP and $CO_2$ emissions in Myanmar, with no evidence of an EKC. This suggests that economic growth in Myanmar has been associated with increasing environmental pollution in both the short- and long-run. Ali et al. [34] extend this discussion by exploring the relationship between economic growth and environmental sustainability in Canada. Utilizing the Dynamic ARDL model, they reveal that economic growth significantly increases carbon emissions and ecological footprints through demand-side effects while reducing supply-side environmental capacity. By the same token, Abdi et al. [35] highlight that economic expansion adversely impacts the environment, leading to a substantial rise in both ecological footprints and carbon dioxide emissions.

Other studies have shown mixed results regarding the EKC hypothesis and the broader impact of economic growth on environmental sustainability. Taylor Adu and Kwaku Denkyirah [36] found no significant relationship between economic growth and environmental degradation in West Africa, which indicates the absence of an EKC in the region. Yang et al. [37] observed a negative long-term cointegration between GDP per capita and pollution indices in China. This suggests that economic growth does not necessarily lead to worsening environmental conditions. Ali et al. [38] further contribute to this discourse by investigating the energy-growth nexus in Canada. Their study, which applies the ARDL model, discovers that economic expansion drives higher energy use, which influences environmental sustainability. In South Asia, Mughal et al. [39] confirmed the EKC hypothesis but also highlighted significant environmental degradation associated with economic growth. Similarly, Shahzadi et al. [40] found that in G-7 nations, financial development, GDP growth, and green investment are positively associated with $CO_2$ emissions, which complicates the narrative that economic growth leads to environmental improvement. Additionally, Ali et al. [34] assess the effects of renewable and non-renewable energy consumption on Canada's economic growth trajectory, finding that both energy sources contribute positively to economic expansion in the short-and long-run, with a more substantial impact under internal macroeconomic conditions.

### 2.2 Energy consumption and ecological sustainability

Energy consumption has been extensively studied for its impact on environmental sustainability, with research focusing on its relationship with carbon emissions and ecological health across various regions and economic contexts. Jun et al. [20] investigated the relationship between energy consumption, economic growth, globalization, and $CO_2$ emissions in South Asian economies from 1985 to 2018. They found that non-renewable energy consumption significantly increases environmental pollution. This study also confirmed the EKC hypothesis, where environmental degradation rises with economic growth before declining after a certain income threshold. Zhao et al. [41] analyzed the effects of energy consumption, financial development, and economic growth on environmental pollution in China using spatial econometric techniques. They reveal that energy consumption is a major contributor to environmental pollution. Similarly, Udemba et al. [22] examined long-term relationships between pollutant emissions, FDI, energy consumption, tourism, and economic growth. Using the ARDL approach, the results indicate a positive association between pollutant emissions and all variables except economic growth. Bildirici and Gokmenoglu [42] explored the impact of terrorism and FDI on environmental pollution using panel cointegration and causality analysis. The research found that energy consumption, economic growth, terrorism, and FDI significantly affect environmental pollution. In 41 BRI countries, Aslam et al. [43] further contribute to this discourse by discovering that a greater share of renewable energy significantly mitigates energy security risks. However, non-renewable energy, although essential for meeting domestic energy demand, contributes to environmental degradation and supply vulnerabilities.

Khan et al. [44] examined the role of financial development and energy consumption in environmental degradation using seemingly unrelated regression (SUR) and the system GMM model. They demonstrated that non-renewable energy consumption exacerbates $CO_2$ emissions. Ulucak et al. [45] focused on the relationship between energy consumption and environmental sustainability using the augmented mean group (AMG) estimator. They concluded that renewable energy consumption reduces environmental degradation, while non-renewable energy consumption negatively affects the ecosystem. Salari et al. [46] analyzed the impact of GDP and different forms of energy consumption on $CO_2$ emissions across U.S. states. The outcomes reveal that renewable energy consumption is negatively correlated with $CO_2$ emissions, whereas non-renewable, industrial, and residential energy consumption positively impacts emissions. Odugbesan and Rjoub [47] analyzed the linkage between economic growth, energy consumption, $CO_2$ emissions, and urbanization using the ARDL Bounds test. Their findings indicated differing patterns across countries, with Nigeria and Indonesia showing unidirectional causality from energy consumption to economic growth, while Turkey and Mexico exhibited a bidirectional relationship. Finally, Shaheen et al. [15] investigated the dynamic interactions between income, energy consumption, urbanization, and $CO_2$ emissions in Pakistan using the ARDL model, finding that both GDP and energy consumption are significant drivers of $CO_2$ emissions.

### 2.3 ICT and ecological sustainability

The intersection of ICT and environmental sustainability has been the focus of extensive research in recent years. Bhujabal et al. [5] explored the interaction between ICT, foreign direct investment (FDI), and environmental pollution in Asia–Pacific nations. They reveal that enhanced ICT infrastructure and increased FDI inflows are linked to significant long-term reductions in environmental pollution. Similarly, Magazzino et al. [13] analyzed the impact of ICT on electricity consumption, air pollution, and economic growth in European Union (EU) countries. Their findings indicated a one-way causal relationship where increased ICT usage leads to higher electricity consumption, raising $CO_2$ emissions and contributing to economic growth. Similarly, Atsu et al. [48] examined the effects of ICT and energy consumption on $CO_2$ emissions in South Africa. Their findings indicated that both ICT usage and fossil fuel consumption significantly contribute to increased $CO_2$ emissions. However, they also found that renewable energy consumption and financial development help to reduce $CO_2$ emissions. Adding to the complexity, the non-linear dynamics between ICT development and $CO_2$ emissions were investigated by Añón Higón et al. [12], who identified an inverted U-shaped relationship. This research suggests that while early ICT advancements may increase emissions, further technological maturity can result in emission reductions.

Regional studies have also contributed to this discourse, with Arshad et al. [49] examining the role of ICT in energy consumption and environmental quality in South and Southeast Asia (SSEA). Their study concluded that ICT-related financial development and services have had a detrimental impact on environmental quality in the region. Further insights come from Amri [8], who studied the effects of ICT on environmental sustainability in Tunisia. The research found that ICT had a negligible impact on $CO_2$ emissions, while trade, financial development, and energy consumption were more significant contributors to environmental degradation. Charfeddine and Umlai [50] expanded on the relationship between ICT, digitization, and environmental sustainability by reviewing studies that utilized conventional ICT metrics alongside environmental metrics focused on air pollution and climate change. The majority of these studies reported a positive correlation between ICT and environmental sustainability. In 23 top manufacturing economies, Aslam et al. [51] suggest that environmental regulations are the most effective means of addressing energy security risks, while environment-related technologies contribute at certain levels. Moreover, the interactive effects of regulations and technology significantly limit energy-related risks. Lastly, Chen et al. [52] examined the influence of ICT usage on environmental quality perception and farmers' participation in domestic waste separation in China. Their study, which involved data from 2,126 Chinese farmers, found that ICT use negatively affected perceptions of environmental quality, which in turn influenced participation in waste separation practices.

### 2.4 Industrialization and ecological sustainability

Industrialization is a key driver of environmental pollution, particularly in terms of GHG emissions. Multiple studies across regions consistently highlight the significant impact of industrialization on environmental degradation. Mahmood et al. [24] found that in Saudi Arabia, both industrialization and urbanization significantly increase $CO_2$ emissions, with urbanization showing a more elastic effect. Notably, their study revealed that rising industrialization has a stronger impact on emissions compared to its decline, which indicates the asymmetry in pollution dynamics. Ahmed et al. [21] expanded on this by examining the Asia–Pacific region, demonstrating that FDI and industrialization contribute to environmental degradation, with FDI significantly increasing $CO_2$ and methane emissions. Chandra Voumik and Sultana [23] analyzed the BRICS nations and found that industrialization and urbanization are major drivers of environmental degradation. However, Abdi and Hashi [25] explored the impact of energy consumption and industrialization from 1990 to 2020. The study found that while energy consumption in Somalia exacerbates environmental degradation, industrialization reduces it. In sub-Saharan Africa (SSA), Mentel et al. [53] confirmed that industrialization, measured as a share of GDP, significantly increases $CO_2$ emissions. In South Asia, Sumaira and Siddique [54] identified a long-term, bidirectional relationship between industrialization and environmental degradation, which reinforces the global trend. Finally, Nasrollahi et al. [55] found that both weak and strong sustainability in MENA and OECD countries were slightly influenced by population growth and industrialization, which had a negative impact. Conversely, technological advancements and implementing international environmental agreements positively contributed to sustainability outcomes in these regions.

### 2.5 Urbanization and ecological sustainability

Urbanization has been widely studied for its impact on environmental sustainability, particularly in relation to carbon emissions and environmental degradation across different regions. Yang et al. [1] analyzed the increase in urbanization-induced $CO_2$ emissions and their effect on terrestrial vegetation, noting a significant rise in $CO_2$ concentrations from 2009 to 2018. Ali et al. [56] explored the relationship between urbanization and $CO_2$ emissions in Singapore. They found that urbanization substantially increases carbon emissions, though efforts to reduce them have shown potential benefits. Sun and Huang [57] investigated the impact of urbanization on carbon emission efficiency, identifying a negative U-shaped relationship. Their study revealed that while initial stages of urbanization improve carbon emission efficiency, further urbanization beyond a certain threshold reduces this efficiency due to the lag in economic growth relative to the increase in carbon emissions. Similarly, Musah et al. [18] found that urbanization contributes to a reduction in $CO_2$ emissions across multiple panels. Khan and Su [6] conducted a panel threshold analysis on Newly Industrialized Countries (NICs). They indicate that urbanization reduces $CO_2$ emissions to an optimal point, after which further urbanization leads to increased emissions. Bajja et al. [58] extended this discussion by examining the connection between urbanization, energy consumption, and environmental quality in six MENA countries from 1990 to 2021. Utilizing multiple econometric methods, including MG, DOLSMG, CCE, AMG, and CS-ARDL, they found that while renewable energy consumption and manufacturing activities improved environmental quality, urbanization and human capital development intensified environmental degradation.

In the African context, several studies have examined the long-term environmental effects of urbanization. Radoine et al. [59] analyzed urbanization trends and their impact on sustainability across six West African countries from 1991 to 2018. Using the Seemingly Unrelated Regression (SUR)-Mean Group (MG) model, the study revealed substantial differences in urbanization rates and their environmental consequences, which indicates the importance of region-specific approaches. Salahuddin et al. [60] also explored the impact of urbanization and globalization on $CO_2$ emissions in 44 SSA countries from 1984 to 2016, applying second-generation panel regression techniques. Their results indicated that urbanization significantly contributes to rising emissions, which reinforces concerns about the environmental trade-offs of rapid urban expansion. Warsame et al. [61] examined the roles of conflict, urbanization, and globalization on environmental degradation using advanced modelling techniques. Their findings demonstrated that urbanization, alongside globalization and conflicts, contributes to long-term environmental degradation. In 41 SSA countries, Abdi [17] revealed that urbanization exacerbates environmental pollution in the long-run, which highlights the challenges faced by rapidly urbanizing regions. Additionally, Bajja et al. [62] further explored the role of human capital development, international trade, financial development, and renewable energy consumption in eight emerging African economies between 1991 and 2021. Their findings confirmed that urbanization, economic expansion, and energy consumption contribute to environmental degradation, while financial development and renewable energy mitigate its effects.

## 3 Data and methodology

### 3.1 Data and variables

This study investigates the relationship between economic growth, energy consumption, ICT development, industrialization, urbanization, and ecological footprints in Somalia from 1990 to 2020. The selected time frame is motivated by Somalia's evolving economic and environmental landscape over the past three decades. The early 1990s marked a period of political instability and economic collapse, which significantly affected energy infrastructure, industrial activity, and urban development. Since the 2000s, Somalia has experienced a gradual economic recovery, expansion in ICT adoption, and increased urbanization, all of which have implications for environmental sustainability. Furthermore, global concerns over climate change and sustainable development intensified during this period, which makes it a relevant timeframe for examining the long-term ecological impact of economic and technological transformations in Somalia. In this analysis, ecological footprints serve as the dependent variable, while industrialization, GDP, energy consumption, ICT, and urbanization are the explanatory variables. Ecological footprints, measured in global hectares (gha), reflect the demand placed on nature by providing a comprehensive indicator of environmental pressure [63]. GDP, expressed in constant 2015 US dollars, serves as a proxy for economic growth and is essential for understanding how economic activities affect environmental outcomes [64].

Energy consumption, measured as primary energy consumption per capita (kWh/person), captures the intensity of energy use, which is a critical factor in assessing environmental degradation due to its close association with carbon emissions [44]. ICT development, represented by an index constructed through principal component analysis (PCA) of mobile subscriptions, telephone subscriptions, and internet users, is included to evaluate the impact of technological advancements on energy efficiency and environmental sustainability [65, 66]. Table A1 in the appendices provides a detailed summary of the PCA results. Industrialization is measured by manufacturing value-added, in constant 2015 prices, as it drives economic growth but also contributes significantly to environmental pressures [67]. Finally, urbanization, measured as the urban population percentage of the total population, is included to assess how changes in population density and urban lifestyles influence ecological footprints [1]. Data for these variables were sourced from the Global Footprint Network (GFN), the World Development Indicators, the Our World in Data platform, and the SESRIC database. Table 1 summarizes the variables used in the analysis, including their codes, descriptions, and data sources.

Table 1 Summary of variables, codes, descriptions, and data sources

| Variable | Symbol | Measurement | Source |
|---|---|---|---|
| Ecological footprints | EF | Global hectares (gha) | GFN |
| GDP | GDP | GDP (constant 2015 US$) | WDI |
| Energy consumption | EC | Primary energy consumption per capita (kWh/person) | OWID |
| Information and communication technology | ICT | ICT index has been constructed from mobile subscriptions, telephone subscriptions, and internet users through PCA | WDI |
| Industrialization | IND | Manufacturing, value added, constant 2015 prices | SESRIC |
| Urbanization | URB | Urban population (% of total population) | WDI |

## 3.2 Statistical analysis

### 3.2.1 Model specification

To empirically examine the influence of economic growth, energy consumption, ICT development, industrialization, and urbanization on Somalia's ecological footprints, this study draws on the model specifications used in Bhujabal et al. [5], Añón Higón et al. [12], Atsu et al. [48], Charfeddine and Umlai [50], Amri [8], Shaheen et al. [15], Abdi et al. [68], and Zhao et al. [41]. These prior studies incorporated variables such as GDP, energy consumption, ICT, industrialization, and urbanization into their models. In order to address potential heteroskedasticity and ensure a straightforward interpretation of the results in percentage terms, all variables are expressed in their natural logarithms. Thus, the model specification for this analysis is:

$$lnEF_t = \alpha_0 + \alpha_1 lnGDP_t + \alpha_2 lnEC_t + \alpha_3 lnICT_t + \alpha_4 lnIND_t + \alpha_5 lnURB_t + \varepsilon_t \quad (1)$$

where *EF* stands for ecological footprints, *GDP* refers to gross domestic product—a proxy for economic growth, *EC* represents energy consumption, *ICT* captures information and communications technology development, *IND* measures industrialization, and *URB* represents urbanization. $\alpha_0$ is the constant term, $\alpha_1$ to $\alpha_5$ are the coefficients to be estimated, *ln* denotes the natural logarithmic transformation, and $\varepsilon_t$ is the error term.

### 3.2.2 Unit root tests

Before estimating the ARDL model, it is essential to determine the stationarity properties of the variables to avoid spurious regression results. This study employs the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to check for unit roots and establish whether the variables are integrated at I(0) or I(1). These tests ensure that no variable is integrated at I(2), which would invalidate the ARDL approach. The augmented Dickey-Fuller (ADF) test is widely used to examine the stationarity of time-series data. It extends the standard Dickey-Fuller test by incorporating lagged differences to account for autocorrelation. The ADF test equation is given as follows:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (2)$$

where $Y_t$ is the tested variable, $\alpha$ represents the constant term, and $\beta t$ captures the trend component. The coefficient $\gamma$ determines whether the series has a unit root, while $\delta_i$ accounts for short-run dynamics. The optimal lag length, $p$, is selected based on information criteria such as AIC or BIC. The Phillips-Perron (PP) test follows a similar structure but differs in how it handles serial correlation and heteroskedasticity in the error term. Instead of including lagged differences, the PP test applies non-parametric corrections to account for these issues. The null hypothesis of both tests suggests the presence of a unit root, which indicates that the series is non-stationary. If $H_0$ is rejected, the series is considered stationary. The PP test equation is formulated as:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \varepsilon_t \quad (3)$$

### 3.2.3 ARDL model and ARDL bounds testing approach

The ARDL model, along with its bounds-testing approach, is a powerful tool for analyzing both long-run and short-run relationships in time series data [69]. It is especially useful for investigating cointegration and causality issues, offering several advantages over traditional cointegration methods [70]. One key strength of the ARDL model is its flexibility, allowing the inclusion of variables with mixed integration orders, either I(0) or I(1), as long as none are I(2) [71]. Moreover, unlike traditional methods, the ARDL model does not impose restrictive assumptions that require all variables to be integrated at the same order, enhancing its adaptability in empirical analysis [72]. This flexibility makes it suitable for a broad range of economic and financial applications, where variables often exhibit different levels of integration. Additionally, the model allows the simultaneous estimation of short-term dynamics and long-term relationships through the unrestricted error correction model (ECM), which makes it particularly effective in small sample sizes. Another advantage is its ability to capture dynamic adjustments between variables, which enables researchers to assess how deviations from long-run equilibrium are corrected over time. This approach helps to address endogeneity by incorporating lags of both the dependent and independent variables, further enhancing its utility in empirical analysis. The ARDL bounds testing technique remains an evolving and efficient method for testing cointegration in time series analysis, and its adaptability continues to make it a preferred choice in applied econometrics. To explore the presence of a long-term relationship between the variables in question, we estimate the conditional ARDL model associated with Eq. (1), expressed as follows:

$$\begin{aligned}\Delta lnEF_t = \alpha_0 + \sum_{i=1}^{a} \beta_1 \Delta lnEF_{t-i} + \sum_{i=1}^{b} \beta_2 \Delta lnGDP_{t-i} + \sum_{i=1}^{c} \beta_3 \Delta lnEC_{t-i} + \sum_{i=1}^{d} \beta_4 \Delta lnICT_{t-i} + \sum_{i=1}^{e} \beta_5 \Delta lnIND_{t-i} \\ + \sum_{i=1}^{f} \beta_6 \Delta lnURB_{t-i} + \varphi_1 lnEF_{t-1} + \varphi_2 lnGDP_{t-1} + \varphi_3 lnEC_{t-1} + \varphi_4 lnICT_{t-1} + \varphi_5 lnIND_{t-1} + \varphi_6 lnURB_{t-1} + \varepsilon_t\end{aligned} \tag{4}$$

where $\Delta$ is the difference operator, while $\alpha_0$ represents the intercept. The optimal lag lengths are indicated by *a, b, c, d,* and *e*. The short-term coefficients are denoted by $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, $\beta_5$, and $\beta_6$, while the long-term coefficients are represented by $\varphi_1$, $\varphi_2$, $\varphi_3$, $\varphi_4$, $\varphi_5$, and $\varphi_6$. In this regard, the ARDL bounds test follows two essential steps. Initially, once the stationarity of the series is established, the optimal lag length for the variables is identified. Next, Fisher's test is applied to evaluate the null hypothesis of no cointegration ($H_0 : \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = \varphi_6 = 0$) versus the alternative hypothesis that a cointegration relationship exists ($H_1 : \varphi_1 \neq \varphi_2 \neq \varphi_3 = \varphi_4 \neq \varphi_5 \neq \varphi_6 \neq 0$). The ARDL bounds testing method involves comparing the calculated Fisher statistic (or F-statistic) with the critical values of the lower bound I(0) and upper bound I(1) at different significance levels (1%, 5%, 10%). If the F-statistic falls below the lower bound I(0), the null hypothesis of no cointegration is accepted. However, if the statistic exceeds the upper bound I(1), the null hypothesis is rejected, signaling the existence of cointegration. Upon confirming cointegration, the model is then adjusted using an unrestricted ECM to evaluate both short-run and long-run dynamics.

### 3.2.4 Dynamic ARDL simulations

The dynamic ARDL model, introduced by Jordan and Philips [73], offers an enhancement over the traditional ARDL approach by capturing both short-run and long-run relationships while accounting for dynamic effects over time. It employs impulse response functions to examine how shocks to one variable influence others. A standout feature of this model is its ability to simulate counterfactual shocks, where one variable is changed while others remain constant, thus allowing a clearer understanding of how variations in a specific factor impact the dependent variable [74]. This flexibility makes it particularly effective in evaluating both positive and negative changes in independent variables and their dynamic adjustments. Furthermore, the dynamic ARDL model integrates bootstrapping techniques, ensuring more robust standard errors and confidence intervals, especially in cases with small sample sizes. It facilitates dynamic simulations, enabling the estimation and visualization of changes in the dependent variable as a result of shifts in a regressor while keeping other variables constant. Before simulations can be performed, however, it is crucial that the regressors are not integrated beyond I(1), and that cointegration is established between the variables [73, 74]. Additionally, diagnostic tests for autocorrelation, heteroskedasticity, normality, and model stability are essential to ensure the reliability of the results. The ECM equation for the dynamic ARDL model is formulated as follows:

$$\Delta lnEF_t = \theta_0 + \delta_0 lnEF_{t-1} + \lambda_1 \Delta lnGDP_t + \delta_1 lnGDP_{t-1} + \lambda_2 \Delta lnEC_t + \delta_2 lnEC_{t-1} + \lambda_3 \Delta lnICT_t + \delta_3 lnICT_{t-1} + \lambda_4 \Delta lnIND_t + \delta_4 lnIND_{t-1} + \lambda_5 \Delta lnURB_t + \delta_5 lnURB_{t-1} + \varepsilon_t \tag{5}$$

where Δ represents the short-run changes in GDP, energy consumption, ICT development, industrialization, and urbanization. Specifically, $\delta_0$ captures the error correction term (ECT), $\lambda_1$ through $\lambda_5$ indicate the short-term effects of changes, while $\delta_1$ through $\delta_5$ represent the long-term effects.

#### 3.2.5 Kernel-based regularized least squares (KRLS)

The KRLS method, introduced by Hainmueller and Hazlett [75] and refined by Asumadu Sarkodie and Owusu [74], is a non-parametric approach ideal for modeling complex, non-linear relationships between variables. It uses kernel functions to map data into a higher-dimensional space, which captures interactions that traditional linear models may miss. KRLS provides accurate estimates of marginal effects and can compute partial derivatives at each data point, offering insights into how these effects vary across observations. A key feature is the regularization term, which prevents overfitting by penalizing large coefficients, improving model generalization. The method uses a Gaussian kernel, where similarity between data points is measured by Euclidean distance, with the kernel value decreasing as the distance increases. This approach offers stability, unbiasedness, and strong empirical performance, making it effective in capturing both global and local relationships. The Gaussian kernel utilized in KRLS can be illustrated as follows:

$$k\left(x_j, x_i\right) = e^{-\frac{\|x_j - x_i\|^2}{\sigma^2}} \tag{6}$$

where $x_i$ and $x_j$ are two data points, and $\|x_j - x_i\|^2$ is the squared Euclidean distance between them. The parameter $\sigma^2$ controls the width of the kernel, and the kernel achieves its maximum value when $x_i = x_j$, meaning the two data points are identical. As the distance between the points increases, the value of the kernel approaches zero. To compute the kernel value at a specific point $x^*$, the mathematical expression for $y$ can be formulated as:

$$y = f(x) = \sum_{i=1}^{N} c_i k\left(x^*, x_i\right) \tag{7}$$

## 4 Empirical results and discussion

### 4.1 Preliminary analysis

Table 2 presents a comparison of the key statistics for the study variables: ecological footprints, economic growth, energy consumption, ICT, industrialization, and urbanization. Ecological footprints, with a mean of 0.064, show positive skewness (0.518) and a kurtosis of 1.986, which indicates a left-skewed distribution with some heavier tails. Economic growth, on the other hand, has a much higher mean of 22.362, accompanied by slight negative skewness (-0.161) and a kurtosis of 1.828, which suggests a more symmetric and flatter distribution compared to ecological footprints. Energy

**Table 2** Descriptive summary

| | lnEF | lnGDP | lnEC | lnICT | lnIND | lnURB |
|---|---|---|---|---|---|---|
| Mean | 0.064 | 22.362 | 5.640 | 0.000 | 18.368 | 3.668 |
| Maximum | 0.209 | 22.885 | 5.848 | 1.292 | 19.100 | 3.832 |
| Minimum | − 0.052 | 21.722 | 5.357 | − 3.497 | 17.564 | 3.504 |
| Std. Dev | 0.080 | 0.371 | 0.139 | 1.353 | 0.493 | 0.113 |
| Skewness | 0.518 | − 0.161 | − 0.245 | − 1.300 | 0.064 | − 0.024 |
| Kurtosis | 1.986 | 1.828 | 2.144 | 3.787 | 1.895 | 1.488 |
| Jarque–Bera | 1.840 | 1.294 | 0.851 | 6.459 | 1.083 | 2.002 |
| Probability | 0.398 | 0.524 | 0.654 | 0.040 | 0.582 | 0.368 |
| Observations | 31 | 31 | 31 | 31 | 31 | 31 |

consumption displays a mean of 5.640, with a moderate negative skewness (-0.245) and a kurtosis of 2.144. This reveals a mildly left-skewed distribution and heavier tails relative to economic growth. ICT shows the greatest deviation from normality, with a mean of 0.000, a pronounced negative skewness (-1.300), and a higher kurtosis (3.787), indicating a sharply left-skewed and peaked distribution. Industrialization has a mean of 18.368, minimal skewness (0.064), and a kurtosis of 1.895, which suggests a near-normal distribution. Moreover, urbanization has a mean of 3.668, with slight negative skewness (-0.024) and the lowest kurtosis (1.488) among the variables, which indicates a flatter and more symmetric distribution. The Jarque–Bera test further highlights the distributional characteristics. While ICT shows significant deviation from normality, the other variables, including ecological footprints, economic growth, energy consumption, industrialization, and urbanization, do not show strong evidence of non-normality because their p-values exceed the 0.05 threshold level.

Table 3 provides an overview of the relationships between ecological footprint and the other independent variables using Spearman correlation. There is a strong negative correlation between ecological footprint and economic growth (-0.926). This indicates a significant inverse association, where higher economic growth is linked to a lower ecological footprint. Similarly, a strong negative relationship is observed between ecological footprint and industrialization (-0.943), as well as between ecological footprint and urbanization (-0.939). This suggests that increased levels of industrialization and urbanization are associated with reductions in ecological footprint. On the other hand, the correlation between ecological footprint and energy consumption is moderately positive (0.784), which shows that higher energy consumption tends to correspond with an increase in ecological footprint. The statistical significance of these correlations demonstrates the strong and meaningful connections between ecological footprint and the independent variables.

## 4.2 Stationarity analysis

Table 4 presents the unit root test results for the study variables using both the ADF and PP methods, tested at both levels (I(0)) and first differences (I(1)). The ecological footprint is non-stationary at I(0), but both ADF and PP tests show strong significance at I(1), indicating stationarity after differencing. Economic growth shows mixed results; while the ADF test becomes significant only at I(1) with a constant, the PP test is significant at both I(0) and I(1) when a trend is included. Moreover, energy consumption is non-stationary at I(0) in the ADF test but achieves stationarity at I(1) in both tests, with particularly strong significance in the PP results. ICT is not stationary at I(0) but shows significance at I(1) according to the PP test. For industrialization, the ADF test demonstrates stationarity at I(0) with a trend, while both ADF and PP tests confirm stationarity at I(1). Urbanization is non-stationary at I(0) but becomes stationary at I(1) in both tests. Given this mixed order of integration, the ARDL method is the most appropriate model for the data, as it is designed to handle variables integrated at different levels.

## 4.3 Lag length selection, model selection and cointegration test

Table 5 evaluates various lag lengths using multiple model selection criteria, with lag 2 emerging as the optimal choice. The selection of lag 2 is supported by its superior performance across key lag length selection criteria, including the final prediction error (FPE), Akaike information criterion (AIC), Hannan-Quinn information criterion (HQIC), and Schwarz Bayesian information criterion (SBIC). Additionally, the likelihood ratio (LR) test further solidifies the selection of lag 2, with a test statistic of 293.34 and a strong statistical significance. In our analysis, the ARDL (2, 2, 2, 1, 2, 2) model was consequently chosen as the optimal specification based on the AIC. On the other hand, Table 6 provides clear evidence of significant long-run cointegration among the variables. The F-statistic value of 11.401

**Table 3** Correlation analysis

| | lnEF | lnGDP | lnEC | lnICT | lnIND | lnURB |
|---|---|---|---|---|---|---|
| lnEF | 1.000 | | | | | |
| lnGDP | − 0.926*** | 1.000 | | | | |
| lnEC | 0.784*** | − 0.766*** | 1.000 | | | |
| lnICT | − 0.922*** | 0.905*** | − 0.847*** | 1.000 | | |
| lnIND | − 0.943*** | 0.991*** | − 0.800*** | 0.884*** | 1.000 | |
| lnURB | − 0.939*** | 0.973*** | − 0.836*** | 0.861*** | 0.974*** | 1.000 |

*, **, and *** represent 1%, 5%, and 10% significance levels, respectively

**Table 4** Unit root tests results

| Variable | ADF | | PP | |
|---|---|---|---|---|
| | Level | | Level | |
| | Constant | Constant and trend | Constant | Constant and trend |
| lnEF | – 1.107 | – 2.577 | – 0.555 | – 2.463 |
| lnGDP | 0.585 | – 4.384*** | 0.752 | – 3.312* |
| lnEC | 0.197 | – 1.500 | – 3.820*** | – 6.294*** |
| lnICT | – 2.709 | – 2.649 | – 4.172*** | – 2.943 |
| lnIND | 0.509 | – 4.442*** | 0.147 | – 2.756 |
| lnURB | 0.094 | – 2.520 | 0.111 | – 2.517 |
| | First difference | | First difference | |
| | Constant | Constant and trend | Constant | Constant and trend |
| lnEF | – 5.455*** | – 6.072*** | – 4.885*** | – 4.837*** |
| lnGDP | – 2.720* | – 2.331 | – 4.532*** | – 4.805*** |
| lnEC | – 5.025*** | – 5.017*** | – 11.621*** | – 11.251*** |
| lnICT | – 1.889 | – 2.404 | – 3.086** | – 3.457** |
| lnIND | – 2.816* | – 2.520 | – 5.470*** | – 5.582*** |
| lnURB | – 4.061*** | – 4.036*** | – 5.474*** | – 5.420*** |

*, **, and *** signify significance levels at the 10%, 5%, and 1%, respectively. ADF indicate the augmented Dickey–Fuller test and PP symbolizes Phillips–Perron test

**Table 5** Lag length selection criteria

| Lag | LL | LR | df | p | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|---|---|
| 0 | 150.449 | – | – | – | 1.0E-14 | – 1.5E+01 | – 1.5E+01 | – 1.5E+01 |
| 1 | 261.898 | 222.9 | 36 | 0.000 | 4.4E-18 | – 2.3E+01 | – 2.3E+01 | – 2.1E+01 |
| 2 | 408.568 | 293.34* | 36 | 0.000 | 1.9e-22* | – 34.7966* | – 34.1404* | – 30.9194* |

*Demonstrates lag order selected by the criterion

**Table 6** ARDL bounds cointegration test

| Test statistics | Value | k | $H_0$ | $H_1$ | Decision |
|---|---|---|---|---|---|
| F-statistic | 11.401 | 5 | No level relationship | Level relationship exists | Long-run cointegration |
| t-statistic | – 5.635 | | | | |
| Significance level (%) | F-statistics | | t-statistics | | |
| | *I(0)* | *I(1)* | *I(0)* | *I(1)* | |
| 10 | 1.81 | 2.93 | – 1.62 | – 3.49 | |
| 5 | 2.14 | 3.34 | – 1.95 | – 3.83 | |
| 2.5 | 2.44 | 3.71 | – 2.24 | – 4.12 | |
| 1 | 2.82 | 4.21 | – 2.58 | – 4.44 | |

exceeds the upper bound critical value of 4.21 at the 1% significance level. This result leads to the rejection of the null hypothesis, which assumes no level relationship, in favor of the alternative hypothesis, confirming the existence of a long-run level relationship. Additionally, the t-statistic of -5.635 is well below the 1% critical value of -4.44, which further supports the presence of long-run cointegration. These test statistics indicate that the variables are cointegrated and share a stable long-term equilibrium connection.

### 4.4 ARDL model estimation

Table 7 presents the ARDL model estimation results. The error correction term (ECT) coefficient of − 0.993 indicates a rapid speed of adjustment, with approximately 99.3% of deviations from the long-run equilibrium being corrected within one period. In the long-run estimation, economic growth exerts a negative and statistically significant impact on ecological footprints. Inferentially, a 1% increase in Somalia's GDP is associated with a 0.385% reduction in ecological footprint, with significance at the 1% level. This outcome reflects the potential of long-term economic expansion to be aligned with improvements in environmental quality. The long-run energy consumption, conversely, has a detrimental impact on ecological footprints in Somalia. A 1% increase in energy consumption results in a 0.504% rise in the ecological footprint, with statistical significance at the 1% level. This indicates the direct contribution of higher energy usage to increased environmental degradation in Somalia, which reflects the harmful effects of energy consumption on ecological sustainability. Moving on to ICT, it shows a significant negative relationship with ecological footprints in Somalia. In the long-run, a 1% increase in ICT reduces ecological footprints by 0.021%, with statistical significance at the 5% level. This suggests that technological advancements, particularly in the ICT sector, may contribute to improved energy efficiency and reduced environmental impact over the long run. Industrialization and urbanization both exhibit positive and significant effects on the ecological footprint in Somalia. Interpretively, a 1% increase in industrialization leads to a 0.270% increase in ecological footprint, while a 1% increase in urbanization results in a 0.231% rise in ecological footprint. These coefficients indicate that both industrial expansion and urban growth are key contributors to increased environmental degradation in Somalia over the long-term.

The short-run coefficients capture the immediate effects of changes in economic growth, energy consumption, industrialization, and ICT on the ecological footprint in Somalia. A 1% change in economic growth is associated with a 0.177% reduction in the ecological footprint, though this result is not statistically significant. Similarly, a 1% change in energy consumption leads to an estimated 0.114% decrease in the ecological footprint, but this effect is also not statistically significant. The negative relationship between ICT and the ecological footprint is also evident in the short run, where a 1% change in ICT corresponds to a 0.011% reduction in the ecological footprint, though this result lacks statistical significance. In contrast, industrialization shows a significant positive short-run effect on the ecological footprint, with a 1% change in industrialization leading to a 0.149% increase in ecological footprint. Urbanization demonstrates a statistically significant impact on the ecological footprint in the short run. A 1% change in urbanization results in a 0.368% increase in the ecological footprint. However, the lagged effect of urbanization

**Table 7** Estimation of the ARDL model

| | ΔlnEF | Coefficient | Std. err. | t | P-value | [95% conf. interval] | |
|---|---|---|---|---|---|---|---|
| ECT | lnEFt-1 | − 0.993 | 0.176 | − 5.630 | 0.011 | − 1.554 | − 0.432 |
| Long-run | $\ln GDP_{t-1}$ | − 0.385 | 0.037 | − 10.320 | 0.002 | − 0.504 | − 0.266 |
| | $\ln EC_{t-1}$ | 0.504 | 0.039 | 12.940 | 0.001 | 0.380 | 0.628 |
| | $\ln ICT_{t-1}$ | − 0.021 | 0.005 | − 3.940 | 0.029 | − 0.038 | − 0.004 |
| | $\ln IND_{t-1}$ | 0.270 | 0.041 | 6.610 | 0.007 | 0.140 | 0.400 |
| | $\ln URB_{t-1}$ | 0.231 | 0.090 | 2.570 | 0.082 | − 0.055 | 0.517 |
| Short-run | $\Delta\ln EF_{t-1}$ | 0.398 | 0.081 | 4.900 | 0.016 | 0.139 | 0.656 |
| | $\Delta\ln GDP_{t}$ | − 0.177 | 0.113 | − 1.570 | 0.215 | − 0.535 | 0.182 |
| | $\Delta\ln GDP_{t-1}$ | 0.205 | 0.143 | 1.440 | 0.247 | − 0.250 | 0.660 |
| | $\Delta\ln EC_{t}$ | − 0.114 | 0.184 | − 0.620 | 0.580 | − 0.699 | 0.471 |
| | $\Delta\ln EC_{t-1}$ | − 0.204 | 0.116 | − 1.760 | 0.176 | − 0.572 | 0.164 |
| | $\Delta\ln ICT_{t}$ | − 0.011 | 0.008 | − 1.370 | 0.263 | − 0.037 | 0.015 |
| | $\Delta\ln IND_{t}$ | 0.149 | 0.060 | 2.470 | 0.090 | − 0.043 | 0.340 |
| | $\Delta\ln IND_{t-1}$ | − 0.137 | 0.069 | − 1.970 | 0.144 | − 0.358 | 0.084 |
| | $\Delta\ln URB_{t}$ | 0.368 | 0.058 | 6.380 | 0.008 | 0.185 | 0.552 |
| | $\Delta\ln URB_{t-1}$ | − 0.278 | 0.081 | − 3.420 | 0.042 | − 0.536 | − 0.019 |
| ARDL(2,2,2,1,2,2) | $R^2$ | 0.993 | Adj. $R^2$ | 0.959 | | | |

**Table 8** Diagnostic statistical tests

| Test | Chi-square statistic | P-value | Decision |
|---|---|---|---|
| Breusch Godfrey LM test | 9.445 | 0.059 | No serial correlation |
| Heteroskedasticity | 19.000 | 0.392 | No heteroskedasticity |
| Cameron-Trivedi test of skewness | 16.990 | 0.387 | No skewness |
| Cameron-Trivedi test of kurtosis | 1.420 | 0.234 | No kurtosis |

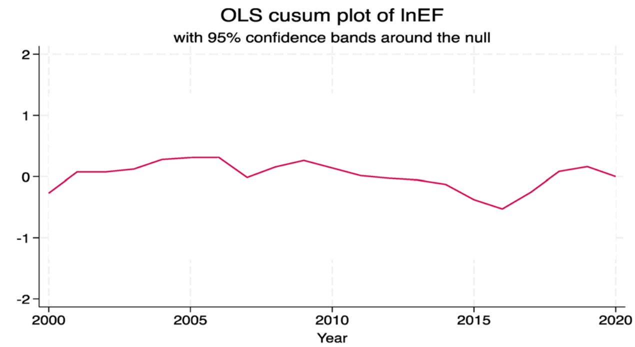


**Fig. 1** The cumulative sum (CUSUM) of OLS residuals for evaluating parameter stability

is negative and significant, with a 1% change in urbanization resulting in a 0.278% reduction in ecological footprint, which suggests that previous periods of urbanization contribute positively to energy efficiency over time.

### 4.5 Diagnostic checking

Table 8 outlines the results of the diagnostic statistical tests performed to evaluate different aspects of the ARDL model's validity. The Breusch-Godfrey LM test reveals no significant evidence of serial correlation in the residuals, indicating that the residuals do not exhibit a systematic correlation pattern. This outcome supports the model's ability to accurately capture the relationships among the variables. Additionally, White's test for heteroskedasticity confirms the absence of heteroskedasticity in the residuals, suggesting that the residuals maintain constant variance, which further reinforces the model's robustness. The results from the Cameron-Trivedi tests for skewness and kurtosis indicate no significant skewness or kurtosis in the residuals, confirming that they follow a normal distribution and do not deviate from normality. Furthermore, the CUSUM plot of OLS residuals, as displayed in Fig. 1, shows that the model's parameters remained stable throughout the sample period. The plot remains comfortably within the 95% confidence interval, which demonstrates no evidence of structural breaks or instability. This consistency indicates the model's reliability in representing the relationships between the variables over time.

### 4.6 Dynamic ARDL simulations model results

Table 9 presents the dynamic ARDL simulation results, which highlights the relationships between ecological footprints and various factors in both the short- and long-run. For economic growth, both the long-run and short-run effects show a reduction in ecological footprints, but these results are statistically insignificant. However, in the long-run, energy consumption reveals a positive relationship with ecological footprints, which is statistically meaningful. This suggests that sustained increases in energy consumption tend to exert upward pressure on ecological footprints over time. Moreover, ICT consistently shows a negative impact on ecological footprints. While the short-run effect is statistically insignificant, the long-run effect is significant, suggesting that advancements in ICT help reduce environmental impact over time. Contrastingly, industrialization exerts a positive influence on ecological footprints. In the short-run, the effect of industrialization on ecological footprints is not significant. In the long run, however, the relationship is significant, which indicates that industrial growth may contribute to increased environmental pressure over time. In the short run, urbanization shows a marginally significant positive effect on ecological footprints, which suggests that immediate changes in urbanization may lead to increased environmental pressure. In the long run, however, the effect of urbanization is positive but statistically insignificant.

**Table 9** Dynamic simulated ARDL model results

| Variable | Coefficient | Std. error | t-statistics | P-value | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| $lnEF_{t-1}$ | 0.223 | 0.227 | 0.980 | 0.355 | − 0.301 | 0.748 |
| ΔlnGDP | − 0.171 | 0.187 | − 0.910 | 0.388 | − 0.604 | 0.261 |
| $lnGDP_{t-1}$ | − 0.239 | 0.185 | − 1.290 | 0.232 | − 0.664 | 0.187 |
| ΔlnEC | − 0.118 | 0.284 | − 0.410 | 0.689 | − 0.772 | 0.537 |
| ΔlnICT | − 0.033 | 0.024 | − 1.400 | 0.200 | − 0.089 | 0.022 |
| ΔlnIND | 0.122 | 0.081 | 1.510 | 0.170 | − 0.064 | 0.308 |
| ΔlnURB | 0.297 | 0.155 | 1.910 | 0.092 | − 0.061 | 0.656 |
| $lnEC_{t-1}$ | 0.438 | 0.229 | 1.910 | 0.093 | − 0.091 | 0.967 |
| $lnICT_{t-1}$ | − 0.028 | 0.012 | − 2.330 | 0.048 | − 0.056 | 0.000 |
| $lnIND_{t-1}$ | 0.208 | 0.092 | 2.270 | 0.053 | − 0.003 | 0.420 |
| $lnURB_{t-1}$ | 0.114 | 0.162 | 0.710 | 0.500 | − 0.259 | 0.487 |
| Constant | − 1.340 | 3.845 | − 0.350 | 0.736 | − 10.207 | 7.527 |

The dynamic ARDL model is highly valuable for forecasting and simulating the effects of hypothetical changes in the regressors. This is crucial for assessing how shocks influence ecological footprints. In this analysis, each figure represents a 10% increase or decrease in a regressor, with other factors held constant. The expected values are depicted by dark blue dots, while the shaded areas (from dark to light blue) represent confidence intervals at 75%, 90%, and 95%. The initial trend line captures short-term effects, and the horizontal line illustrates long-term outcomes. Figure 2 shows that a 10% shift in economic growth significantly impacts ecological footprints. In the short-term, a decrease in GDP causes the ecological footprint to rise, with the predicted values consistently above the baseline, although the confidence intervals widen in the long-term. Over time, an increase in GDP leads to a significant reduction in ecological footprints. The predicted values fall below the baseline, which indicates a statistically significant effect over time. This suggests that economic growth contributes to reducing ecological degradation, likely due to improved technology and environmental policies. Figure 3 demonstrates that a 10% reduction in energy consumption results in a significant reduction in ecological footprints in the short-term, with tighter confidence intervals indicating robustness. However, increasing energy consumption leads to a significant rise in the ecological footprint as the predicted values move above the baseline, and

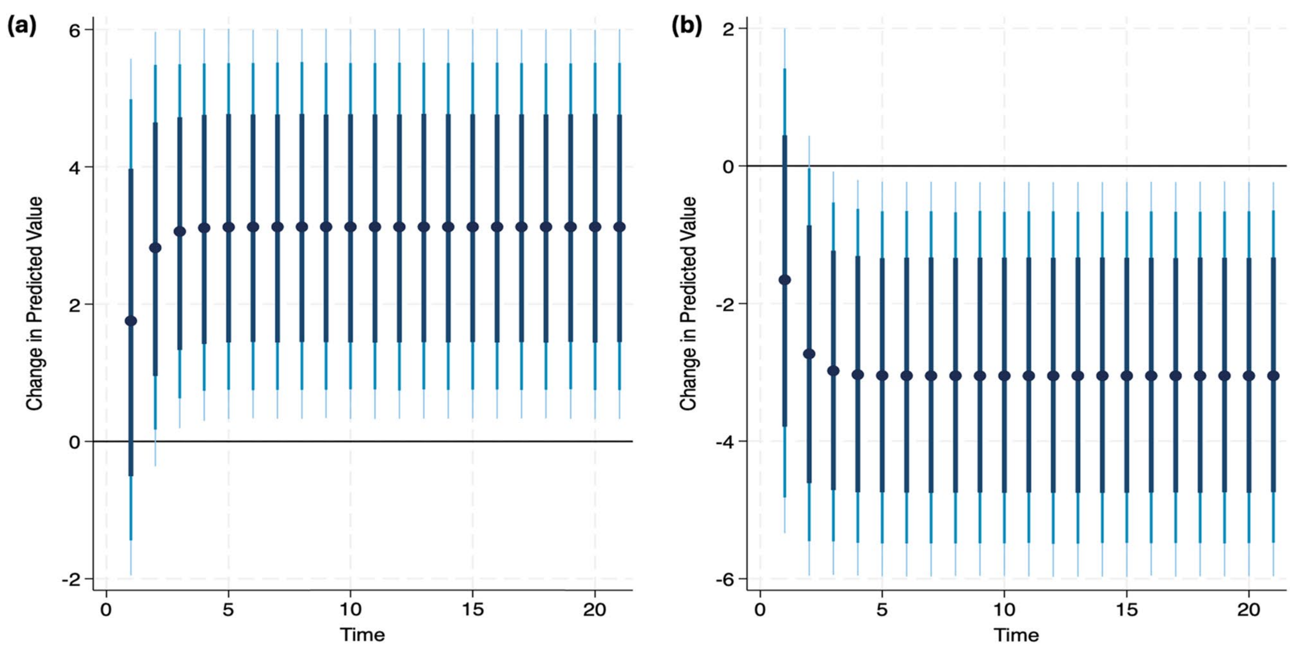


**Fig. 2** An impulse response plot captures the effect of GDP changes on ecological footprints. **a** depicts the impact of a 10% decrease in GDP, while **b** shows the effect of a 10% increase. The dots represent the average predicted values, and the shaded regions, transitioning from dark to light blue, correspond to the 75%, 90%, and 95% confidence intervals, respectively

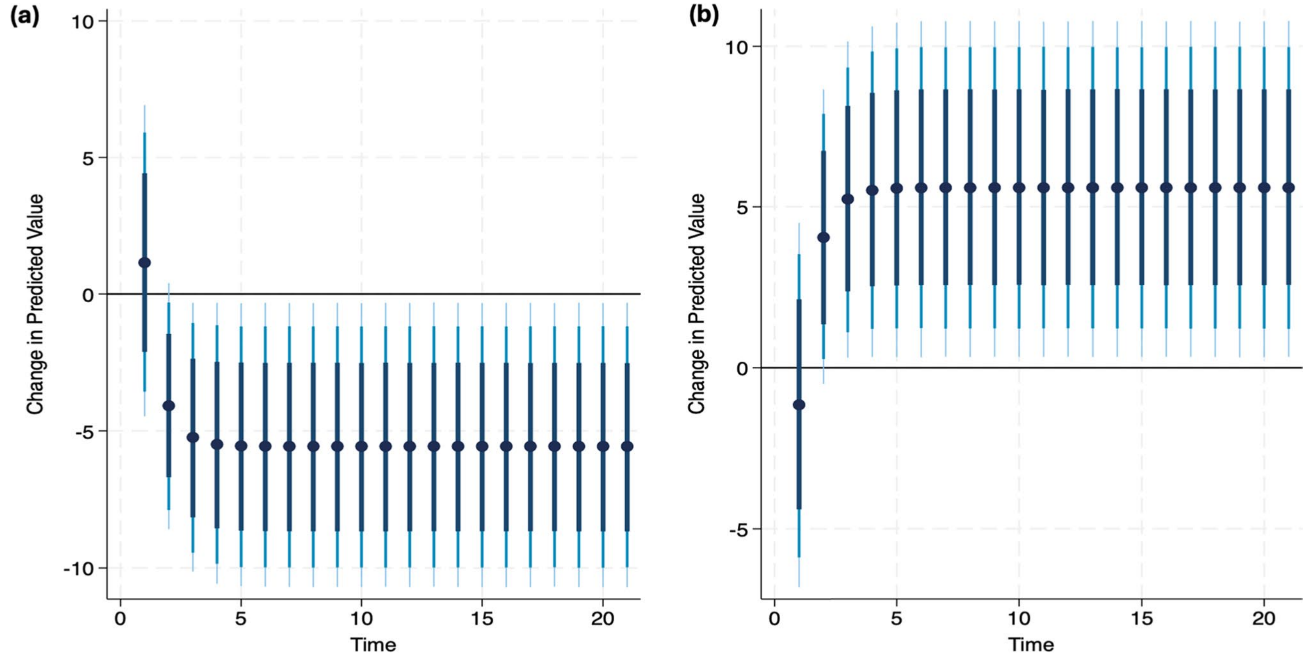


**Fig. 3** An impulse response plot captures the effect of energy consumption changes on ecological footprints. **a** depicts the impact of a 10% decrease in energy consumption, while **b** shows the effect of a 10% increase

the confidence intervals show a clear and sustained deviation. This reinforces the environmental costs associated with increased energy use.

Figure 4 depicts that a 10% shift in ICT has a significant impact on ecological footprints in the short-term. A 10% decline in ICT usage leads to an increase in the ecological footprint, though the confidence intervals suggest variability. In contrast, increasing ICT usage has a significant negative impact on ecological footprints, as the predicted values fall

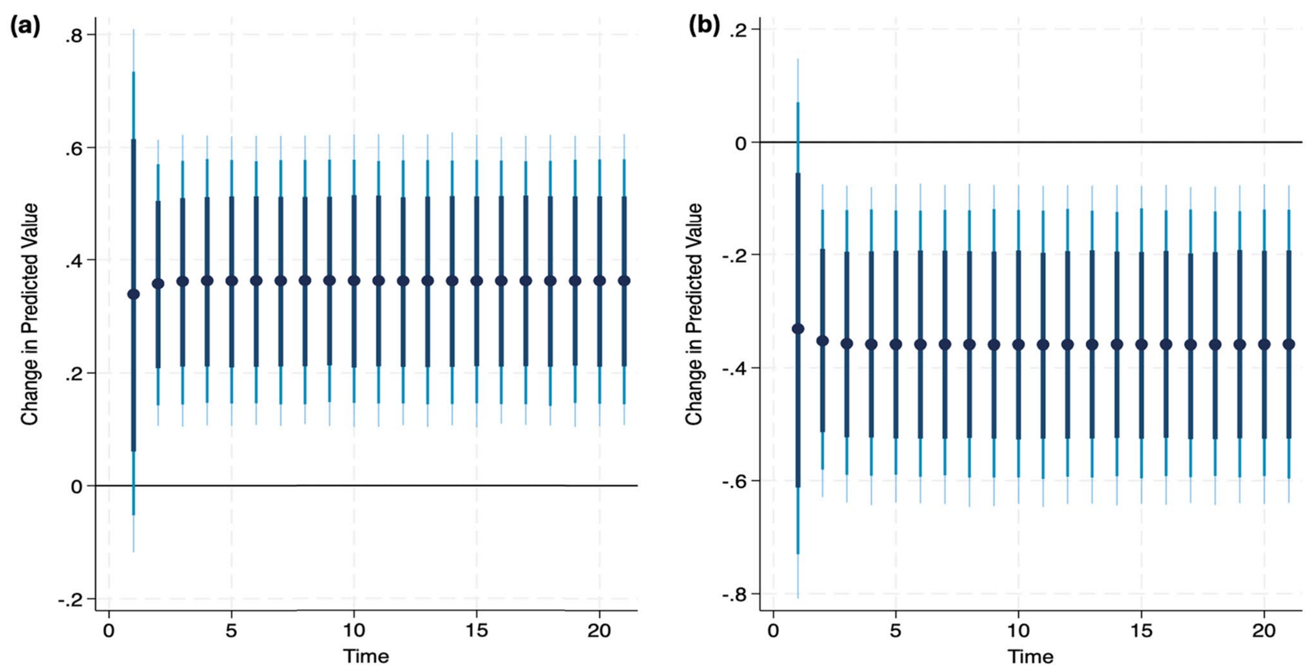


**Fig. 4** An impulse response plot captures the effect of ICT changes on ecological footprints. **a** depicts the impact of a 10% decrease in ICT, while **b** shows the effect of a 10% increase

below the baseline. This suggests that advancements in ICT help reduce ecological degradation by enhancing efficiency and resource management. In addition, Fig. 5 reveals that a 10% shock in industrialization has a significant impact on ecological footprints in the short term. A 10% decrease in industrialization leads to a reduction in the ecological footprint, though the effect is smaller compared to the increase. A 10% increase in industrialization results in a significant rise in the ecological footprint, as shown by the predicted values consistently above the baseline. This consistent upward trend indicates that as industrial activities expand, the environmental impact grows significantly, likely due to increased resource consumption, emissions, and waste generation. Furthermore, Fig. 6 indicates that a 10% oscillation in urbanization has a significant impact on ecological footprints in the short-term. It shows that decreasing urbanization reduces the ecological footprint, while increasing urbanization leads to a significant rise in ecological footprints, with the predicted values rising above the baseline and confidence intervals remaining consistent. This demonstrates that urbanization contributes significantly to environmental strain, particularly as urban areas expand.

## 4.7 Kernel-based regularized least squares

Table 10 presents the pointwise derivatives obtained using the KRLS method. Each variable's average pointwise derivative is accompanied by its standard error, t-statistic, and p-value to assess the significance of the relationships. For economic growth, the average pointwise derivative is -0.046, indicating a statistically significant negative relationship. This result suggests that increases in economic growth reduce ecological footprints, although this effect diminishes at higher percentiles where economic growth eventually exerts a positive influence on ecological footprints. However, energy consumption exhibits a significant positive effect on ecological footprints, with an average pointwise derivative of 0.108. This indicates that as energy consumption increases, so do ecological footprints, and the effect becomes stronger at higher percentiles. The marginal effects of ICT reveal a statistically significant negative impact on ecological footprints, with an average derivative of – 0.008. This suggests that improvements in ICT lead to reductions in ecological footprints, with the effect being most pronounced at lower percentiles. For industrialization, the average pointwise derivative is – 0.020, also indicating a significant negative relationship. However, the marginal effect of industrialization decreases at higher percentiles, where industrial expansion is associated with an increase in ecological footprints. Urbanization, on the other hand, shows an insignificant effect on ecological footprints, with an average derivative of – 0.013. The diagnostics in Table 10 highlight strong model performance. The regularization parameter (lambda) is 0.057, while the bandwidth (sigma) is 5, which ensures a balance between fit and complexity. The model demonstrates excellent goodness of fit with an R-squared of 0.986, explaining 98.6% of

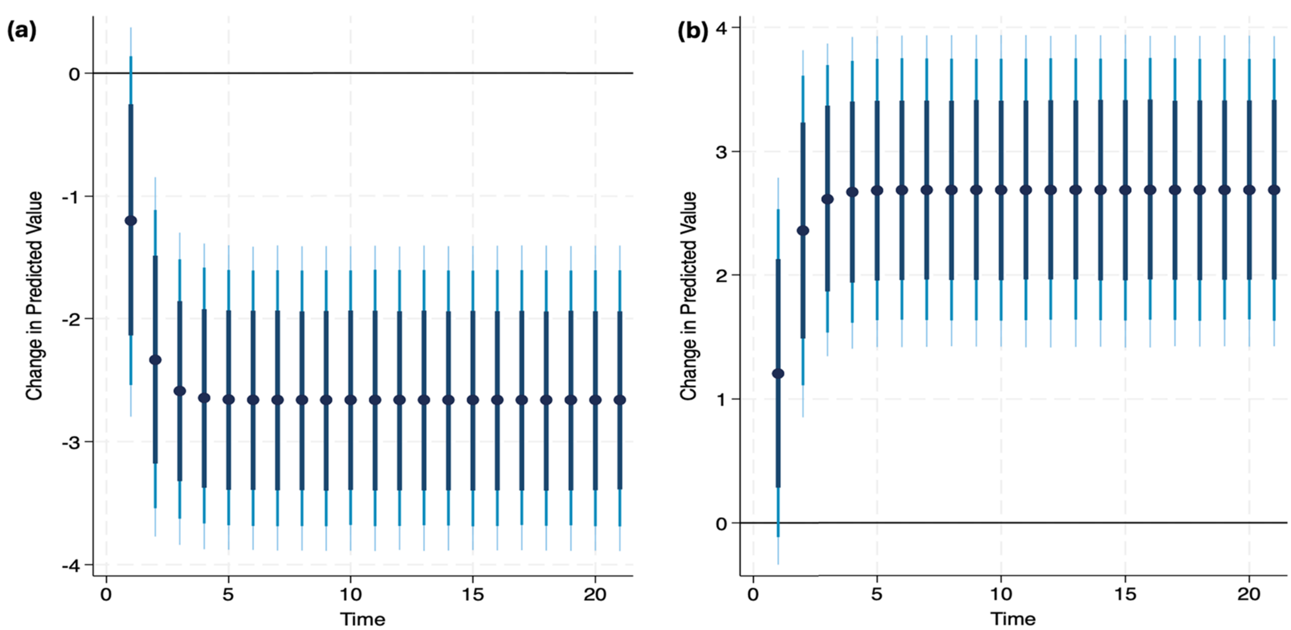


**Fig. 5** An impulse response plot captures the effect of industrialization changes on ecological footprints. **a** depicts the impact of a 10% decrease in industrialization, while **b** shows the effect of a 10% increase

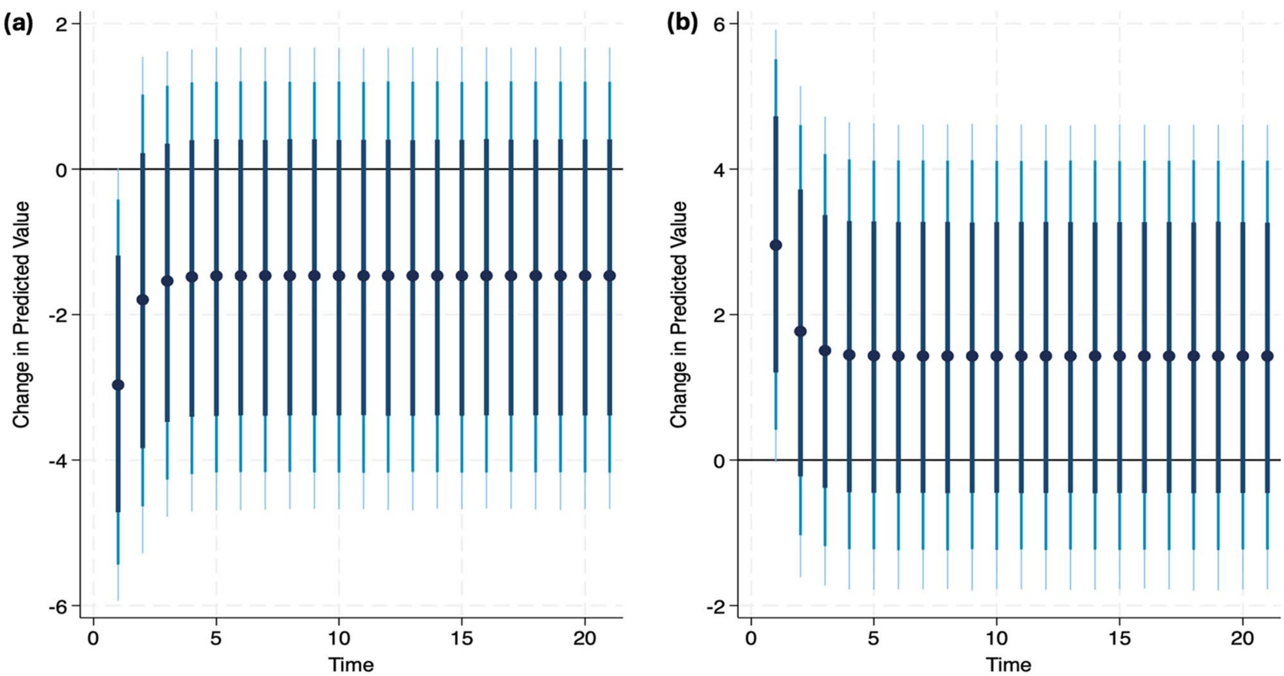


**Fig. 6** An impulse response plot captures the effect of urbanization changes on ecological footprints. **a** depicts the impact of a 10% decrease in urbanization, while **b** shows the effect of a 10% increase

**Table 10** Pointwise marginal effects estimated via KRLS

| Variable | Average | Standard error | t-statistic | P-value | P25 | P50 | P75 |
|---|---|---|---|---|---|---|---|
| lnGDP | − 0.046 | 0.010 | − 4.501 | 0.000 | − 0.105 | − 0.048 | 0.025 |
| lnEC | 0.108 | 0.038 | 2.883 | 0.011 | 0.079 | 0.107 | 0.159 |
| lnICT | − 0.008 | 0.003 | − 2.404 | 0.029 | − 0.016 | − 0.009 | 0.000 |
| lnIND | − 0.020 | 0.008 | − 2.377 | 0.030 | − 0.064 | − 0.029 | 0.030 |
| lnURB | − 0.013 | 0.039 | − 0.332 | 0.744 | − 0.101 | − 0.078 | 0.087 |
| *Diagnostics* | | | | | | | |
| Lambda | 0.057 | Sigma | 5 | $R^2$ | 0.9862 | Observations | 31 |
| Tolerance | 0.021 | Eff. df | 8.914 | Looloss | 0.09932 | | |

the variability in ecological footprints. The leave-one-out loss (Looloss) of 0.099 further confirms the model's robust predictive performance.

An alternative way to evaluate the variability of the effects is by presenting a histogram of the pointwise marginal effects, as illustrated in Fig. 7. The histogram highlights the presence of substantial heterogeneity in the effects of GDP, energy consumption, ICT, industrialization, and urbanization on ecological footprints. This demonstrates that average marginal effects provide only partial insight into the varying impacts of these factors, which indicates that their influences on the ecological footprint differ significantly across different situations. Each histogram reflects the unique contributions of these factors, which illustrates that their environmental impacts are not consistent. As depicted in Fig. 8, an analysis exploring the reasons and patterns behind the variation in the marginal effects of GDP, energy consumption, ICT, industrialization, and urbanization was conducted by plotting the marginal effects against the levels of these variables. The results demonstrate how the marginal effects estimate from the Lowess smoother accurately trace the derivative of the nonlinear relationship between these factors and ecological footprints. The figure shows that marginal effects are generally negative at higher levels of GDP, ICT, industrialization,

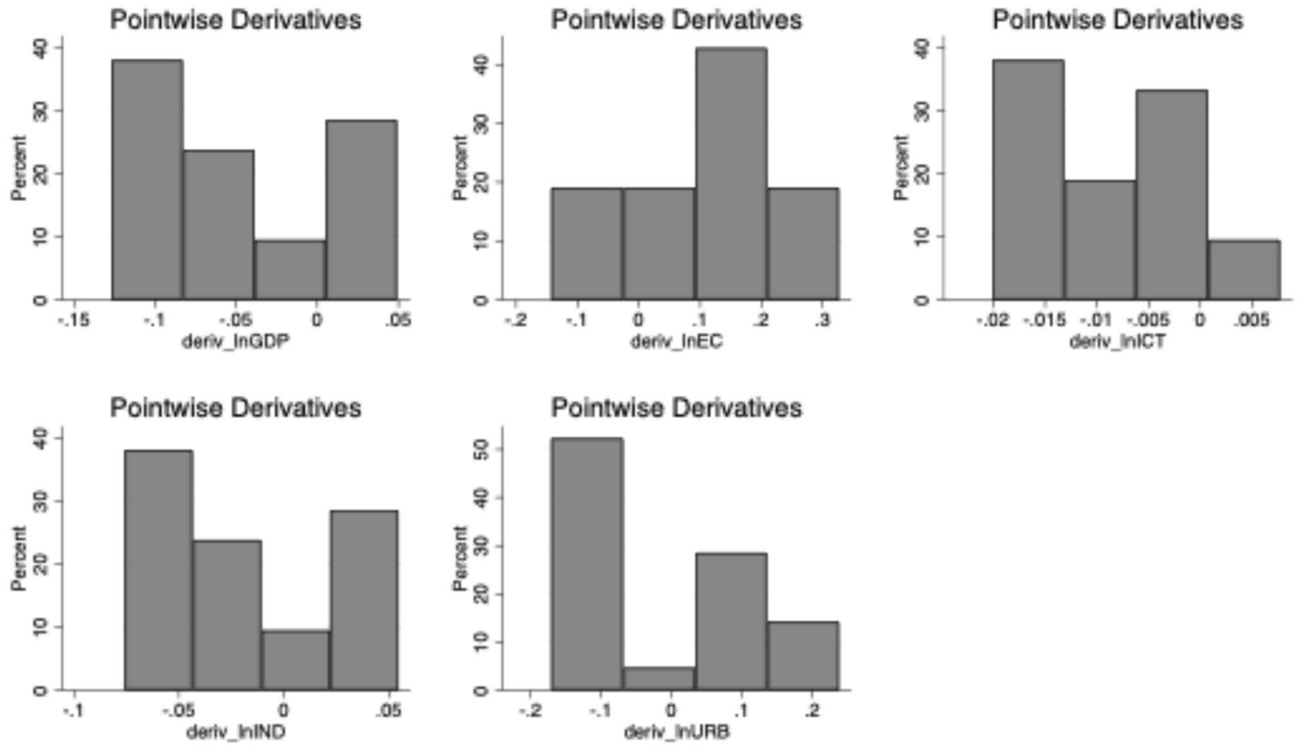


**Fig. 7** Distribution of pointwise marginal effects of GDP, energy consumption, ICT, industrialization, and urbanization on ecological footprints

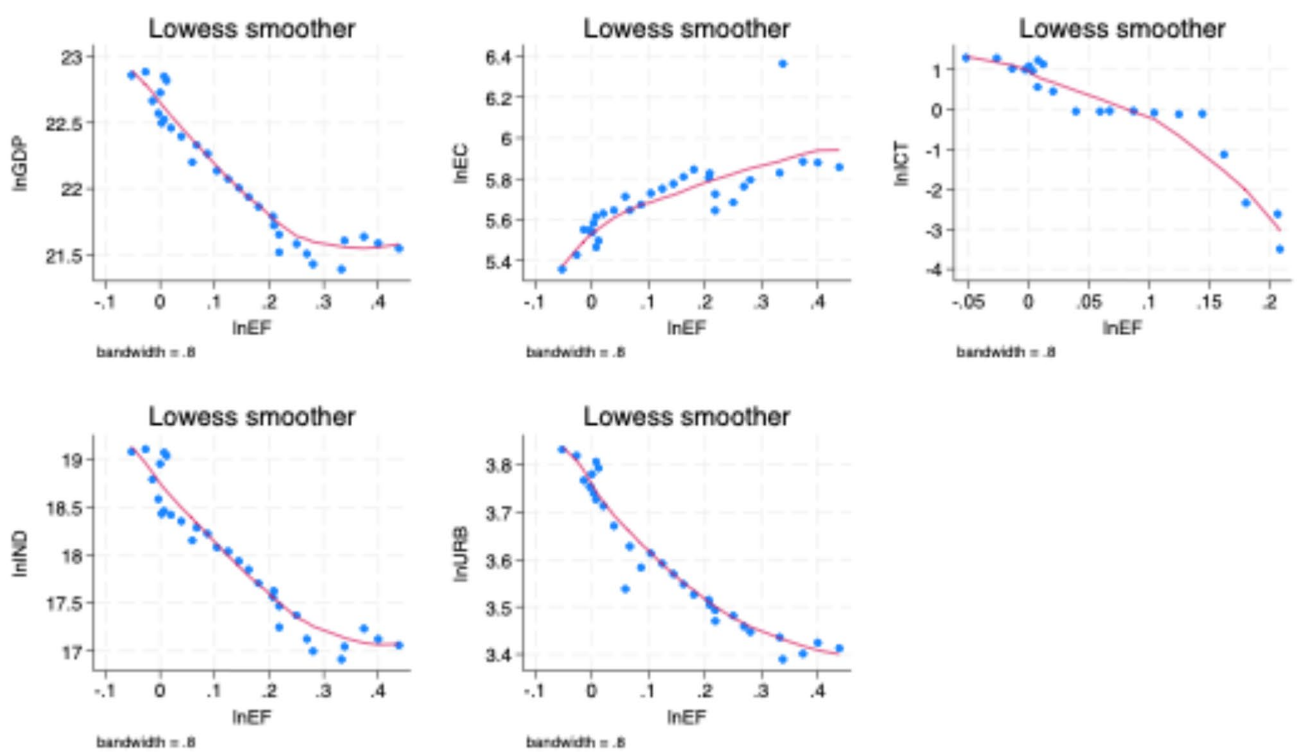


**Fig. 8** Representation of Pointwise marginal effects of GDP, energy consumption, ICT, industrialization, and urbanization on ecological footprints

and urbanization, which indicates reductions in ecological footprints, while positive effects are observed at higher levels of energy consumption. These findings demonstrate the nonlinear dynamics between each factor and its impact on the environment.

### 4.8 Discussion of the results

The negative relationship between economic growth and ecological footprints in Somalia, as found in our study, indicates that as GDP increases, the environmental impact decreases. This supports the Environmental Kuznets Curve (EKC) hypothesis, which posits that after a certain level of income is reached, further economic growth leads to environmental improvements. This aligns with studies in the EU-28 [31] and China [32], which found similar relationships. In contrast, the persistent positive relationship between GDP growth and environmental degradation found in Myanmar [33], Somalia [68], and G7 nations [40] reveals regional differences. Somalia, like other low-income countries, may benefit from adopting technologies and practices that limit environmental damage as the economy grows. According to Mohamed and Abdi [76], Somalia's economy has been steadily recovering despite challenges, with growth driven largely by agriculture, construction, and trade. This growing economic activity, when managed sustainably, could help mitigate the country's ecological footprint, which is particularly important given Somalia's vulnerability to climate change and environmental degradation [77].

The study's outcomes that energy consumption increases ecological footprints in Somalia align with extensive research linking non-renewable energy sources to environmental degradation [20, 41]. In Somalia, energy use heavily relies on biomass, charcoal, and imported fossil fuels, which contribute significantly to deforestation and $CO_2$ emissions. This dependence on non-renewable energy has far-reaching environmental consequences, which exacerbates the country's ecological footprint. The International Energy Agency (IEA, [78]) reported that Somalia has one of the lowest electrification rates in the world, with the majority of the population lacking access to modern energy services, thereby heavily relying on traditional, environmentally harmful energy sources. As Somalia's energy demand increases with population growth and urbanization [61], managing this demand in an environmentally sustainable way is essential to avoid further environmental degradation.

Contrastingly, the negative impact of ICT on ecological footprints in Somalia suggests that increased ICT adoption contributes to reducing environmental degradation. This finding is in line with Bhujabal et al. [5] and Añón Higón et al. [12], which support the role of ICT in improving resource efficiency and reducing pollution. Somalia has made significant strides in ICT infrastructure development, particularly in the telecommunications sector, which has grown rapidly despite the country's complex political environment. ICT plays an important role in improving productivity in sectors such as agriculture, financial services, and trade. The expansion of mobile banking and internet access has also created opportunities for green initiatives, such as using technology to monitor natural resources and optimize energy use. However, despite these advancements, the ICT sector remains underdeveloped compared to regional peers, and the lack of infrastructure continues to pose challenges for fully leveraging ICT's potential to reduce the country's ecological footprint.

The positive association between industrialization and ecological footprints found in Somalia reflects the broader trend seen in other developing regions, where industrial growth leads to increased environmental degradation. Studies such as Sumaira and Siddique [54] and Mentel et al. [53] emphasize the environmental costs associated with industrial expansion in South Asia and SSA. Somalia's industrial sector, though still in its nascent stages, has been growing, particularly in the areas of manufacturing, construction, and agro-processing. As the country rebuilds its economy, industrial activities are expected to expand, placing additional pressure on natural resources. Industrialization is crucial for Somalia's long-term economic development, but the lack of environmental regulations and oversight poses a significant challenge to managing its environmental impact [25]. Given the weak regulatory framework, industrial expansion in Somalia risks accelerating environmental degradation, particularly through inefficient energy use and increased pollution from industries such as construction and manufacturing.

The direct linkage between urbanization and ecological footprints observed in Somalia mirrors global trends where rapid urbanization increases environmental degradation, as seen in studies from SSA [17] and Singapore [56].

Somalia's urban population has been growing rapidly, particularly in cities such as Mogadishu, Hargeisa, and Kismayo, driven by migration from rural areas, internal displacement, and population growth [79]. Urban areas in Somalia are expanding without sufficient infrastructure, leading to increased pollution, inefficient waste management, and higher energy consumption. Informal settlements and poorly planned urban areas in Somalia are particularly vulnerable to environmental risks such as flooding, deforestation, and air pollution. As the country continues to urbanize, the environmental impact of unregulated urban growth could significantly exacerbate Somalia's ecological footprint. The lack of urban planning, combined with the pressures of rapid population growth, presents a formidable challenge for managing the environmental consequences of urbanization in Somalia.

## 5 Summary and practical guidance

Amid escalating environmental degradation, identifying sustainable development pathways has become a global priority. As nations balance economic growth with environmental preservation, the interplay between industrial activity, energy consumption, and technology emerges as a crucial determinant of sustainability. This study provides essential insights into the short- and long-run effects of these key variables on Somalia's ecological footprint, advancing the understanding of environmental sustainability in the region. Utilizing dynamic ARDL and KRLS approaches, the study uncovers several significant findings. In the long-run, economic growth negatively and significantly impacts ecological footprints, whereas energy consumption exerts a significant and harmful effect. Notably, ICT adoption consistently demonstrates a negative relationship with ecological footprints in both the short- and long-run. Conversely, industrialization and urbanization exhibit significant positive effects on ecological footprints in both time horizons. Furthermore, histograms of pointwise marginal effects reveal substantial heterogeneity in the impacts of GDP, energy consumption, ICT, industrialization, and urbanization on ecological footprints. These effects also exhibit nonlinear relationships, as indicated by pointwise marginal effects.

Given the study's findings, policy measures should focus on mitigating the environmental impact of energy consumption, industrialization, and urbanization while leveraging ICT and economic growth for sustainability. Since energy consumption significantly increases ecological footprints, Somalia should prioritize transitioning to renewable energy by incentivizing solar and wind investments, enforcing energy efficiency standards, and reducing reliance on biomass and fossil fuels, which would help curb long-term environmental degradation. Industrialization's adverse effects necessitate policies promoting cleaner production technologies, circular economy principles, and stricter emission regulations to minimize environmental harm, ensuring that economic expansion does not come at the expense of ecological sustainability. Similarly, urbanization's long-term ecological strain highlights the demand for sustainable urban planning, including green infrastructure, efficient waste management, and compact city designs that limit carbon footprints while supporting economic growth. ICT's demonstrated role in reducing ecological degradation signifies the importance of expanding digital infrastructure, integrating smart grid technologies, and enhancing environmental monitoring through digital tools, allowing for more efficient resource management. While economic growth reduces Somalia's ecological footprint in the long-run, sustaining this trend requires embedding sustainability into economic planning by promoting green investments, eco-friendly business practices, and sustainable agriculture to ensure that Somalia's development is resilient and ecologically sustainable.

This study has several limitations that future research should address to enhance the understanding of environmental sustainability in Somalia. First, the study primarily employs macro-level data, which may overlook sectoral variations in how industrialization, urbanization, and ICT adoption influence ecological footprints, warranting future research with disaggregated data for more precise policy recommendations. Second, while the study captures short- and long-run effects, it does not account for structural breaks or external shocks, such as conflicts or climate-related disasters, which could significantly alter the relationships among the variables. Third, the research relies on time-series analysis, which, while effective for examining long-term trends, may not fully capture the evolving dynamics of environmental sustainability in real-time, suggesting the need for high-frequency data and real-time monitoring techniques. Additionally, this study does not explore the interactive effects between explanatory variables, such as how ICT adoption may moderate the impact of energy consumption or industrialization on ecological footprints, an area that future research could investigate. Lastly, given that policy implementation varies in effectiveness across governance structures, future studies should consider the role of institutional quality and environmental regulations in shaping sustainability policies' effectiveness, which proposes a more integrated perspective on ecological footprint management in Somalia.

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**Data availability** The datasets used and/or analyzed during the current study are available from the author on reasonable request.

## Declarations

**Ethical approval and consent to participate** This study follows all ethical practices during writing. We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

**Consent for publication** Not applicable.

**Competing interests** The authors declare no competing interests.



## Appendix

See Table 11

**Table 11** Principal component analysis

| Panel A: Principal components/correlation matrix | | | | |
|---|---|---|---|---|
| Component | Eigenvalue | Difference | Proportion | Cumulative |
| 1 | 1.832 | 0.696 | 0.611 | 0.611 |
| 2 | 1.136 | 1.104 | 0.379 | 0.989 |
| 3 | 0.032 | | 0.0107 | 1 |
| Panel B: Principal components (eigenvectors) | | | | |
| Variable | Component 1 | Component 2 | Component 3 | Unexplained |
| lnMOB | 0.690 | − 0.318 | 0.651 | 0 |
| lnTEL | 0.090 | 0.929 | 0.358 | 0 |
| lnINT | 0.718 | 0.189 | − 0.670 | 0 |

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