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Green Agriculture and Human Development for Achieving Environmental Sustainability in Sub-Saharan Africa

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Abstract

The promotion of sustainable agricultural practices is crucial for achieving environmental sustainability. Moreover, there is limited documentation on how green agriculture moderates the impact of the pursuit of human development on environmental sustainability. Consequently, this study aims to examine the impact of green agriculture and human development on the ecological footprint across 31 African countries from 1996 to 2022. To this end, we employ dynamic panel regression techniques from Kripfganz & Schwarz (2019), instrumental variable regression, and quantile regression to account for heteroscedasticity, endogeneity, and conditional heterogeneity. The findings reveal that green agriculture increases the ecological footprint, as does human development. However, this increase occurs at a decreasing rate for green agriculture and at an increasing rate for the pursuit of human development. Furthermore, the attenuated magnitude of the interaction coefficient suggests that the practice of green agriculture mitigates the adverse impact of human development efforts on environmental sustainability. Additionally, Dumitrescu-Hurlin panel causality results confirm a bidirectional causal relationship between green agriculture and the ecological footprint. The proactive effect between human development and the ecological footprint is also validated. To enhance environmental sustainability, policymakers should promote and mainstream green agricultural practices through awareness campaigns.

Keywords

Green Agriculture, Human Development, Ecological Footprint, Sub-Saharan Africa

1. Introduction

Over the past two decades, environmental sustainability has gained increasing prominence. According to Cammaer (2016), fossil fuel consumption is a key driver of environmental degradation, particularly climate change, global warming, air pollution, and acid rain (Guo & Wang, 2023; Wilkes & Zhang, 2016; Boix-Fayos & De Vente, 2023). Furthermore, fossil fuels contribute to major health concerns by increasing greenhouse gas emissions in the atmosphere. Green agriculture, designed to minimise environmental impact while ensuring productivity and food security, is based on agroecological principles aimed at enhancing the resilience of agricultural ecosystems (OECD, 2013). Key practices of green agriculture include the use of biological inputs, the preservation of biodiversity, and the sustainable management of soils, as demonstrated by Khedulkar et al. (2024), who highlighted that these practices can improve soil fertility while reducing the use of chemical inputs. Renewable energies, particularly biomass and solar energy, play a crucial role in this model, as indicated by Kindo et al. (2024), who emphasise their capacity to reduce dependence on fossil fuels and lower greenhouse gas emissions. However, poorly managed practices, such as excessive biomass use or inappropriate methods, can paradoxically lead to negative effects, including deforestation (Mergoni et al., 2024). Although both green agriculture and renewable energies share a goal of sustainability, Norström et al. (2014) distinguish their roles, with the former focusing on the sustainability of agricultural practices and the latter on the production of clean energy. A systemic approach combining these two sectors is essential to mitigate environmental risks and ensure a sustainable transition (Norström et al., 2014).

Consequently, the United Nations Climate Change Conference (COP26) in Glasgow underscored the imperative need to adopt appropriate environmental policies that promote large-scale reliance on renewable energy sources, such as biomass, solar, hydropower, wind, and geothermal energy. These measures aim to reduce dependence on fossil fuels while mitigating environmental degradation and advancing the achievement of sustainable development goals (Akhil et al., 2024; Khedulkar et al., 2024). Wang et al. (2023) emphasised that both production processes and human development must be factored into the design of climate and development policies. By replacing fossil fuels in green energy production, renewable energy sources can significantly curtail environmental degradation and mitigate climate change (Mergoni et al., 2024; Samoraj et al., 2024).

The 2019 Global Status Report (REN21) indicates, for instance, that biomass accounts for more than 6% of global energy supply and 55% of renewable energy production (excluding traditional biomass use) (Moreno Vargas et al., 2023). Beyond serving as an alternative to fossil fuels, green energy offers several advantages. First, green energy can be utilised in electricity generation, residential heating, cooking, industry, and transport sectors (Christine, 2024). Second, green energy production is relatively straightforward, with abundant raw materials available. Third, green energy can contribute to soil regeneration, enhancing water quality, biodiversity, and soil fertility (Cammaer, 2016). Fourth, it is a carbon-neutral energy source (Schoonjans, 2024). Finally, green energy production can stimulate local economies by creating jobs in its value chain (Wilkes & Zhang, 2016). However, green production and consumption can sometimes have adverse effects on both the environment and human health, including deforestation, resource depletion, biodiversity loss, and food insecurity. Nonetheless, the literature on the relationship between green production and environmental quality remains inconclusive. Some studies suggest that green production can have negative environmental impacts (Boix-Fayos & De Vente, 2023), whereas others argue that it enhances environmental quality (Akhil et al., 2024; Khedulkar et al., 2024).

Human development and its contribution to environmental sustainability have become an active area of research. Human development reflects progress and societal well-being, considering factors such as education, income, health, and living standards (Islam, 2024; Cotula, 2016). A higher level of human development correlates with better health, education, and income. Studies by Janmaimool et al. (2024) indicate that increased education levels enhance productivity, responsibility, and innovation. According to Veronoka & Martin, human development influences the formulation of health and education policies and guides the implementation of environmental policies. Rather than focusing solely on economic growth, human development expands individual freedoms and opportunities, including access to education, healthcare, and environmental protection (Norström et al., 2014). Zimek & Baumgartner (2024) assert that improvements in human well-being lead to an increased social demand for environmental quality. Additionally, Popescu (2019) argues that higher human development levels raise public awareness of the need to combat environmental degradation. For instance, Ugochukwu (2019) finds that human development positively contributes to environmental protection, whereas Akhil et al. (2024) contend that human development does not necessarily foster environmental sustainability.

The above discussion highlights that the debate on the effects of green agriculture on the ecological footprint remains unresolved. Furthermore, it is still unclear how and to what extent human development benefits or harms the environment. The inconclusive findings of previous studies raise the question of whether green agriculture could moderate the effects of human development on environmental quality. Prior research on the human development–environment nexus suggests that higher education levels can lead to greater environmental awareness, reduced resource consumption, lower waste generation, and decreased carbon emissions, thereby reducing the ecological footprint (Kindo et al., 2024; Shumaila & Mi, 2024). However, empirical studies on the moderating role of green agricultural practices in mitigating the environmental impact of human development remain scarce. This study, therefore, examines the effects of green agriculture and human development on the ecological footprint of African countries. Additionally, it incorporates an interaction term in the model to investigate the interactive effect of green agriculture and human development on the ecological footprint.

This study holds particular significance for African countries for several reasons. Firstly, the African region is deeply concerned about the adverse effects of climate change on its geography and the vulnerability of its biodiversity. Secondly, compared to other regions of the world, Africa possesses substantial potential for green energy due to the availability of solar, wind, hydro, land, harvested residues, and bioenergy crops (Arzo & Hong, 2024). However, the continent remains heavily reliant on polluting energy sources, exacerbating environmental degradation and climate change. For instance, the African Energy Commission (Bhatt et al., 2024) reports that biomass is the primary source of energy or traditional input in Africa, accounting for approximately 430 million tonnes of oil equivalent (Mtoe) in 2017, nearly half (48%) of the total available energy supply (TAES). On the other hand, this strong dependence on traditional bioenergy continues to hinder progress towards sustainable development, particularly in achieving the Sustainable Development Goals (SDGs). Thirdly, despite the significant improvements in human development recorded across African countries over the past three decades, the region still faces numerous challenges, including poverty and limited access to education, healthcare, and basic infrastructure. Achieving sustainable development that balances economic growth, social progress, and environmental protection remains a key priority for African nations (Ugochukwu, 2019). Consequently, examining the relationship between green agriculture, human development, and environmental sustainability can provide insights into the sustainability of current energy practices and help identify strategies to promote cleaner and more sustainable energy sources. Furthermore, it can assist policymakers in identifying trade-offs and synergies between energy access, economic development, and environmental sustainability, ultimately guiding the formulation of policies that foster inclusive and sustainable development in Africa.

This study offers four key contributions. Firstly, in contrast to previous research on the African context, it employs the ecological footprint (EFP) of production and consumption, which provides a more comprehensive measure of environmental sustainability than CO_2 emissions (Sampene et al., 2024). Secondly, to the best of the authors' knowledge, this study is the first to examine the synergistic effects of green agriculture and human development on environmental sustainability in Africa (Nguyen-Thi-Kim et al., 2024). Thirdly, to mitigate estimation biases and inefficiencies, the study applies robust panel estimation techniques that account for heterogeneity, cross-sectional dependence, and endogeneity (Martinez-Baron et al., 2024). Fourthly, beyond assessing conditional means, this study captures the heterogeneous impacts of green agriculture and human development, as well as their interactive effect on the conditional distribution of the ecological footprint. To this end, the study employs the generalised quantile regression method within an instrumental variable (IV) framework to address potential endogeneity issues arising from reverse causality (Baker et al., 2024).

The principal findings of this study are as follows: firstly, green agriculture exerts a weak positive effect on the ecological footprint. Secondly, the pursuit of human development contributes to an increase in the ecological footprint. Thirdly, green agricultural practices, despite their diminishing positive influence on the environment, moderate the impact of human development on the ecological footprint. Lastly, causality tests indicate the existence of bidirectional causal relationships between green agriculture, human development, and the ecological footprint.

The remainder of this article is structured as follows: Section 2 provides an empirical overview of the existing literature. Section 3 outlines the econometric approach and data used in the study, while Section 4 presents and discusses the study's findings. Finally, Section 5 concludes by highlighting the policy implications of the results.

2. Literature Review and Hypothesis Development

This section synthesises the literature on the relationship between green agricultural production, human development, and environmental sustainability. It is divided into three subsections: green energy consumption and environmental sustainability (2.1), human development and environmental sustainability (2.2), and the interaction between green agriculture, human development, and environmental sustainability (2.3).

2.1. Green Agriculture and Environmental Sustainability

According to the OECD (2013), green agriculture is a concept that seeks to integrate sustainable and environmentally friendly agricultural practices while maintaining optimal productivity. It is based on principles such as reducing the ecological footprint, ensuring the sustainable use of natural resources, minimising chemical inputs, promoting biodiversity, harnessing renewable energy sources, and improving the socio-economic conditions of farmers.

The ecological footprint, as a comprehensive indicator of environmental sustainability, goes beyond merely measuring CO_2 emissions by incorporating various dimensions of human impact on ecosystems, such as the footprint of agricultural land, water use, and infrastructure. According to Anita, Bianka, & Dávid (2024), it assesses the land and water area required to produce the consumed resources and absorb the generated waste. Bhatt et al. (2024) demonstrated that the ecological footprint captures the indirect effects of human activities, such as deforestation and over-exploitation of water resources, which are not reflected in CO_2 emission measurements. Baker et al. (2024) illustrated how certain agricultural practices, while reducing greenhouse gas emissions, can increase land use, thus amplifying the ecological footprint. In the context of green agriculture in Sub-Saharan Africa, Moreno Vargas et al. (2023) highlighted that limited access to modern technologies can lead to increased pressure on land and forests, exacerbating the ecological footprint. Thus, the ecological footprint becomes a critical tool for assessing the true sustainability of green agriculture, incorporating indirect effects and enabling comparison with ecosystems' capacity for regeneration, as concluded by Guo & Wang (2023).

There is an extensive body of literature on the environmental impact of the green economy. However, the debate regarding its positive or negative effects remains unresolved. The majority of studies have used CO_2 emissions as a measure of environmental degradation (Cammaer, 2016; Wilkes & Zhang, 2016; Boix-Fayos & De Vente, 2023; Schoonjans, 2024; Mergoni et al., 2024; Ray, 2022). Relatively few studies have examined this relationship using the ecological footprint, which is a more comprehensive measure of environmental sustainability than CO_2 emissions.

For instance, Christine (2024) demonstrates that green energy improves environmental quality, particularly in terms of the ecological footprint. Using the Fourier Toda & Yamamoto (1995) causality test, Shandilya et al. (2024) identified a unidirectional effect from green production to cultivated land. Their findings suggest that green production contributes to reducing the environmental damage caused by agriculture. Similarly, Boix-Fayos & De Vente (2023) reported that in G7 countries, green production reduced environmental sustainability by negatively affecting ecological footprints over the period 1990-2020.

Mergoni et al. (2024) and Akhil et al. (2024) found that green production increases the ecological footprint in the five major energy-consuming countries reliant on biomass-based agricultural inputs and in the member countries of the South Asian Association for Regional Cooperation (SAARC), respectively. In contrast, Samoraj et al. (2024) argue that green production enhances environmental sustainability, particularly the ecological footprint, in Belt and Road Initiative (BRI) countries over the period 1995-2020. They contend that the beneficial effect of green agriculture operates through foreign direct investment (FDI) and technological innovation.

Similarly, Moreno Vargas et al. (2023) reported that the transition to green energy reduced the ecological footprint in BRICS countries between 1992 and 2019. However, Christine (2024) highlighted significant disparities in their findings. They analyse the impact of green production on the ecological footprint in the 10 largest biomass-consuming countries over the period 1970-2018. Their results indicate that green production degrades the environment in four countries (Finland, Italy, India, and the United States) while improving it in six others (Austria, Brazil, China, Germany, Sweden, and the United Kingdom).

In light of the above discussion, we propose the following hypothesis:

Hypothesis 1. Green agriculture may have a positive and significant impact on environmental sustainability.

2.2. Human Development and Environmental Sustainability

Studies on the effects of human development on environmental quality remain limited. Most of these studies have used human capital or education as a measure of human development. Islam (2024) employs panel data to explore the relationship between CO_2 emissions, economic development, and human capital in emerging economies. The author concludes that higher levels of education help minimise CO_2 emissions, whereas primary education has a limited impact. Cotula

(2016) highlights that human capital can have differentiated effects on the environment, depending on education levels and the targeted economic sectors. Janmaimool et al. (2024) emphasise the importance of education in promoting sustainable agricultural practices, noting that increased knowledge reduces environmental degradation.

Janmaimool et al. (2024) examine the impact of human development in 21 European countries, revealing that when driven by resource-intensive economic growth, it leads to higher CO_2 emissions. Veronoka & Martin find that education focused on clean technologies can counteract these negative effects by fostering the adoption of environmental innovations. Norström et al. (2014) analyse economic sectors and show that human capital reduces emissions in manufacturing industries but increases them in residential sectors.

Popescu (2019) explores G7 countries and finds that human capital is associated with a reduction in CO_2 emissions, primarily through investments in green technologies. Ugochukwu (2019) identifies a positive impact of human capital on environmental sustainability in developing countries but underscores the necessity of appropriate governance policies. Akhil et al. (2024) study OECD countries and conclude that human development enhances environmental quality, improving both CO_2 emissions and the ecological footprint.

Kindo et al. (2024) demonstrate that the effect of human development on emissions is highly dependent on economic structures and industrial dynamics. Shumaila & Mi (2024) illustrates how higher education levels in manufacturing industries encourage emissions reductions through technological innovation. Sampene et al. (2024) examine emerging economies and confirm that human development, when integrated into sustainability policies, contributes to lowering CO_2 emissions. Zimek & Baumgartner (2024) show that improving human capital, combined with stringent environmental policies, yields positive environmental outcomes. Finally, Arzo & Hong (2024) and Bhatt et al. (2024) conclude that human development strengthens the energy transition and enhances environmental quality, particularly when accompanied by effective governance.

Based on the above discussion, we propose the following hypothesis:

Hypothesis 2. Human development may have a positive relationship with environmental sustainability.

2.3. Green Agriculture, Human Development and Environmental Sustainability

The theoretical link between green agriculture, human development, and environmental sustainability can be explained through the concept of the "energy-environment-development nexus." This framework acknowledges the interdependence and complex relationship between the green economy (including green agriculture) human development, and environmental sustainability.

Firstly, green energy from renewable resources can play a significant role in meeting the energy needs of developing countries. Access to affordable and reliable energy sources for agriculture, including green energy, is crucial for human development, as it facilitates various socio-economic activities such as lighting, cooking, heating, energy production, biomass generation, green fertiliser production, and electricity supply (Anita et al., 2024). According to Xu et al. (2024), green energy generates lower carbon emissions compared to fossil fuels and can also contribute to waste management by utilising organic materials, thereby reducing pollution and landfill emissions. However, as highlighted by the Sustainable Development Solutions Network (2012) and Sampene et al. (2024), if green resources are exploited unsustainably in agriculture such as through deforestation for fuelwood, this can lead to environmental degradation, biodiversity loss, and increased greenhouse gas emissions. The effectiveness of green agriculture, therefore, hinges on responsible management and utilisation practices.

Secondly, human development and environmental sustainability are interconnected. As Nguyen-Thi-Kim et al. (2024) points out, sustainable development aims to meet present needs without compromising the ability of future generations to meet theirs. Achieving human development objectives, such as poverty reduction and improved living standards, must be pursued while minimising negative environmental impacts. Martinez-Baron et al. (2024) explain that as countries develop, they invest in research and development, which fosters the discovery and adoption of cleaner technologies. These include renewable energy sources, energy-efficient technologies, and cleaner industrial processes. Such advancements, as demonstrated by Sampene et al. (2024), contribute to reducing the carbon intensity of economic activities, thereby promoting environmental sustainability.

Thirdly, promoting the sustainable consumption of green energy through environmental education is essential for mitigating environmental pressures, as argued by Xu et al. (2024). The moderating role of green agriculture in the relationship between human development and environmental sustainability is based on the need to balance access to renewable resources, socio-economic development, and responsible energy management practices that minimise environmental degradation while ensuring long-term sustainability. Higher levels of human development often lead to technological advancements that can improve energy efficiency and reduce environmental impacts.

Based on this discussion, we propose the following hypothesis:

Hypothesis 3. Green agriculture may moderate the effect of human development on environmental sustainability.

3. Methodology

3.1. Data

This study relies on annual data to synthesise the effect of green agriculture and human development on environmental sustainability in African countries. Based on data availability, our study is limited to a dataset covering 31 African countries over the period 1996-2022. In line with Price (2000), Nguyen-Thi-Kim et al. (2024), and Martinez-Baron et al. (2024), this study employs ecological footprint of consumption (EFPcons) (measured in global hectares per capita) and ecological footprint of production (EFPprod) (measured in global hectares per capita) as proxies for environmental sustainability.

According to the National Footprint and Biocapacity Accounts (2021), the ecological footprint is defined as "a measure of the biologically productive land and water area required by an individual, population, or activity to produce all the resources it consumes, to accommodate its occupied urban infrastructure, and to absorb the waste it generates, using prevailing technology and resource management practices." Its calculation incorporates anthropogenic activities related to agriculture (crop and livestock production), fiber production, wood regeneration, CO_2 absorption from fossil fuel combustion, and physical infrastructure development (Anita et al., 2024). Data on ecological footprints are sourced from the Global Footprint Network (GFN).

Following Xu et al. (2024), we adopt the global use of renewable resources for agricultural production (measured as the share of renewable resources in total resource supply) as a proxy for green agriculture. These data are retrieved from the Green Growth Indicators database of the Organisation for Economic Co-operation and Development (OECD, 2013). Additionally, the Human Development Index (HDI) is used as a proxy for human development (Nguyen-Thi-Kim et al., 2024). Data on human development are obtained from the United Nations Development Programme (UNDP).

Lastly, three control variables are selected based on relevant literature on the determinants of environmental sustainability: globalisation, economic growth, and technology. The globalisation index is sourced from the KOF Swiss Economic Institute, while data on economic growth and technology are retrieved from the World Bank's World Development Indicators (Sampene et al., 2024). **Table 1** presents the variables used and the list of countries.

Table 1. Specification of variables.

Variable	Metric	Presentation	Source
Ecological footprint of consumption	Global hectares per capita	EFPcons	NFA (2023)
Ecological footprint of production	Global hectares per capita	EFPprod	NFA (2023)
Green agriculture	Resources in Green agricultural production	GREENA	OECD (2013) Database
Human Development Index	Scale: 0-1	HDI	UNDP (2023)
Globalisation	Scale: 1-100	Globa	KOF Swiss Economic Institute (2023)
Economic growth	GDP growth rate (%) (constant 2010 US$)	GDP	World Bank (2023)
Technology	Internet usage (% of population)	Techno	World Bank (2023)

Source: authors.

It is observed in Table 1 that both the ecological footprint of production (EFP-prod) and that of consumption (EFPCons) are positively influenced by human development (HDI) and green agriculture (GREENA). However, this positive influence exhibits an increasing rate for human development and a decreasing rate for green agriculture. Indeed, an improved quality of life leads to higher consumption of natural resources. Green agriculture contributes to reducing the ecological footprint by promoting sustainable practices, although this effect diminishes as these practices become more intensive or are poorly implemented. Thus, while human development drives a continuous increase in ecological pressure, green agriculture tends to mitigate it progressively, underscoring the necessity of transitioning towards more sustainable production and consumption models.

3.2. Econometric Modelling

The relationship between green agriculture, human development, and the ecological footprint is complex and multifaceted. When derived from sustainable sources, green agriculture can be considered a renewable and low-carbon energy option (Akhil et al., 2024). This has the potential to reduce CO_2 emissions and the overall ecological footprint. However, the impact of green agriculture depends on several factors, including the scale of its extraction, land-use changes, and the efficiency of energy conversion processes (Khedulkar et al., 2024; Zimek & Baumgartner, 2024). Unsustainable extraction of green energy can lead to deforestation, biodiversity loss, soil degradation, and increased carbon emissions, thereby exacerbating the ecological footprint (Wilkes & Zhang, 2016; Ray, 2022).

Moreover, the link between human development and the ecological footprint stems from the environmental impact of human activities. Human development, primarily characterised by economic growth and improved living conditions, often necessitates increased resource consumption and energy use. This can lead to a higher ecological footprint, as more resources are extracted, waste is generated, and carbon emissions rise (Islam, 2024; Shandilya et al., 2024). However, sustainable human development approaches promote efficiency, conservation, and the use of renewable resources to minimise the ecological footprint. By focusing on factors such as education, healthcare, and social progress, human development can foster greater environmental awareness and the adoption of sustainable environmental practices, ultimately reducing the ecological footprint (Popescu, 2019; Samoraj et al., 2024).

Economic growth is often associated with increased consumption and production, which can result in greater resource extraction, green agriculture expansion, and waste generation. As economies grow, there is rising demand for goods and services, which places additional pressure on natural resources and ecosystems. This can contribute to a larger ecological footprint, as more resources are required to sustain economic activities (Cotula, 2016; Veronika & Martin, 2020).

Globalisation refers to the increasing interconnectedness and integration of economies and societies worldwide. It has facilitated the expansion of international trade, investment, and technological advancements. While globalisation has brought benefits such as improved access to goods and services, it has also intensified resource extraction and production processes. This can lead to a higher ecological footprint, as resources are exploited across different regions and transported over long distances, thereby increasing green agriculture activity and emissions (Cammaer, 2016; Ugochukwu, 2019).

Technological advancements also have the potential to both increase and reduce the ecological footprint. On the one hand, technological innovations can lead to more efficient resource use, cleaner production processes, and the development of renewable energy sources. This can help reduce ecological footprints by minimising resource consumption and environmental impact (Janmaimool et al., 2024). On the other hand, technological advancements can also result in the development and adoption of resource-intensive technologies, such as large-scale industrial agriculture or energy-intensive manufacturing processes (Arzo & Hong, 2024; Boix-Fayos & De Vente, 2023). This can contribute to increased ecological footprints.

Accordingly, we specify in Equation (1) that the ecological footprint (EFP) is a function of green agriculture (GREENA), human development (HDI), economic growth (GDP), globalisation (Globa), and technology (Techno).

$$\ln EFP_{it} = \alpha_0 + \beta_1 \ln GREENA_{it} + \beta_2 HDI_{it} + \beta_3 \ln GDP_{it} + \beta_4 \ln Globa_{it} + \beta_5 \ln Techno_{it} + \varepsilon_{it} \quad (1)$$

where ln denotes the natural logarithm, i and t refer to the N countries and T time periods, respectively. α_0 is a constant parameter, and $\beta_1 - \beta_5$ are the coefficients to be estimated, while ε_{it} represents the stochastic error term.

In many developing countries, green agriculture is often associated with inefficient and unsustainable practices. This leads to greater extraction and use of natural resources, potentially resulting in negative environmental consequences (Wilkes & Zhang, 2016). Given that green agriculture in Africa primarily involves less destructive traditional farming methods, such as converting agricultural residues into light or fully decomposed compost, it is expected to have a relatively minor adverse impact on environmental sustainability (Ray, 2022; Mergoni et al., 2024). Therefore, β_1 is expected to be positive.

Following Akhil et al. (2024), Shandilya et al. (2024), we employ the Human Development Index (HDI) as a measure of human development. The HDI is a multidimensional indicator encompassing three key components: health (measured by life expectancy), education (approximated by the average years of schooling), and income (measured by gross national income per capita) (Islam, 2024; Samoraj et al., 2024). According to previous empirical studies (Popescu, 2019; Kindo et al., 2024), as human development progresses, both citizens and policymakers become more aware of environmental quality and take initiatives to improve it. However, human development is expected to exert a trade-off effect on environmental sustainability, as the pursuit of higher living standards in contexts of food insecurity and economic vulnerability may lead to less desirable environmental practices (*i.e.,* $\beta_2 < 0$).

Moreover, β_3 is expected to be positive, as higher incomes enable individuals to increase their demand for goods and services, thereby can intensify green agriculture and, consequently, the ecological footprint (Boix-Fayos & De Vente, 2023).

The effect of globalisation (*i.e.,* β_4) may be either positive or negative, depending on a country's comparative advantage and the stringency of its environmental regulations (Cammaer, 2016; Schoonjans, 2024). Finally, the environmental impact of technological advancements remains ambiguous, as technology can either enhance environmental quality through cleaner production methods and processes or degrade it by increasing investments in energy-intensive ICT infrastructure (Arzo & Hong, 2024). Therefore, β_5 may be either positive or negative.

To examine the relationship between human development and the ecological footprint, Equation (1) is extended to include an interaction term between the adoption of green agricultural practices and human development. This is in line with our third hypothesis, which posits that improvements in human development can mitigate the adverse effect of green agriculture on environmental sustainability. Consequently, Equation (2) is employed to test the indirect effect of green agriculture on the ecological footprint:

$$\begin{aligned} \ln EFP_{it} = \alpha_0 + \beta_1 \ln GREENA_{it} + \beta_2 HDI_{it} + \beta_3 \left(\ln GREENA \times HDI\right)_{it} \\ + \beta_4 \ln GDP_{it} + \beta_5 \ln Globa_{it} + \beta_6 \ln Techno_{it} + \varepsilon_{it} \end{aligned} \quad (2)$$

where (lnGREENA × HDI) represents the interaction term between green agriculture and human development. $\beta_1 - \beta_6$ are the coefficients to be estimated, while the remaining symbols and variables remain unchanged.

3.3. Estimation Strategy

3.3.1. Cross-Sectional Dependence Test

The cross-sectional dependence test is employed in panel data analysis to determine whether there exists interdependence or correlation among individual units (e.g., countries, firms) within the panel. It helps identify whether the assumption of independence across observations is violated, which is crucial for accurate statistical inference in panel data models. This study tests for cross-sectional dependence using the CD test developed by Pesaran (2004), represented in Equation (3):

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=I+1}^{N} \hat{\rho}_{ij} \right) \quad (3)$$

where N and T denote the cross-sectional and time dimensions, respectively, and $\hat{\rho}_{ij}$ represents the coefficient of the cross-sectional correlation of residuals.

3.3.2. Panel Unit Root Test

The second-generation panel unit root test is a statistical method used to determine whether a panel dataset exhibits a unit root, which indicates non-stationarity. It extends the traditional unit root test for time-series data by incorporating both cross-sectional and time dimensions in panel datasets. This test helps researchers ascertain whether the variables in a panel dataset are stationary or non-stationary. Accordingly, the Cross-Sectionally Augmented Dickey-Fuller (CADF) test (Pesaran, 2007) is applied to verify stationarity. The CADF statistic is obtained from the following equation:

$$\Delta Y_{it=} a_i + b_i Y_{i,t-1} + c_i \overline{Y_{t-1}} + c_i \Delta \overline{Y_i} + \omega_{it} \tag{4}$$

where Δ represents the difference operator, Y is the estimated variable, and ω_{it} denotes the error terms. The model is stable only when the null hypothesis is rejected; otherwise, a "spurious regression" may occur.

3.3.3. Cointegration Test

To examine the long-term relationship between variables, the Westerlund (2007) cointegration analysis, which is robust in addressing cross-sectional dependence (CD), is employed. The Westerlund (2007) cointegration testing procedure is more reliable than traditional cointegration tests such as Pedroni (2004) and Kao & Chiang (2001), as it corrects for the issue of cross-sectional dependence. The equation for the test statistics in Westerlund's cointegration test is expressed as follows:

$$\Delta Y_{it=\delta_i'} d_t + a_i \left(Y_{i,t-1} - \beta_i' X_{i,t-1} \right) \sum\nolimits_{j=1}^{p_i} a_{ij} \Delta Y_{i,t-1} + u_{it} \tag{5}$$

where Y is the dependent variable, X represents the independent variable, i denotes cross-sectional units, t represents time, d_t includes deterministic components, p_i and q_i are the lag lengths and shift orders that vary across individual cross-sectional units, and α_i represents the speed of error correction towards long-term equilibrium.

The Westerlund (2007) cointegration analysis accounts for four separate test statistics: two panel statistics (P_t, P_a) and two group statistics (G_t, G_a).

3.3.4. Long-Term Estimation Methods

Given that this study employs panel data from 31 African countries spanning the period 1996 to 2022, we propose a set of panel data estimation techniques to address the premises concerning the impact of green agriculture and human development on environmental sustainability.

First, the analysis of the interaction between green agriculture and human development (Hypothesis 3) provides clear evidence that green agricultural practices can mitigate the adverse effects of human development pursuits on the ecological footprint. Indeed, human development efforts in contexts of food insecurity can exacerbate environmental degradation (Martinez-Baron et al., 2024). However, although not entirely free of pollution, green agriculture pollutes at a decreasing rate compared to conventional agricultural practices (Nguyen-Thi-Kim et al., 2024). These findings support the arguments of Veronika &Martin (2020), who assert that promoting green agricultural practices enhances public awareness of environmental sustainability, thereby increasing pressure on public authorities and fostering community participation to contribute to a cleaner environment. Thus, as human development improves, populations may adopt technologies that comply with environmental standards (Baker et al., 2024).

Regarding the control variables, the negative effect of globalisation on the ecological footprint aligns with Veronika & Martin (2020), who found that globalisation improves environmental quality. These findings suggest that Africa's increasing interconnectedness and economic integration are beneficial not only for economic development but also for environmental sustainability (Xu et al., 2024). The results also indicate that economic growth has a detrimental effect on environmental sustainability. Holding other factors constant, an increase in per capita GDP intensifies pressure on the environment (Price, 2000). This finding implies that economic growth in African countries is associated with increased resource extraction, production, and consumption, thereby exacerbating the ecological footprint (Anita et al., 2024). Consequently, African nations should accompany their growth strategies with sustainable practices related to resource production and consumption (Sampene et al., 2024).

Finally, the results reveal a mixed effect of technology on environmental sustainability. This finding suggests that technological advancement leads to an increase in the consumption-based ecological footprint, while its effect on the production-based ecological footprint is negative and significant (Sustainable Development Solutions Network, 2012; Xu et al., 2024). However, the standard errors proposed by Kripfganz & Schwarz (2019) do not generally account for the potential endogeneity issue arising from omitted variable bias, reverse causality, or measurement errors. Therefore, this study applies an instrumental variable (IV) estimation based on the two-step generalised method of moments (GMM) with fixed effects (FE), followed by the IV-GMM approach, to address endogeneity in the panel data models.

The IV-GMM method is a robust approach for fully addressing endogeneity in panel data models. Endogeneity arises when explanatory variables are correlated with the error term, leading to biased and inconsistent parameter estimates. IV-GMM ensures consistent parameter estimation by using instrumental variables, which are correlated with the endogenous explanatory variables but uncorrelated with the error term (Baum et al., 2003). IV-GMM estimates parameters by minimising the distance between the sample moments and the population moments, where the sample moments are constructed using instrumental variables. Additionally, the standard errors of Kripfganz & Schwarz (2019) are incorporated into the IV-GMM framework to control for potential heteroskedasticity and cross-sectional dependence in the data.

Nonetheless, both Kripfganz & Schwarz (2019) and IV-GMM fail to capture the behaviour of estimates at different points of the distribution (Binder & Coad, 2011), as they only reflect the conditional mean effect of biomass-based agriculture and human development on the conditional mean of environmental quality measures. Therefore, the panel quantile regression method is employed to examine the heterogeneous effects of agriculture and human development on environmental sustainability.

The panel quantile regression method evaluates the heterogeneous effects of regressors across the distribution of the dependent variable. Koenker & Bassett

(1978) were the first to introduce the panel quantile regression method, based on an objective function minimising the absolute value of residuals. Compared to traditional specification techniques that focus on mean effects, quantile regression provides consistent and efficient estimates in the presence of outliers (Chernozhukov & Hansen, 2008) and accommodates both normal and non-normal error distributions (Koenker & Bassett, 1978).

The quantile regression model developed by Koenker & Bassett (1978) can be expressed as follows:

$$x_{it=\lambda_i} + \sum_{k=1}^{K} \varphi_{ik} x_{t-1} + \sum_{k=1}^{K} \delta_{ik} Y_{it-k} + \varepsilon_{it} \tag{6}$$

$$\text{with} \quad Y_{it=X'_{it}} \beta_\theta + u_{\theta it}$$

where Y represents the dependent variable (in this study, the ecological footprint), X is a vector of regressors (green agriculture, human development, the interaction variable, and all other control variables), β is the vector of parameters to be estimated, and u denotes a vector of error terms. The function Quant $\theta(y_{it}/x_{it})$ identifies the θ^{th} conditional quantile of Y given X.

We apply the generalised quantile regression method implemented within an IV Powell (2020) framework. This approach addresses endogeneity concerns and incorporates a non-additive fixed effect structure developed by Powell, ensuring that the error term is non-separable while allowing for parameter variations. The generalised quantile regression method provides consistent and efficient quantile regression estimates and accommodates both linear and nonlinear estimators. It is also robust for panels short time horizon and is relatively computationally efficient (Powell, 2020).

3.3.5. Panel Causality Test

The panel causality test is employed to examine the cause-and-effect relationship between variables within a panel dataset. It allows for the determination of whether changes in one variable lead to changes in another while accounting for potential cross-sectional dependence and individual heterogeneity. This test is commonly used in panel data analysis to investigate causal relationships and understand the dynamics between variables over time. The Dumitrescu-Hurlin panel causality test, developed by Dumitrescu & Hurlin (2012), is applied to examine the causal link between the study variables. This causality test accommodates cross-sectional dependence and heterogeneity (Dogan & Inglesi-Lotz, 2017). Furthermore, it can be utilised in cases where T > N or N > T (Su et al., 2021). The underlying equation is used to verify the causal association between x and y:

$$y_{it=\lambda_i} + \sum_{k=1}^{K} \beta_{ik} y_{t-1} + \sum_{k=1}^{K} \gamma_{ik} x_{it-k} + \varepsilon_{it} \tag{7}$$

$$x_{it=\lambda_i} + \sum_{k=1}^{K} \varphi_{ik} x_{t-k} + \sum_{k=1}^{K} \delta_{ik} Y_{it-k} + \varepsilon_{it} \tag{8}$$

where k represents the optimal lag length; y and x are the causally related variables; and γ_{ik}, β_{ik}, φ_{ik} et δ_{ik} denote the autoregressive and regression parameters, respectively.

4. Results

4.1. Descriptive Statistics, Variable Graphs, and Variance Inflation Factor Test

Table 2 presents the descriptive statistics for all estimated variables. It shows that the mean (standard deviation) of the Human Development Index (HDI) is 0.482 (0.118), green agriculture is 16.190 (1.084), the ecological footprint of consumption is 0.332 (0.403), the ecological footprint of production is 0.219 (0.405), globalisation is 3.950 (0.214), economic growth is 6.125 (0.839), and technology is 0.245 (2.491). Similarly, the maximum (minimum) values for HDI are 0.244 (0.684), green agriculture is 14.548 (18.205), the ecological footprint of consumption is −0.467 (1.351), the ecological footprint of production is −0.525 (1.411), globalisation is 3.107 (8.160), economic growth is 5.475 (8.160), and technology is −8.131 (4.392). The table suggests that the ecological footprint of consumption and production, HDI, green agriculture, economic growth, globalisation, and technology exhibit an upward trend.

In the subsequent sections, the models are subjected to a more robust analysis using Kripfganz & Schwarz's regression, IVGMM, and panel quantile regressions. Before proceeding with the estimations, it is crucial to assess the presence of multicollinearity, as its existence could lead to misleading results. To this end, the Variance Inflation Factor (VIF) test is employed to detect multicollinearity. The VIF measures the extent to which the variance of estimated regression coefficients is inflated due to multicollinearity. A high VIF value indicates strong correlations among predictor variables, which can result in unreliable and unstable regression outcomes. Table 3 reports the VIF results for the models with the ecological footprint of consumption (Model 1) and the ecological footprint of production (Model 2). The findings confirm the absence of multicollinearity among the regressors, as all VIF values are below 10 and the tolerance factors (1/VIF) exceed 0.1.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std.Dev	Min	Max
LnEFPcons	837	0.332	0.403	−0.467	1.351
LnEFPprod	837	0.219	0.405	−0.525	1.411
LnGREENA	837	16.190	1.084	14.548	18.205
LnGloba	837	3.950	0.214	3.107	4.266
LnGDP	837	6.126	0.839	5.475	8.160
HDI	837	0.482	0.1185	0.244	0.684
LnTechno	837	0.245	2.491	−8.131	4.392

Source: authors.

4.2. Results of Cross-Sectional Dependence, Unit Root, and Cointegration Tests

As previously mentioned, the issue of cross-sectional dependence leads to biased and inconsistent results. Therefore, we examine whether the cross-sections are independent using Pesaran's (2007) test for detecting cross-sectional dependence among the variables. The results presented in **Table 4** indicate that the null hypothesis of cross-sectional independence is significantly rejected at the 1% level.

Following the results of the cross-sectional dependence test, second-generation unit root tests, specifically the CIPS and CADF tests are employed to assess the presence of unit roots in the series. These tests are used because they account for cross-sectional dependence and heterogeneity among the series. The results of the CIPS and CADF tests, reported in **Table 5**, reveal that all variables are stationary at their first difference. This eliminates the possibility of conducting inconsistent regression analyses with these data.

Based on the stationarity test results, the Westerlund (2007) panel cointegration test is conducted to determine the existence of a long-term relationship between the variables. The Westerlund test results, presented in **Table 6**, reject the null hypothesis of no cointegration, with significance observed in both panel statistics (Pt and Pa) and group statistics (Gt and Ga). Consequently, the cointegration among the variables suggests the existence of a long-term relationship between environmental sustainability, green agriculture, human development, economic growth, globalisation, and technology.

Table 3. Multicollinearity test.

Variable	Model 1		Model 2	
	VIF	1/VIF	VIF	1/VIF
HDI	9.02	0.124	9.02	0.124
LnGDP	5.57	0.168	5.57	0.168
LnGloba	4.57	0.218	4.57	0.218
LnTechno	2.34	0.427	2.34	0.427
LnGREENA	1.35	0.642	1.35	0.642
Mean VIF	4.36		4.36	

Source: authors.

Table 4. Cross-sectional dependence test in panel data.

Variables	CD-test	*p*-value
LnEFPcons	5.32	0.00
LnEFPprod	6.00	0.00
LnGREENA	57.37	0.00
LnGloba	97.13	0.00
LnGDP	80.67	0.00
HDI	42.29	0.00
LnTechno	82.61	0.00

Source: authors.

Table 5. Unit root test results in panel data.

Variable	CIPS		PESCADF	
	Level	1st difference	Level	1st difference
LnEFPcons	−3.022***	−5.032***	−0.352	−3.579***
LnEFPprod	−2.704***	−4.458***	−2.120	−3.152***
LnGREENA	−2.04	−2.829*	−2.329	−3.146***
LnGloga	−2.571	−4.278***	−2.858***	−3.272***
LnGDP	−1.342	−3.835***	−2.770**	−3.154***
HDI	−1.302	−2.153***	−2.519	−3.071***
LnTechno	−858***	−1.302	−1.706	−2.344***

Source: authors.

Table 6. Panel cointegration test.

	Model 1		Model 2	
	Value	Robust *p*-value	Value	Robust *p*-value
Gt	−3.764***	0.004	−5.940***	0.001
Ga	−5.114**	0.023	−6.841**	0.074
Pt	−6.889***	0.004	−9.353***	0.007
Pa	−9.001***	0.037	−11.318***	0.073

Source: authors.

4.3. Long-Term Estimation Results

We first present the results estimated by the dynamic panel estimators of Kripfganz & Schwarz (2019). The estimation results are shown in **Table 7**, where models (1)-(4) report the estimates with the consumption ecological footprint (EFPcons) as the dependent variable, while models (5)-(8) display the results with the production ecological footprint (EFPprod) as the dependent variable. The results indicate that green agriculture is positively associated with measures of environmental sustainability. Specifically, a 1% increase in green agriculture leads to an increase in both EFPcons and EFPprod by approximately 0.347% and 0.224%, respectively.

Regarding human development, its effect on both EFPcons and EFPprod is also positive and statistically significant at the 1% level, with a greater magnitude than that of green agriculture. Indeed, both green agriculture and human development increase the ecological footprint, though differently: green agriculture does so at a decreasing rate, while the pursuit of human development does so at an increasing rate. The interaction between green agriculture and human development has a positive and significant effect on both EFPcons and EFPprod. However, the magnitude of the interaction coefficients (0.501 and 0.636 for consumption and production ecological footprints, respectively) suggests that green agricultural practices mitigate the polluting impact of human development. To ensure the complete elimination of endogeneity bias, the models are re-estimated using the

Instrumental Variables Generalised Method of Moments (IVGMM) estimation approach.

The IVGMM model is applied to corroborate the treatment of endogeneity, and the estimation results are summarised in Table 8. In line with standard practice, we discuss the results of Hansen's statistical test for overidentification of instruments. The Hansen test statistics are non-significant, indicating that the instruments satisfy the orthogonality condition. According to the results, green agriculture is positively associated with both the consumption and production ecological footprints at a significance level of 1%. The Human Development Index (HDI) negatively affects environmental sustainability through its positive and significant impact on the ecological footprint. The interaction coefficients between green agriculture and human development are positive and statistically significant at the 1% level, but with a smaller magnitude due to the decreasing positive influence of green agriculture on the ecological footprint. This suggests that green agricultural practices interact with human development by mitigating the polluting effects of the latter to reduce the ecological footprint. Another factor contributing to environmental sustainability is globalisation, with its negative coefficients being significant at the 1% level. The results also show that economic growth leads to an increase in the ecological footprint, with a positive and significant impact at the 1% level. The coefficients for technology are positive and significant in models (1) to (4), while its coefficient is negative and significant in models (5) to (8).

Table 9 and Table 10 present the results of the effect of green agriculture and human development on the consumption and production ecological footprints based on panel quantile regressions. The results in Table 9 show that green agriculture is positively associated with the ecological footprint across all quantiles, with coefficients ranging from 0.256 to 0.366. For human development, we observe that a unit increase results in a rise of 0.698 to 1.430 units in EFPcons across all quantiles. At the same time, the interaction between green agriculture and human development is positive and significant in all quantiles, with coefficients ranging from 0.122 to 0.201.

Regarding the results reported in Table 10, green agriculture is positive and significant at the lower, median, and upper quantiles (10th-80th quantile), with a green agriculture coefficient ranging from 0.285 to 0.328. Thus, all else being equal, green agricultural practices affect the environment in Africa, although at a decreasing rate. For human development coefficients, the results reveal a positive relationship between HDI and environmental sustainability, with coefficients ranging from 1.199 to 2.217. The interaction term for green agriculture and human development shows a positive relationship, with coefficients fluctuating between 0.062 and 0.326. Thus, the results of the panel quantile regression are consistent with the findings from Kripfganz & Schwarz (2019) and IVGMM presented above.

Regarding the control variables, the coefficients for economic growth and globalisation for all dependent variable values echo the results obtained from

Kripfganz & Schwarz (2019) and IVGMM estimations discussed earlier. Additionally, the coefficients for technology are positive for all values of the EFPcons quantiles (**Table 9**), while its effect on EFPprod (**Table 10**) is negative and significant for other quantiles (50th-90th quantile).

Table 7. Results with Kripfganz and Schwarz's estimators.

	Ecological Footprint of Consumption				Ecological Footprint of Production			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnGREENA	0.301***		0.347***	0.211***	0.117***		0.194***	0.224***
	(0.056)		(0.057)	(0.057)	(0.030)		(0.027)	(0.048)
HDI		0.675***	1.331***	1.122***		1.636***	2.039***	1.123***
		(0.248)	(0.176)	(0.38)		(0.220)	(0.152)	(0.229)
LnGREENA*HDI				0.501 **				0.636***
				(0.218)				(0.202)
LnGloba	−0.426***	−0.259***	−0.270***	−0.320***	−0.464***	−0.219***	−0.218***	−0.321***
	(0.092)	(0.095)	(0.096)	(0.067)	(0.032)	(0.070)	(0.059)	(0.064)
LnGDP	0.197***	0.348***	0.312***	0.234***	0.055***	0.279***	0.249***	0.249***
	(0.043)	(0.029)	(0.041)	(0.043)	(0.040)	(0.026)	(0.028)	(0.046)
LnTechno	0.014 ***	0.023***	0.011***	0.012	−0.031***	−0.014***	−0.021***	−0.013***
	(0.003)	(0.007)	(0.004)	(0.004)	(0.007)	(0.002)	(0.003)	(0.003)
L.LnEFP	0.774***	0.596**	0.712**	0.785***	0.623***	0.845***	0.714***	0.755***
	(0.003)	(0.242)	(0.304)	(0.006)	(0.004)	(0.005)	(0.006)	(0.007)
Constant step 1	4.532***	0.699**	7.199***	5.011***	0.174	0.165	2.602***	5.266
	(0.665)	(0.325)	(0.989)	(0.308)	(0.476)	(0.301)	(0.416)	(0.357)
Constant step 2	0.177***	0.328***	0.302***	0.214***	0.035***	0.249***	0.229***	0.229***
	(0.023)	(0.019)	(0.041)	(0.033)	(0.020)	(0.027)	(0.018)	(0.036)
Observations after iterations	813	817	820	815	821	816	814	819
Hansen *P*-value	0.263	0.162	0.417	0.358	0.524	0.573	0.596	0.482

Source: authors, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8. Results with IVGMM.

	Ecological Footprint of Consumption				Ecological Footprint of Production			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnGREENA	0.309*** (0.049)		0.310*** (0.050)	0.163*** (0.028)	0.166*** (0.025)		0.204*** (0.025)	0.178*** (0.025)
HDI		0.931*** (0.222)	1.302*** (0.078)	0.858*** (0.148)		1.828*** (0.158)	2.171*** (0.099)	1.039*** (0.150)
LnGREENA*HDI				0.375*** (0.233)				0.432*** (0.121)
LnGloba	−0.440*** (0.050)	−0.337*** (0.052)	−0.265*** (0.045)	−0.133*** (0.091)	−0.439*** (0.034)	−0.165*** (0.048)	−0.168*** (0.046)	−0.209*** (0.094)

Continued

lnGDP	0.167*** (0.031)	0.382*** (0.035)	0.332*** (0.033)	0.133*** (0.026)	0.053*** (0.022)	0.283*** (0.016)	0.251*** (0.019)	0.138*** (0.029)
LnTechn	0.005** (0.002)	0.027*** (0.003)	0.012*** (0.002)	0.016*** (0.007)	−0.047*** (0.007)	−0.014*** (0.002)	−0.024*** (0.002)	−0.018*** (0.006)
L.LnEFP	0.674*** (0.003)	0.497** (0.242)	0.612** (0.304)	0.895*** (0.007)	0.723*** (0.004)	0.845*** (0.005)	0.734*** (0.007)	0.655*** (0.006)
Constant	1.674** (0.843)	1.497*** (0.055)	2.612** (1.331)	2.895*** (0.078)	1.723*** (0.076)	1.845*** (0.089)	1.734*** (0.066)	1.655*** (0.089)
Observations after iterations	796	794	798	794	795	797	798	797
AR1 *P*-value	0.005	0.034	0.025	0.004	0.006	0.005	0.007	0.045
AR2 *P*-value	0.343	0.653	0.534	0.637	0.285	0.387	0.483	0.572
Hansen *P*-value	0.176	0.341	0.2909	0.330	0.156	0.388	0.160	0.292

Source: authors, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 9. Quantile regression for Ecological Footprint of Consumption.

Dependent variable: Ecological Footprint of Consumption									
Quantiles									
	10	20	30	40	50	70	60	90	80
LnGREENA	0.256*** (0.000)	0.305*** (0.001)	0.266*** (0.001)	0.303*** (0.001)	0.342*** (0.001)	0.366*** (0.000)	0.372*** (0.001)	0.338*** (0.001)	0.304*** (0.002)
HDI	1.364*** (0.003)	1.236*** (0.007)	1.314*** (0.003)	1.430*** (0.006)	1.370*** (0.010)	1.269*** (0.012)	0.949*** (0.017)	0.897*** (0.012)	0.698*** (0.015)
LnGREENA*HDI	0.122 (0.002)	0.201*** (0.002)	0.117*** (0.003)	0.143*** (0.004)	0.177*** (0.004)	0.159*** (0.005)	0.144*** (0.003)	0.189*** (0.004)	0.170*** (0.0002)
LnGloba	−0.182*** (0.001)	−0.378*** (0.002)	−0.306*** (0.001)	−0.233*** (0.002)	−0.186*** (0.002)	−0.237*** (0.002)	−0.212*** (0.002)	−0.157*** (0.002)	−0.043*** (0.005)
LnGDP	0.296*** (0.001)	0.304*** (0.002)	0.336*** (0.000)	0.329*** (0.002)	0.321*** (0.002)	0.308*** (0.003)	0.248*** (0.001)	0.251*** (0.002)	0.294*** (0.001)
LnTechno	0.016*** (0.000)	0.017*** (0.000)	0.017*** (0.000)	0.012*** (0.000)	0.004*** (0.000)	0.001*** (0.000)	0.007*** (0.000)	0.005*** (0.000)	0.010*** (0.000)
Observations	837	837	837	837	837	837	837	837	837
Mean AR	0.787	0.758	0.63	0.60	0.757	0.57	0.79	0.58	0.57

Source: authors, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 10. Quantile regression for Ecological Footprint of Production.

Dependent variable: Ecological footprint of Production									
Quantiles									
	10	20	30	40	50	70	60	90	80
LnGREENA	0.285*** (0.000)	0.254*** (0.001)	0.253*** (0.003)	0.252*** (0.003)	0.312*** (0.003)	0.317*** (0.002)	0.328*** (0.001)	0.318*** (0.002)	0.323*** (0.000)
HDI	2.129*** (0.007)	2.217*** (0.006)	2.149*** (0.009)	1.850*** (0.019)	1.658*** (0.016)	1.688*** (0.011)	1.536*** (0.005)	1.221*** (0.006)	1.199*** (0.003)

Continued

LnGREENA*HDI	0.062*** (0.006)	0.326*** (0.009)	0.104*** (0.0010)	0.257*** (0.0011)	0.203*** (0.006)	0.244*** (0.008)	0.088*** (0.006)	0.120 (0.008)	0.103 (0.009)
LnGloba	−0.194*** (0.002)	−0.220*** (0.003)	−0.186*** (0.002)	−0.176*** (0.007)	−0.183*** (0.005)	−0.156*** (0.004)	−0.143*** (0.002)	−0.197*** (0.004)	−0.167*** (0.000)
LnGDP	0.420*** (0.001)	0.448*** (0.002)	0.438*** (0.001)	0.430*** (0.003)	0.351*** (0.003)	0.358*** (0.002)	0.330*** (0.001)	0.305*** (0.001)	0.288*** (0.000)
LnTechno	0.009*** (0.000)	0.011*** (0.000)	0.009*** (0.000)	0.003*** (0.000)	−0.002*** (0.000)	−0.005*** (0.000)	−0.012*** (0.000)	−0.017*** (0.000)	−0.015*** (0.000)
Observations	837	837	837	837	837	837	837	837	837
Mean AR	0.62	0.78	0.64	0.78	0.61	0.64	0.63	0.61	0.61

Source: authors, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.4. Results of the Panel Causality Test

The causal relationships between the variables are examined using the Dumitrescu-Hurlin (DH) (2012) panel causality test. The DH test results, presented in **Table 11**, indicate the existence of a bidirectional causal relationship between environmental footprint indicators (EFP) and human development. This suggests that changes in the level of human development lead to changes in environmental sustainability, and vice versa. These findings highlight the need for policymakers to formulate human development policies that prioritise environmental protection to mitigate the ecological footprint.

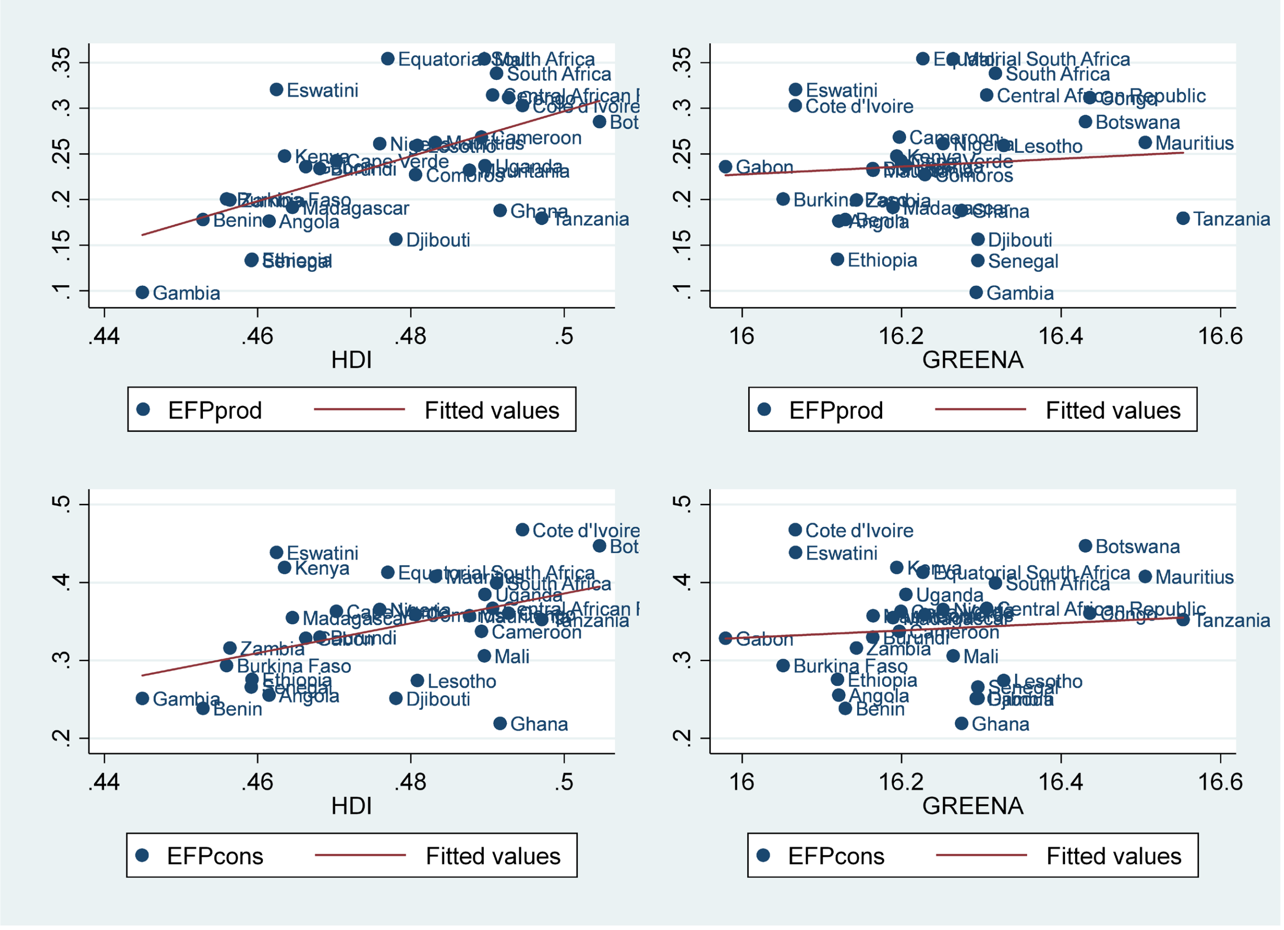
The causality test results also reveal a bidirectional causal link between green agriculture and the ecological footprint. A similar bidirectional causal association between the use of green resources (including renewables) and the ecological footprint was identified by Islam (2024) in a study covering nine countries, namely Austria, Brazil, China, Germany, Sweden, Finland, Italy, the United Kingdom, and the United States. Furthermore, the results confirm a bidirectional causality between GDP and the ecological footprint. The analysis of the bidirectional relationship between green agriculture and the ecological footprint is complex due to the influence of numerous exogenous factors, such as climate change, population growth, environmental policies, agricultural technologies, and market accessibility, which may introduce biases into causal conclusions (Anita, Bianka, & Dávid, 2024). These factors alter agricultural yields and the adoption of practices, as well as economic motivations and access to advanced technologies, indirectly affecting the environment (Baker et al., 2024).

The empirical findings also indicate the presence of a two-way causality between technology and the ecological footprint. A comparable result was reported by Moreno Vargas et al. (2023) in their study on the water-energy-food nexus in biodiversity conservation. Additionally, this study identifies a bidirectional causal relationship between globalisation and the ecological footprint (**Figure 1**).

Table 11. Results of Dumitrescu-Hurlin panel causality test.

	lnEFPcons	lnEFPprod	lnGREENA	lnGloba	HDI	lnGDP	LnTechno
LnEFPcons	–	5.705***	9.389***	5.341*	11.473**	12.738***	2.183**
LnEFPprod	3.489***	–	10.220***	7.149***	7.465***	5.721***	1.881**
LnGREENA	8.564***	4.942***	–	11.505***	4.226***	8.932**	6.360***
LnGloba	6.622**	7.358*	6.559***	–	2.394**	11.798*	5.501*
HDI	9.777***	6.312***	8.102***	5.978***	–	8.614***	5.627***
LnGDP	11.974***	4.867***	3.308**	9.096***	18.136***	–	6.146***
LnTechno	9.307***	5.871***	19.967**	4.327***	9.038***	5.646***	–

Source: authors, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.



Source: authors.

Figure 1. Ecological footprint as a function of human development and green agriculture.

4.5. Discussion

This study examines the effect of green agriculture and human development on the ecological footprint in 31 African countries from 1996 to 2022. Regarding the first hypothesis, the results presented in **Tables 8-11** indicate that green agriculture reduces environmental sustainability by increasing the ecological footprint

(EFPcons and EFPprod). These findings reflect the fact that a heavy reliance on biomass in agriculture reduces biocapacity by hindering the regenerative capacity of natural resources (Samoraj et al., 2024). Hence, our results may reflect an imbalance between the rate of resource extraction for agriculture and the rate of resource regeneration. Moreover, Wang et al. (2023) argue that agricultural production based on biomass could lead to a range of other environmental issues, including the degradation of water quantity and quality, soil and nutrient erosion, deforestation, and land competition. Furthermore, other studies show that green agriculture increases ecological footprints through its impact on greenhouse gas emissions (Boix-Fayos & de Vente, 2023).

The increase in the ecological footprint caused by green agriculture in Africa can be explained by several specific mechanisms related to agricultural practices and particular socio-economic contexts. First, the expansion of agricultural land, often associated with organic farming, leads to significant deforestation, as highlighted by Akhil et al. (2024), who emphasise that the extension of cultivated land for these practices significantly contributes to forest loss in Africa. This phenomenon contrasts with the ecological intensification observed in Europe, where technologies such as precision agriculture help limit deforestation (Anita et al., 2024). Furthermore, extensive irrigation, frequently used in certain forms of green agriculture in Africa, increases water stress, a situation exacerbated by inefficient irrigation practices such as flood irrigation, as pointed out by Bhatt et al. (2024). Moreover, the reliance on organic inputs like manure and compost, although beneficial for soil fertility, can paradoxically increase greenhouse gas emissions, as indicated by Moreno Vargas et al. (2023). Additionally, the lack of mechanisation and the use of traditional farming methods limit agricultural efficiency in Africa, resulting in inefficient land use and increased pressure on local ecosystems (Baum et al., 2003). Finally, although crop diversification can enhance biodiversity, it suffers from low yield optimisation in Africa, leading to inefficient land use (Cotula, 2016). To mitigate these effects, more sustainable agricultural practices, such as optimised agroforestry, more efficient irrigation, and green mechanisation, are proposed as solutions by Binder & Coad (2011).

With regard to African countries, recent statistics reveal a heavy dependence on biomass energy. According to the World Bank (2023), only 19% of households in Sub-Saharan Africa had access to clean fuels and technologies for their agrifood chains in 2021 (6% and 37% in rural and urban areas, respectively). However, the use of traditional cooking methods, such as open fires and inefficient stoves, can lead to high levels of indoor air pollution, increased biomass extraction, and ultimately, a decline in environmental sustainability (Wang et al., 2023). This finding aligns with Moreno Vargas et al. (2023), who report a positive and statistically significant effect of water and renewable energy resources in transitional agricultural systems. Nonetheless, Khedulkar et al. (2024) highlights the need for less environmentally degrading enzymatic and microbiological transformations to ensure green growth in agriculture.

Regarding the ecological impact of human development (Hypothesis 2), the results show that the Human Development Index (HDI) exerts a statistically significant increasing effect on both EFPcons and EFPprod. Assuming all other factors remain unchanged, this suggests that higher levels of human development increase environmental pressure in African countries. This can be explained by the ongoing efforts of African nations to ensure food security, often at an environmental cost. This result is relatively novel in the literature, but existing studies suggest that promoting human development contributes to achieving environmental sustainability.

The increase in the ecological footprint in Sub-Saharan Africa, linked to human development, results from a complex interaction between several factors such as education, income, health, urbanisation, and consumption. Increased access to education, particularly in rural and peri-urban areas, promotes urbanisation and alters lifestyles by encouraging higher consumption of energy and natural resources, as demonstrated by Khedulkar et al. (2024). Additionally, rising income leads to increased demand for consumer goods and energy services, often driven by fossil fuel resources (Mergoni et al., 2024; Samoraj et al., 2024). Improvements in healthcare, while beneficial for life expectancy, also result in greater resource consumption and increased pressure on energy-intensive medical infrastructure (Kao & Chiang, 2001). Furthermore, rapid urbanisation and industrialisation exacerbate the pressure on natural ecosystems, increasing the consumption of non-renewable resources and threatening biodiversity (Shandilya et al., 2024). To address these challenges, strategies such as the integration of environmental education, green innovation, and environmental governance focused on sustainable urbanisation are necessary to balance human development with environmental sustainability (Kindo et al., 2024).

As societies develop, a lack of spatial planning and organisation affects sustainable environmental practices (Javier et al., 2024). This can result in a failure to implement policies and regulations aimed at promoting sustainable resource management, waste transformation, and conservation efforts. Our findings align with those of Arzo & Hong (2024), who advocate for better land-use planning and activity organisation to achieve Sustainable Development Goal 16 in Türkiye by promoting peaceful and inclusive societies for sustainable development.

The analysis of the interaction between green agriculture and human development (Hypothesis 3) provides clear evidence that green agricultural practices can mitigate the negative effects of human development on the ecological footprint. Indeed, the pursuit of human development in situations of food insecurity can exacerbate environmental degradation (Martinez-Baron et al., 2024). However, while not entirely pollution-free, green agriculture pollutes at a decreasing rate compared to traditional agricultural practices (Nguyen-Thi-Kim et al., 2024). These findings support the arguments of Zimek & Baumgartner (2024). who assert that promoting green agricultural practices enhances public awareness of environmental sustainability, thereby increasing pressure on public authorities and fostering community participation in efforts to maintain a cleaner environment.

As human development improves, populations may increasingly adopt technologies that comply with environmental standards (Baker et al., 2024).

Regarding the control variables, the negative effect of globalisation on the ecological footprint is consistent with the findings of Veronika & Martin (2020), who observed that globalisation enhances environmental quality. These results suggest that Africa's increasing interconnectedness and economic integration not only benefit economic development but also contribute to environmental sustainability (Xu et al., 2024). The results further indicate that economic growth has a detrimental effect on environmental sustainability. Holding all else constant, an increase in per capita GDP accelerates environmental pressure (Price, 2000). This finding implies that economic growth in African countries is associated with increased resource extraction, production, and consumption, which, in turn, amplifies the ecological footprint (Anita et al., 2024). Consequently, African nations should complement their growth strategies with sustainable production and consumption practices (Sampene et al., 2024). Finally, the results show that the effect of technology on environmental sustainability is mixed. This outcome suggests that technological advancements lead to an increase in consumption-based EFP, while their effect on production-based EFP is negative and significant (Sustainable Development Solutions Network, 2012; Su et al., 2021). The study of the effects of technologies on environmental sustainability reveals a mixed impact, with technological innovations providing notable benefits while potentially generating unforeseen negative effects. According to Bhatt et al. (2024), agricultural technologies can increase productivity while reducing pressures on ecosystems, but they can also contribute to deforestation, as seen in precision farming, or to the ecological footprint of the materials required for the manufacture of technologies, such as solar panels. Binder & Coad (2011) also highlight that the adoption of sustainable technologies can sometimes lead to the expansion of cultivated land at the expense of forests, thus exacerbating biodiversity loss. Sustainable agricultural intensification technologies, such as precision farming, aim to optimise yields while reducing the resources used, but Khedulkar et al. (2024) note their limited accessibility in developing countries. Regarding renewable energy for irrigation, while it reduces dependence on fossil fuels, Guo & Wang (2023) point to the ecological footprint of solar panels and electronic waste. Furthermore, geographic information systems (GIS) and blockchain, while promising for sustainability, can generate high energy costs, as Shahbaz et al. indicate, emphasising the importance of energy optimisation. Lastly, Sampene et al. (2024) stress the importance of accessibility, inclusivity, and comprehensive life cycle assessment of technologies to ensure their effectiveness. In summary, although technologies offer potential solutions to enhance sustainability, their impact largely depends on the policies and management that accompany them.

5. Conclusion and Implications

This study examines the impact of green agriculture and human development on environmental sustainability. It also explores the moderating effect of green agriculture on the relationship between human development and environmental sustainability. The analysis is based on data from 31 African countries over the period 1996-2022. To account for the heterogeneity of cultural practices that may influence variations in agricultural practices across countries, the baseline estimation was conducted using the dynamic panel estimator for time-invariant variables (Kripfganz & Schwarz, 2019). Robustness was subsequently verified through estimation with instrumental variables and panel quantile regression.

The findings reveal that green agriculture, albeit at a decreasing rate, reduces environmental sustainability due to its relatively destructive impact on the ecological footprint of consumption and production. Furthermore, the results indicate that human development significantly increases the ecological footprint at an accelerating rate, thereby compromising environmental sustainability. The moderation analysis further reveals that green agriculture interacts with human development to reduce environmental pressure. Additionally, globalisation significantly mitigates the ecological footprint, whereas economic growth deteriorates environmental quality. Moreover, the findings suggest that the effect of technology is mixed and depends on the specific measure of the ecological footprint. Finally, the results of the Dumitrescu-Hurlin panel causality test indicate a bidirectional relationship between green agriculture, human development, and the ecological footprint.

The findings of this study carry significant implications for public policy, economic development, and society. From a policy perspective, they call for a reconfiguration of agricultural and environmental strategies in Africa by integrating agroecological practices tailored to local contexts and promoting sustainable economic growth. Economically, the need to invest in agricultural innovation and green technologies emerges as essential for limiting the ecological footprint while fostering financial incentives for a transition towards environmentally friendly agricultural practices. From a societal standpoint, the impact of human development on environmental sustainability highlights the importance of ecological education and more responsible consumption patterns.

Furthermore, achieving a balance between modernisation and the preservation of traditional agricultural knowledge is imperative to ensuring an inclusive and effective transition towards sustainable agriculture while safeguarding food security and reducing inequalities in access to green resources. Enhanced human development may also make citizens more likely to adopt technologies that comply with environmental standards.

Future research should address some of the limitations of this study. The data used may not cover a sufficiently long period or all regions within African countries, potentially introducing biases into the analysis and limiting the generalisability of the findings. External factors such as financial crises, insecurity, and climate change, which could influence the relationships between green agriculture, human development, and environmental sustainability, are not accounted for in this study. By incorporating these additional factors, future studies could provide a more comprehensive and nuanced understanding of the interactive effects of green agriculture and human development on environmental sustainability in Africa.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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