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Energy Poverty, Environmental Degradation and Agricultural Productivity in Sub-Saharan Africa

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Abstract

Agricultural productivity remains pivotal to the sustenance of the economies and livelihoods of Sub-Saharan Africa (SSA) countries. Given the emerging threat of energy and environmental uncertainties globally, this study makes a foray into understanding the link among energy poverty, environmental degradation and agricultural productivity in 35 SSA nations in particular, and the nature of their impacts across the sub-region constituents namely; the Central, Eastern, Western and Southern sub-regional blocs in general. To begin, our identified variables comprised of the following: Energy Poverty Index, derived using the principal component analysis, agricultural value added as a share of GDP served as a measure of agricultural productivity and ecological footprint to represent environmental degradation. Subsequently, the instrumental variable generalized method of moment (IV-GMM) technique was implemented for the aggregate SSA model, while the IV-two stage least square technique was adopted for the sub-regional estimations for the Central, East, West and South African blocs respectively. Major findings from the SSA model revealed that whereas the index of energy poverty has a significant positive influence, ecological footprint exhibited an inverse and significant impact on agricultural productivity, while the Central, East, West and South African models yielded mixed results given regional disparities in economic development, regional variations in agricultural productivity and an imbalance of available resources. Policy recommendations were suggested to, among other things, transform the energy, environmental and agricultural fortunes of the region.

Keywords: Agricultural Productivity, SSA; Energy Poverty, Environmental Degradation, Africa's sub-region

1. Introduction

Agriculture is crucial to human existence and meeting the Sustainable Development Goals (SDGs). This is contingent on the fact that an improved agricultural sector can advance food security, increase revenue generation, and expand employment, all of which are critical for human and economic prosperity (Kwakwa et al. 2022; Muoneke et al. 2022). In Africa, over half of the continent's population is employed in the agricultural sector, which also contributes significantly to the overall gross domestic product in the region (AGRA 2018). More recent efforts to boost the fortunes of the sector comprise the 2003 Maputo Declaration to devote at least 10% of national budgetary spending on agriculture to boost output by at least 6% and improve food security (NEPAD 2003), the Malabo Declaration (2014) to stimulate accelerated agricultural growth and eradicate hunger by 2025 (AGRA 2018). Also, several agricultural intervention programs have been implemented by the African Development Bank (AfDB) namely the Feed Africa component of the "High 5s" agenda, the second Climate Change Action Plan (2016-2020), the Jobs for the Youth in Africa Strategy (2016-2025) and the Strategy for Agricultural Transformation in Africa (2016-2025) (AGRA 2018).

These efforts demonstrate that agricultural development in Africa can be a crucial means of escaping poverty and advancing sustainable economic development (Omoju et al. 2020; Salahuddin et al. 2020; Kwakwa et al. 2022). However, despite these interventions and the sector's importance in realizing the development potential of SSA, agricultural productivity has been experiencing a recent decline. For instance, statistics from the World Bank (2021) show that agricultural productivity decreased from 20.6% in 1991 to 17.2% in 2021. Intriguingly, whilst SSA has seen the largest rate of agricultural output globally since the year 2000, much of the growth has been based on an increase in cultivated area and not productivity gains (USAID 2021). Among other things, the fate of global agricultural productivity is increasingly susceptible to environmental deterioration like climate change, nutrient depletion, and poor soil quality (Salahuddin et al. 2020; Ching et al.2021; Ozdemir 2021). Climate change, primarily caused by carbon dioxide (CO2) emissions has increased pest infestation and decreased agricultural opportunities, irrigation resources, and soil fertility (Malhi et al. 2021). Also, livestock and crop production, input supplies, hydrological balance, and other aspects of the agricultural system are all impacted by changes in the climate and impact food production and distribution (Ching et al 2021).

Regardless of its relativelyminimum contribution to global environmental damage, SSA is the region most at risk from climate change owing to its reliance on rain-fed agriculture (Alhassan et al. 2019; Salahuddin et al. 2020; Dimnwobi et al. 2021; Onuoha et al. 2021). Agriculture is a major income source and economic security for SSA's rural dwellers and rural poor respectively, nonetheless, climate variability poses a significant risk to agriculture and food production in the region. Additionally, although climate change has an impact on all sectors, the agricultural sector is frequently the most exposed (Bessah et al. 2021; Kogo et al. 2021; Zagaria et al. 2021). In 2020, for example, there was widespread flooding in SSA, claiming several lives and destroying properties (WMO 2021). As a result, environmental deterioration has posed a significant danger to agricultural productivity in the region because of its limited capacity to respond effectively. Energy is another critical factor that influences agricultural productivity (Amuakwa-Mensah and Surry 2021; Shi et al 2022). It is estimated that 30% of global energy consumption is linked to agricultural production activity (Karamian et al. 2021). The limited amount of arable land, expanding population, growing food security threats and desire for a better quality of life have all contributed to a rise in agricultural energy use (Nabavi-Pelesaraei et al. 2016).

More worrisome is the fact that SSA countries are experiencing an increase in the population of people without access to electricity and clean cooking technology. For instance, globally, the number of people without electricity access has progressively reduced, from 1680 million in 2000 to 770 million in 2019. During the same period, the number of people in SSA without access to electricity climbed from 506 million to 578 million (IEA 2020). Roughly 905 million people in SSA lack access to modern cooking fuels, with 848 million relying on unclean fuels which have severe health implications to augment their energy needs (IEA 2019). Across the sub-regions in SSA, access to electricity and clean cooking is not homogenous. As per IEA (2020), 24%, 39%, 47%, and 56% of Central Africans, Southern Africans (except South Africa), East Africans, and West Africans respectively had electricity access in 2019. Similarly, 10% of Central Africans, 12% of West Africans, 13% of East Africans, and 17% of Southern Africans (except South Africa) had access to clean cooking in 2018 (IEA 2019). The foregoing shows that the high prevalence of energy poverty (which is defined as the inability to access sustainable modern energy services) in the region hampers sustainable development (Dimnwobi et al. 2022a)

Given the foregoing background information, we examine and provide useful insights to address the following research questions: (1) What is the impact of energy poverty on agricultural productivity in SSA? (2) What is the effect of environmental degradation on agricultural productivity in SSA? (3) Do these impacts differ across SSA sub-regions? In providing answers to these research questions, our paper extends the literature in the following ways. First, it contributes to the literature on sustainable development by providing the implications of energy poverty and environmental degradation on agricultural productivity in SSA. Aside from SSA being the most energy-poor region of the globe, the region is most vulnerable to climate change despite its little contribution to global carbon emissions, while the agricultural productivity of the region has been declining. Second, to avoid the notion that energy poverty, environmental degradation, and agricultural productivity are homogenous across SSA, this study disaggregates the sample into four SSA sub-regions (Central, East, South, and West). In so doing, the study's outcome will be critical not only for comparison but for distinct regional policymaking. Third, unlike past studies that have utilized CO2 emission to proxy environmental degradation, this study utilized the ecological footprint (EF) which is widely recognized as a critical indicator of environmental pollution and sustainability and which captures the direct and indirect consequences of production and consumption activities on the environment (Ullah et al. 2021; Boukhelkhal 2022; Ehigiamusoe et al. 2022). EF calculates the environmental effects of producing goods and services as well as assessing both carbon and non-carbon environmental components. Unlike traditional proxies (such as sulfur, CO2, etc), which only assess a portion of environmental deterioration (air pollution), EF provides a comprehensive measure of the environment. Given that SSA is a primary sector-driven economy and the most vulnerable to climate change, it is imperative to utilize a holistic environmental measurement (EF) as it encompasses many environmental factors such as carbon footprint, built-up land, cropland, grazing land, forestry and fishing ground (Bulut 2020; Arogundade et al. 2022).Fourth, to ascertain a comprehensive impact of energy poverty, this study employed contemporary inclusive energy poverty proxies namely rural electrification, urban electrification, national electricity access, access to modern energy for cooking as well as renewable energy consumption and renewable electricity output. The motivation for considering diverse energy poverty aspects is to investigate the nexus between energy poverty and agricultural productivity using different measures of energy poverty. Fifth, we extend the literature by adopting a robust estimating technique capable of addressing various issues that have previously been overlooked in the literature such as various omission biases and endogeneity problems. Specifically, we applied the instrumental variable generalized method of moment (IV-GMM) because it controls variable omission bias and endogeneity, and generates robust estimates. Lastly, the outcome of this study will offer important insights into the development and execution of national and regional agriculture policies which will assist in repositioning the sector to drive SSA sustainable development attainment.

The remainder of this paper is structured as follows: Section 2 contains a review of pertinent literature. Section 3 describes the data and analytical strategy while section 4 documents the empirical findings. Section 5 summarizes the research findings and presents some policy recommendations.

2. Literature Review

The empirical literature provides more specifics on the prevailing state of research in our study area and is documented in two strands. The first focused on the nexus between environmental degradation and agricultural productivity while the other part is on the implications of energy poverty on agricultural productivity.

2.1. Environmental Degradation and Agricultural Productivity

Employing the dynamic computable general equilibrium (CGE) model on five South Asian economies, Bandara and Cai (2014) showed that agricultural sectors in these economies were anticipated to be negatively impacted by climate change-induced productivity shifts, resulting in food scarcity by 2030. Ehuitché (2015) applied an optimal control and error correction model (ECM) technique to analyze the connection between deforestation and agricultural productivity in Côte d’Ivoire from 1962 to 2010. The study discovered that deforestation has a significant and detrimental impact on agricultural productivity. Chandio et al. (2019) established that CO2 emissions have a favourable impact on Pakistan’s rice production. Using microdata, Rayamajhee et al. (2020) highlighted that rising precipitation levels have a negative influence on Nepal's rice output.

In a related study in Pakistan between 1971 and 2014, Ahsan et al. (2020) employed the autoregressive distributed lag (ARDL) approach and highlighted that CO2 emissions have a beneficial effect on cereal crop productivity. Salahuddin et al. (2020) relied on data from 24 SSA economies between 1984 and 2016 and discovered that environmental pollution has a negative influence on agricultural productivity in the region. In Somalia, Mohamed and Nageye (2020) established that agricultural production is negatively influenced by climate change and land degradation. Eshete et al. (2020) appraised the influence of CO2 emissions on household welfare and agricultural productivity in Ethiopia. Using the CGE, the study showed that CO2 emissions have a negative influence on household well-being and agricultural productivity.

Chandio et al. (2020a) employed ARDL to appraise how China's agricultural output has changed as a result of global climate change between 1982 and 2014 and the study demonstrates that CO2 emissions significantly impact agricultural output. In a comparative study of Turkey between 1968 and 2014, Chandio et al. (2020b) reported that cereal yield is negatively affected by CO2 emission. Likewise, Ahmad et al. (2020) applied ARDL and reported that CO2 emissions have a negative and significant impact on agricultural production in Pakistan. In a related study in China, Pickson et al. (2020) employed ARDL and discovered that cereal production is severely influenced by CO2 emissions. Yuzbashkandi and Khalilian (2020) highlighted that higher precipitation and temperatures are favourable to soybean output in Iran.

Focusing on Somalia between 1985 and 2016, Warsame et al. (2021) conclude there is no significant influence of environmental degradation on crop productivity. Khan et al. (2021) applied the ARDL to unearth the implications of CO2 emissions on China's fruit crop production between 1961 and 2018 and the authors found that fruit crop productivity is negatively influenced by CO2 emission. Studying 53 economies between 1996 and 2017, Ching et al. (2021) appraised the influence of environmental deterioration on food production and conclude that environmental pollution is detrimental to food production. In selected Asian economies between 1980 and 2016, Ozdemir (2021) discovered a negative effect of carbon emissions on agricultural productivity. Chandio et al. (2021) assessed the implications of financial development and climate change on agricultural productivity in selected Asian economies between 1990 and 2016 and the authors established that agricultural production is negatively affected by climate change. In a recent study in Ghana, Kwakwa et al. (2022) revealed that carbon emissions have a detrimental effect on agricultural development. Likewise, in Pakistan, Ramzan et al. (2022) evaluate the impact of agricultural labour, fertilizers, feeds, lands as well as carbon emissions on agricultural productivity between 1961 and 2018. The authors revealed that CO_2 emissions exert a significant strain on agricultural productivity. Analogously, Chopra et al. (2022) highlighted that agricultural productivity is decreased by environmental degradation in ten Asian economies sampled.

2.2. Energy Poverty and Agricultural Productivity

Candelise et al. (2022) appraised the implications of electricity access on food security in 54 developing nations between 2000 and 2014 and discovered that electricity access is critical for food security. Shi et al. (2022) appraised the influence of energy poverty on agricultural technical efficiency in 30 Chinese provinces from 2002 to 2019. The findings show that energy poverty substantially reduced agriculture technical efficiency indicating that energy poverty hurts agricultural productivity. A study by Shuaibu and Nchake (2021) in SSA reported that infrastructure development (measured using the nation's electricity access) is linked with increased agricultural productivity. Amuakwa-Mensah and Surry (2021) assessed the agricultural productivity effects of rural electrification in 43 SSA nations between 1990 and 2016 and the authors conclude that rural electricity stimulates agricultural productivity

Omoju et al. (2020) examined the implications of electricity access on SSA's agricultural productivity between 1980 and 2017. The study established while rural electrification has no significant effect on agricultural productivity, national and urban electricity access stimulates agricultural productivity. Chandio et al. (2018) applied the ARDL to Pakistan's data between 1984 and 2016 and found that electricity consumption stimulates agricultural productivity. Utilizing the three-stage least squares method as well as Colombian microdata, Esteban et al (2018) explored the influence of electricity access on agricultural productivity and quality of life and revealed that electrification boosts agricultural productivity in Colombia

Assunção et al. (2017) utilized Brazil's microdata to unearth the influence of electrification on deforestation and agricultural productivity and the study highlighted among other things that electrification expands crop productivity in Brazil. In selected SSA nations between 1980 and

2013, Ozturk (2017) discovered that energy poverty (measured using electricity access) hampers agricultural sustainability. In a micro investigation of Pakistan, Ali et al. (2016) highlighted that water pumps powered by alternate energy sources (biogas, solar, and diesel) stimulate agricultural production. Using household-level data, Khandker and Koolwal (2010) discovered that electrification had a positive effect on Bangladesh's agricultural prices. The study further confirmed that increased electrification boosts agricultural productivity. Fan et al (2000) reported that rural infrastructure (electricity and roads) promotes agricultural productivity in India

3. Methodology

3.1. Data Description

This study's data comes from 35 SSA countries and spans the years 2005 to 2020. At the execution of this research, data availability was limited by the number of nations in the sample and the frequency of the indicators. The nations studied are contained in Appendix 1. The data was gathered from two major sources namely the World Development Indicators (WDI) database of the World Bank and the Global Footprint Network Database. In alignment with recent agriculture literature (Raifu and Aminu 2019; Omoju et al. 2020; Ozdemir 2021; Kwakwa, et al. 2022), we employed agricultural value added as a share of GDP to measure agricultural productivity. Similarly, following environmental sustainability literature (Dimnwobi et al. 2021; Ullah et al. 2021; Ansari et al. 2022; Ehigiamusoe et al. 2022), we utilized ecological footprint which has been identified as a comprehensive measure of the environment to capture environmental degradation. The study followed recent energy poverty literature (Apergis et al. 2021; Nguyen et al. 2021; Nguyen and Su 2021a; Nguyen and Su 2021b; Dimnwobi et al. 2022b) in employing six dimensions of energy poverty namely rural electrification, urban electrification, national electricity access, access to modern energy for cooking as well as renewable energy consumption and renewable electricity output to capture energy poverty. In line with related studies (Raifu and Aminu, 2019; Omoju et al. 2020; Amuakwa-Mensah and Surry, 2021; Kwakwa et al. 2022) we utilized financial development, labour force participation rate, urbanization, and capital as the control variables. For instance, financial development enables farmers to embrace contemporary agricultural technologies and make investments in agriculture thereby increasing agricultural productivity and improving farmers' livelihoods. It offers farmers financial assistance so they can buy contemporary inputs like high-yielding varieties, fertilizers, agrochemicals, and machinery, all of which considerably increase agricultural production (Chandio et al. 2021; Kwakwa et al. 2022). Rapid urbanization accompanied by extensive vegetation removal for infrastructure construction and the utilization of inefficient consumer goods could harm agricultural production due to CO2 emissions (Malik and Ali 2015). Capital is critical to the agricultural sector and the productivity of the sector is contingent on the quality and amount of capital devoted to the sector (Raifu and Aminu 2019;Amuakwa-Mensah and Surry 2021). Table I contains the data summary.

Table I: Data Summary

Variable	Definition	Data source
Agricultural productivity (AGRPROD)	Agriculture, forestry, and fishing, value added (% of GDP)	World Bank (2021)
Energy poverty 1 (EP1)	Access to electricity (% of population)	World Bank (2021)
Energy poverty 2 (EP2)	Access to electricity, urban (% of urban population)	World Bank (2021)
Energy poverty 3 (EP3)	Access to electricity, rural (% of rural population)	World Bank (2021)
Energy poverty 4 (EP4)	Access to clean fuels and technologies for cooking (% of population)	World Bank (2021)
Energy Poverty 5 (EP5)	Renewable energy consumption (% of total final energy consumption)	World Bank (2021)
Energy poverty 6 (EP6)	Renewable electricity output (% of total electricity output)	World Bank (2021)
Environmental degradation (ENDEG)	Ecological footprint (Gha)	Global Footprint Network Database
Financial development (FD)	Domestic credit to private sector (% of GDP)	World Bank (2021)
Urbanization (URB)	Urban population (% of total population)	World Bank (2021)
Labor force participation rate (LFP)	% of total population ages 15+	World Bank (2021)
Capital (CAP)	Gross capital formation (% of GDP)	World Bank (2021)

Source: Authors Computation

3.2. Model and Justification

A variety of economic agents could be a determining factor in agricultural productivity and these factors include energy poverty, environmental degradation, financial development, urbanization and capital. Building on the past empirical submissions (Amuakwa-Mensah and Surry 2021; Shuaibu and Nchake 2021; Acheampong et al 2022), this study presents an IV-GMM panel model in the form of a baseline model that addresses our first research question:

$$Y_{it} = \alpha_i + \beta X_{it} + \gamma Z_{it} + \delta_{it} + \varepsilon_{it} \quad (1)$$

Where i and t signify countries and years, respectively. Y is the agricultural productivity; X is a vector of our variable of interest, that is Energy poverty, Environmental degradation and Z represents a vector of control variables; δ and ε are country fixed effect and noise effect respectively, and α, β, and γ are parameters to be estimated. To account for energy poverty in our modeling framework, we used access to electricity (% of population), access to electricity, urban (% of urban population), access to electricity, rural (% of rural population), access to clean fuels and technologies for cooking (% of population), renewable energy consumption (% of total final energy consumption) and renewable electricity output (% of total electricity output). An index or composite indicator for energy poverty called EPindex is formed using the principal component using the following formula, thus;

$$EPindex = \sum_{i-1}^{n} w_i FV_i \tag{2}$$

In Eq. (2), FVi is the value of individual indicators of energy poverty at a particular period and wi is the weight of each indicator to the EPindex variation explained by all the variables and is determined using principal component analysis. The EPindex is estimated as a linear combination of the six variables proxy for energy poverty using the individual contributions of the variables (energy poverty) to the standardized variance of PC 1 as the weights (wi). The control variables (Z) were selected taking into account financial development, urbanization, labor force participation rate (LFP), and gross capital formation. The parameters estimates and their respective a priori expectation are, $\beta < 0$ and $\gamma > 0$. Details of the variables are captured in Table I. Treading on the path of the second objective (the effect of environmental degradation on agricultural productivity in SSA) and third research objective which account for the impacts of energy poverty and environmental degradation on agricultural productivity which may differ across the regions in SSA, by grouping the sample into sub-sample as thus: Central Africa, East Africa, West Africa, and South Africa

The following stages are discussed as preliminaries, thus: i) We address one of the main econometric challenges in cross-country by examining the Pesaran (2004) cross-sectional dependence (CSD) in panel data set. This examination is vital because of the deep interconnection between the countries. ii) We further ascertain the statistical properties of the data series, leading to the adoption of the cross-sectional augmented Dickey-Fuller (CADF) tests orchestrated by Pesaran (2007). This technique is scholarly credited for accounting for heterogeneity and assumes cross-sectional dependence.

The motivation behind IV-GMM is as follows: it is superior to ordinary least-squares robust in the presence of endogeneity, omitted variable(s) bias, and autocorrelation (Dzator et al. 2021). It is efficient where the number of cross-sectional units is higher than the number of time periods (N>T) Accordingly, the instrumental variable generalized method of moment (IVGMM) technique can handle variable omission bias, gives consistent estimates, and produces efficient outcomes in the presence of unknown heteroscedasticity in comparison to its orthogonality requirement (Baum et al., 2002). The reliability and validation of this method are estimated in a single step (Cameron & Trivedi, 2005). Diagnostic tests such as Kleibergen–Paap F-statistics and Hansen J are accounted for to confirm instruments' authenticity and model reliability.

4. Presentation of results

Table II documents the descriptive statistics and correlation analysis. From Table II, the result shows that the average agrprod, epindex, endeg, labour and capital are 19.274, 8.2409, 1.4485, 67.845, and 23.931 with 12.876, 1.9227, 0.6792, 11.060 and 9.838 as their corresponding standard deviations in the full sample. At regional levels, we noticed that the highest average value of agrprod is 28.498 (Eastern Africa), followed by 25.760 (West Africa) and 14.239 (Central Africa with 9.913 for Southern Africa as the least mean value. The correlation analysis presented under each descriptive result reveals that all the explanatory variables except labur have inverse linkage with agrprod in the full sample. A similar result was observed in Eastern, Southern, and Western Africa respectively, whereas FD and labour have positive correlations with agrprod in Central Africa.

Table II. Descriptive Statistics

	AGRPROD	EPINDEX	ENDEG	LABOUR	CAPITAL	FD	URB
FULL SAMPLE							
Mean	19.274	8.2409	1.4485	67.8455	23.9310	22.7473	40.673
SD	12.876	1.9227	0.6792	11.0605	9.83811	24.3248	16.950
MIN	0.8931	-4.7394	0.4832	44.2981	1.5254	1.2001	9.3753
MAX	60.611	3.6911	3.8211	88.3500	79.400	142.422	90.090
agrprod	1.0000						
epindex	-0.7000	1.0000					
Endeg	-0.6183	0.6781	1.0000				
Labour	0.4622	-0.5921	-0.5715	1.0000			
Capital	-0.1953	0.1392	0.0811	-0.0377	1.0000		
Fd	-0.3579	0.5404	0.4027	-0.2437	0.0951	1.0000	
Urb	-0.5521	0.5847	0.4174	-0.5030	0.1703	0.1229	1.0000
Central Africa							
Mean	14.2391	-0.1932	1.4452	64.931	25.088	9.358	58.7883
SD	11.8162	2.1972	0.5931	9.9111	12.894	4.266	16.5583
MIN	0.8932	-4.5811	0.7402	48.204	4.5704	1.200	37.4801
MAX	41.850	2.7751	2.9003	82.831	79.400	19.190	90.0902
agrprod	1.0000						
epindex	-0.8144	1.0000					
Endeg	-0.6584	0.7165	1.0000				
Labour	0.6751	-0.5629	-0.7337	1.0000			
Capital	-0.4414	0.3728	0.1658	-0.1938	1.0000		
Fd	0.0191	0.2222	0.2046	-0.0798	-0.0962	1.0000	
Urb	-0.7918	0.8651	0.6991	-0.7711	0.3939	0.3197	1.0000
East Africa							
Mean	28.498	-1.4332	0.972	79.008	23.945	17.672	20.381
SD	7.2242	1.5602	0.221	5.6660	8.211	6.4866	6.230
MIN	16.255	-4.7393	0.600	66.810	8.810	7.4256	9.375
MAX	45.883	1.5213	1.490	88.350	41.018	36.700	35.227
agrprod	1.0000						
epindex	-0.3262	1.0000					
Endeg	-0.1479	0.1685	1.0000				
Labour	0.3661	-0.2284	-0.3132	1.0000			
Capital	-0.1652	0.3676	0.5439	0.1275	1.0000		
Fd	-0.3547	0.3058	-0.0999	-0.4404	-0.3915	1.0000	
Urb	-0.5528	0.6179	0.5598	-0.0928	0.6703	-0.0592	1.0000
Southern Africa							
Mean	9.9132	0.7653	1.8000	68.3294	23.889	36.6953	41.505
SD	8.3232	1.8433	0.9491	12.2811	10.260	36.2733	13.718
MIN	1.8004	-2.9593	0.4832	48.9441	1.5255	3.8612	21.829
MAX	30.763	3.6913	3.8200	86.9400	60.060	142.422	67.354
agrprod	1.0000						
epindex	-0.7992	1.0000					
Endeg	-0.7258	0.8399	1.0000				
Labour	0.6435	-0.7681	-0.8405	1.0000			
Capital	-0.1011	-0.1629	-0.0818	0.0361	1.0000		
Fd	-0.6255	0.7412	0.6486	-0.5654	0.0811	1.0000	
Urb	-0.5126	0.4472	0.2824	-0.1017	0.2031	0.5362	1.0000
West Africa							

	AGRPROD	EPINDEX	ENDEG	LABOUR	CAPITAL	FD	URB
Mean	25.760	0.1126	1.3673	63.2761	23.384	19.194	41.000
SD	12.158	1.5796	0.3033	8.1800	8.3454	14.185	11.836
MIN	4.6301	-3.4995	0.9004	44.2981	9.1126	2.6603	16.208
MAX	60.611	3.0933	2.1204	79.5201	52.6701	73.190	66.652
agrprod	1.0000						
epindex	-0.7861	1.0000					
Endeg	-0.3005	0.3373	1.0000				
Labour	0.4256	-0.4413	0.4398	1.0000			
Capital	-0.5164	0.4053	0.4323	-0.1434	1.0000		
Fd	-0.6005	0.6828	0.2021	-0.2907	0.5079	1.0000	
Urb	-0.4934	0.6741	0.0544	-0.5184	0.0471	0.4405	1.0000

Source: Authors Computation

According to Dong et al. (2018), testing for cross-sectional independence in dynamic panels where the number of cross-sectional units is higher than the number of time periods (N>T) is important to avoid inefficient and misleading estimates. Table III shows evidence of cross-sectional dependency, therefore we reject the null hypothesis of no cross-sectional dependence and implement IV-GMM that is capable of handling cases of heterogeneity among data series.

Table III: Cross-sectional dependency

	Full Sample		Central Africa		Eastern Africa		Southern Africa		Western Africa	
Variables	CD-test	p-value	CD-test	p-value	CD-test	p-value	CD-test	p-value	CD-test	p-value
agrprod	7.4971	0.0000	0.8462	0.3981	-0.3462	0.729	5.5476	0.0000	0.0674	0.9472
epindex	60.2861	0.0000	4.7584	0.0000	13.5862	0.0000	16.6864	0.0000	24.0710	0.0000
Endeg	5.2842	0.0000	0.1015	0.9191	4.1166	0.0000	4.6534	0.0000	0.1424	0.8872
Labour	44.1363	0.0000	8.2932	0.0000	6.5862	0.0000	5.1481	0.0000	25.0524	0.0000
Capital	6.2643	0.0000	1.7818	0.0754	3.6883	0.0000	2.2047	0.0000	6.7657	0.5062
Fd	33.9544	0.0000	12.9348	0.0000	-1.7013	0.0894	4.9057	0.0000	18.1811	0.0000
Urb	66.0312	0.0000	15.1678	0.0000	14.6841	0.0000	5.2348	0.0000	30.9474	0.0000

Source: Authors Computation

Table IV: IV GMM RESULTS FOR THE FULL AGGREGATE SAMPLE (DEPENDENT VARIABLE: LNAGRPROD)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
LnENDEG	-3.8379***	-3.5110***	-3.2807***	-3.6730***	-2.527***	-3.8690***	-3.5398***
	[0.3882]	[0.2645]	[0.2294]	[0.2666]	[0.2131]	[0.4160]	[0.2609]
lnCapital	-0.1943*	-0.19014	-0.1957**	-0.2015*	-0.1915**	-0.2076*	-0.2670***
	[0.1134]	[0.1061]	[0.0995]	[0.1084]	[0.0857]	[0.1171]	[0.1018]
Lnalabour	-2.3163***	-2.2252***	- 2.2052***	-2.1119***	-1.8266***	-2.3878***	-2.0193***
	[0.4908]	[0.4371]	[0.4079]	[0.4568]	(0.3090)	[0.5149]	[0.4231]
lnFD	0.1646**	0.1978***	0.2202***	0.1530***	0.2535***	0.1908***	0.1511**
	[0.0718]	[0.0641]	[0.0599]	[0.0683]	[0.0517]	[0.0719]	[0.0613]
lnURB	-0.4148	-0.4069***	-0.3098**	-0.3110**	-0.0776	-0.3484**	-0.2850**
	[0.1501]	[0.1440]	[0.1226]	[0.1309]	[0.1022]	[0.1437]	[0.1225]
EPINDEX	0.0528**						
	[0.0264]						
lnEP1		0.1694					
		[0.1106]					
lnEP2			-0.0661				
			[0.1424]				
lnEP3				0.1548***			
				[0.0461]			
lnEP4					-0.1904***		
					[0.0286]		
lnEP5						-0.3435**	
						[0.1582]	
lnEP6							-0.2168***
							[0.0330]
Constant	6.5413***	6.0190**	6.1625***	5.8538***	5.0135***	7.1595***	6.1953***
	[1.0133]	[0.8556]	[0.8191]	[0.8879]	[0.6171]	[1.2571]	[0.8677]
OBS	525	525	525	525	525	525	525
R2	0.844	0.8643	0.8778	0.8568	0.9209	0.8433	0.8744
HJS	0.5400	0.5620	1.0450	0.5320	2.9310	1.0140	3.0720
P(HJS)	0.7634	0.7549	0.5936	0.7665	0.2315	0.6024	0.2152
KPLM	71.0422	83.4162	88.3354	80.2344	82.1281	54.7911	84.8377
P(KPLM)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
KPWF	40.3791	71.9321	88.5133	73.2367	73.4334	34.8044	90.8851

Source: Authors Computation

Note: Robust standard errors in parentheses. (HJS) represents the Hansen J-statistics of over-identification; p(HJS) is the p-value for Hansen J-statistics of over-identification; (KPLM) stands for the Kleibergen-Paaprk Lagrange Multiplier of under-identification; p(KPLM) is the p-value of Kleibergen-Paaprk Lagrange Multiplier of under-identification; (KPWF) represents Kleibergen-Paaprk Wald F-statistic of robust weak instrument test. The p-value for the Hansen J-statistics [p(HJS)] suggests that instruments are not over-identified; The p-value for Kleibergen-Paap Lagrange Multiplier test [p(KPLM)] also suggests the instruments are not under-identified and the Kleibergen-Paap Wald F-statistics [(KPWF)] show that the instruments are not weak. These post-estimation results suggest that the instruments are valid and reliable. *p <0.10, **p <0.05, ***p <0.01.

Table IV contains the two-step system GMM results for the full sample of Sub-Sahara Africa. From the results in Table IV, model 1 gives the baseline output with energy poverty index computed via principal component analysis while models 2-7 include disaggregated energy poverty starting from energy poverty 1 to 6 respectively. The findings reveal that the index of energy poverty has a significant positive influence on agricultural productivity at a 5% level of significance. The estimated coefficient of the energy poverty index is 0.0528 indicating that a 1% rise in the energy poverty index (epindex) is associated with a 0.053 increase in agricultural productivity. This could be due to the slow implementation of Sustainable Development Goals (SDGs) Goal 7, which aims for sustainable development that includes sustainable agricultural productivity by making access to electricity a reality by 2030. However, this finding cannot be generalized in the case of SSA, considering the uneven development in the region. Thus, we further explored the various components of energy poverty (disaggregated energy poverty variables) and their respective impact on agricultural productivity. The results of the disaggregated energy poverty variables in models 2 to 7 indicate that rural electrification (EP3) exerts a positive and significant effect on agricultural productivity. This outcome is unsurprising given that as more rural communities gain access to electricity, it supplements current factor inputs and boosts labor productivity. Our outcome aligns with Amuakwa-Mensah and Surry (2021) while disagreeing with the initial submissions of Omoju et al. (2020). Access to clean fuels (EP4), RE consumption (EP5), and RE output (EP6) exert a significant negative effect on agricultural productivity in SSA. The negative effect of these variables on agricultural productivity in SSA may be linked to inefficiency and huge costs of clean fuels, renewable production, and consumption in SSA. The study further revealed that national electricity access (EP1) and urban electrification (EP2) have no significant influence on agricultural productivity in SSA. This outcome aligns with Ozturk (2017). This unexpected outcome could be attributed to the fact that most electricity access at the national and urban level in SSA is channeled to other real sectors of the economy in SSA because the agricultural sector in the region is not mechanized and involves physical drudgery

The result also shows that environmental degradation (ENDEG) proxied by ecological footprint exhibit an inverse and significant impact on agricultural productivity in all the models. This implies that the rise in pollution via environmental degradation hampers the productivity of the agricultural sector in SSA. This outcome is plausible given that the agricultural sector in the region has depended on rainfall over the years. Howbeit, the growing effects of climate change and global warming have resulted in unpredictable rainfall patterns, unusually high temperatures, and flooding in many areas of the region, which have a severe influence on agricultural activity.

This outcome aligns with previous submissions of Mohamed and Nageye (2020); Ahmad et al. (2020) and Kwakwa et al. (2022)

Regarding the control variables, capital, labour and urbanization have a negative and significant influence on agricultural productivity except for capital in model two which was not significant. This implies that a rise in capital, labour, and urbanization reduces the productivity of the agricultural sector in the SSA. The significance of labour in the growth process cannot be overstated as it is prominent in the classic growth model. However, the negative effect of labour obtained by our study could be contingent on the fact that youths in the region are not getting engaged in agricultural-related activities. Our outcome on capital disagrees with an economic theory that suggests that pushing more capital to the agricultural sector would promote investment activity and increase the sector output. This outcome is unsurprising given the level of insecurity in most nations of SSA which will result in a drop in capital investment. Given the agricultural sector output in the regions and the security challenges facing the nations in SSA, the meagre capital will be channeled to productive sectors as well as security. The outcome of our study on labour disagrees with the earlier submissions of Omoju et al. (2020) and Kwakwa et al. (2022) while the outcome on capital agrees with Omoju et al. (2020). On the other hand, agricultural productivity is reduced by urbanization. This is not surprising given that rapid urbanization accompanied by extensive vegetation removal for infrastructure construction and the utilization of inefficient consumer goods harm agricultural production due to $CO2$ emissions. This outcome aligns with Malik and Ali (2015) and Kwakwa et al. (2022).

The coefficient of financial development (FD) on the other hand, indicates that a rise in FD enhances agricultural productivity. Financial development enables farmers to embrace financing options in the financial system to afford contemporary agricultural technologies and make investments in agriculture thereby increasing agricultural productivity and improving farmers' livelihoods. It offers farmers financial assistance so they can buy up-to-date inputs like high-yielding varieties, fertilizers, agrochemicals, and machinery, all of which considerably increase agricultural production. Our outcome aligns with Raifu and Aminu (2019) and Kwakwa et al. (2022)

4.2. Sub-regional analysis

Table V: IV (2SLS) ESTIMATION FPR SUB-SAMPLE CENTRAL AFRICA (DEPENDENT VARIABLE-LNAGRPROD)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
LnENDEG	-2.3352***	-2.5368***	-2.4883***	-2.6876***	-2.4946***	-0.2131**	-2.9115***
	[0.4663]	[0.4235]	[0.3827]	[0.2442]	[0.3487]	[0.1063]	[0.6014]
lnCapital	-0.3308**	-0.2593	-0.3145**	-0.4306***	-0.3413**	-0.3533***	-0.4156**
	[0.1573]	[0.1663]	[0.1661]	[0.1085]	[0.1664]	[0.0490]	[0.1998]
lnLabour	-1.8175	-3.0738**	-2.2636**	-5.9470***	-1.9267**	-0.0535	-2.4412***
	[1.1086]	[1.2118]	[0.9824]	[0.7400]	[0.8951]	[0.2346]	[0.9266]
lnFD	0.7539***	0.8210***	0.7907***	0.9079***	0.7545***	0.4516***	0.8696***
	[0.1561]	[0.1481]	[0.1479]	[0.0967]	[0.1547]	[0.0451]	[0.1773]
lnURB	-1.6061**	-3.3878***	-2.0402***	-5.5087***	-1.4049***	0.2621***	-1.8574***
	[0.8467]	[0.1202]	[0.7386]	[0.4524]	[1.0739]	[0.1473]	[0.5352]
EPINDEX	-0.01635						
	[0.0391]						
lnEP1		0.4289					
		[0.3210]					
lnEP2			0.0675				
			[0.2801]				
lnEP3				0.6891***			
				[0.0735]			
lnEP4					-0.0652		
					[0.1262]		
lnEP5						0.5249***	
						[0.0254]	
lnEP6							-0.1991
							[0.1877]
Constant	7.0761**	11.6743***	8.4889***	20.8711***	7.0243***	4.1856***	9.0782***
	[3.2089]	[3.446]	[2.3941]	[1.952]	[2.894]	[0.587]	[2.262]
OBS	90	90	90	90	90	90	90
R2	0.9408	0.9368	0.9362	0.9724	0.9362	0.994	0.9242
HJS	2.0222	10.7192	2.7866	16.7295	1.8155	16.4584	1.9226
P(HJS)	0.3641	0.0047	0.2483	0.0002	0.4035	0.0003	0.3825
ACLS	39.2493	47.5781	49.9114	67.2247	54.0555	67.3191	34.2061
P(ACLS)	0.0000	0.0000	0.0000	0.000	0.0000	0.0000	0.0000
CDWF	20.8811	30.2822	33.6159	79.6900	40.6042	80.1411	16.5532

Source: Authors Computation

Note: Robust standard errors in parentheses. (HJS) represents the Hansen J-statistics of over-identification; p(HJS) is the p-value for Hansen J-statistics of over-identification; (ACLS) stands for the Anderson canon. corr. LM statistic of under-identification; p(ACLS) is the p-value of Anderson canon. corr. LM statistic of under-identification; (CDWF) represents Cragg-Donald Wald F statistic of robust weak instrument test. *p <0.10, **p <0.05, ***p <0.01.

To further broaden the understanding of the subject matter, the study conducted additional analyses based on geographical groupings of nations within the SSA region. Except for North Africa, which is part of the Arab League, SSA accounts for four of Africa's five regions namely Central Africa, Southern Africa, Western Africa and Eastern Africa. The study utilized 6 countries from Central Africa, 6 countries from East Africa, 11 nations from Southern Africa and 12 nations from West Africa. In the sub-samples, we implemented the two-stage least squares technique which is robust when external instruments are weak, and use to discover structural parameters in regression models with endogenous regressors (Lewbel 2012). Lewbel (2012) two-stage least squares approach creates heteroskedasticity-based instruments from the auxiliary equation residuals multiplied by each exogenous variable in mean-centered form. Lewbel (2012) claims that the two-stage least squares estimator does not rely on usual exclusion limits and delivers similar estimates to external instruments. Table V reports the two-stage least square output for the Central African region. The result indicates that the energy poverty index as shown in model 1, has no significant impact on agricultural productivity. However, we observed that on individual effects, rural electrification (EP3) and RE consumption (EP5) enhance agricultural productivity in the sub-region. This means that a rise in EP3 and EP5 increases agricultural productivity in the Central African region. Other energy poverty measures have no significant influence on agricultural productivity. The observation of EP3 is in line with the findings of Amuakwa-Mensah and Surry (2021) who found that rural electricity stimulates agricultural productivity, but contradicts the outcome of Omoju et al. (2020). For the case of the relationship between environmental degradation and agricultural productivity in Central Africa, we observed that ENDEG significantly hampers agricultural productivity in the region as indicated by all the models. This implies that a rise in ecological footprint will significantly reduce the productivity of agriculture in the region. This finding corresponds to the findings of Ozdemir (2021); Chandio et al. (2021); Ramzan et al. (2022) and Chopra et al. (2022). Again, capital, labour, and urbanization exert negative and significant influence on agricultural productivity except for capital in model two and labour in models 1 and 6 which were not significant. This implies that a rise in capital, labour, and urbanization reduces the productivity of the agricultural sector in the Central African region. The coefficient of financial development (FD) also shows that a rise in FD enhances agricultural productivity.

Table VI: IV (2SLS) ESTIMATION FPR SUB-SAMPLE EAST AFRICA (DEPENDENT VARIABLE - LNAGRPROD)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
LnENDEG	1.2822***	1.4208***	1.1166***	1.4833***	0.6245***	0.5691**	0.6107***
	[0.2391]	[0.2711]	[0.1863]	[0.3273]	[0.1983]	[0.2344]	[0.1790]
lnCapital	-0.2594**	-0.2923**	-0.2284***	-0.2419**	-0.1047	-0.0243	-0.1139
	[0.1051]	[0.1140]	[0.0870]	[0.1259]	[0.0869]	[0.0865]	[0.0851]
Lnlabour	2.2108***	2.5132***	1.7892***	2.7238***	1.2558***	1.3226***	1.8261***
	[0.4161]	[0.4691]	[0.3260]	[0.5760]	[0.3560]	[0.3341]	[0.3480]
lnFD	-0.3003***	0.2684***	0.2808***	0.1795**	0.2875***	0.0784	0.2085***
	[0.0754]	[0.0764]	[0.0628]	[0.0830]	[0.0840]	[0.1180]	[0.0646]
lnURB	-0.1013***	-1.2572***	-0.76814***	-1.1449***	-0.7882***	-0.5675***	-0.4791***
	[0.1321]	[0.1621]	[0.0861]	[0.1735]	[0.0948]	[0.1688]	[0.0980]
EPINDEX	0.0531***						
	[0.0096]						
lnEP1		0.3175***					
		[0.0601]					
lnEP2			0.5637***				
			[0.0781]				
lnEP3				0.1153***			
				[0.0281]			
lnEP4					0.0661***		
					[0.0231]		
lnEP5						0.422	
						[0.6490]	
lnEP6							0.2065]***
							[0.0521]
Constant	-0.5062	-1.352*	-1.2937 **	-1.758***	0.5781	-1.0108	-1.3584**
	[0.6941]	[0.7761]	[0.6221]	[0.9321]	[0.6998]	[1.5578]	[0.6851]
OBS	90	90	90	90	90	90	90
R2	0.9971	0.9969	0.9979	0.262	0.9977	0.9975	0.9978
HJS	10.9471	11.5622	9.0246	11.9121	27.2778	33.0221	30.9191
P(HJS)	0.0042	0.0031	0.0111	0.0026	0.0000	0.0000	0.0000
ACLS	24.257	22.462	28.288	18.999	25.601	26.586	28.307
P(ACLS)	0.0000	0.000	0.0000	0.0000	0.0000	0.0000	0.0000
CDWF	9.9621	8.9811	12.3770	7.2250	10.7340	11.3191	12.3894

Source: Authors Computation

Note: Robust standard errors in parentheses. (HJS) represents the Hansen J-statistics of over-identification; p(HJS) is the p-value for Hansen J-statistics of over-identification; (ACLS) stands for the Anderson canon. corr. LM statistic of under-identification; p(ACLS) is the p-value of Anderson canon. corr. LM statistic of under-identification; (CDWF) represents Cragg-Donald Wald F statistic of robust weak instrument test. *p <0.10, **p <0.05, ***p <0.01.

Table VI presents the IV two-stage least square output for the Eastern African region. The result reveals that the energy poverty index as shown in model 1, exerts a positive and significant influence on agricultural productivity in the sub-region. Individually, all energy poverty indicator exhibits a positive and significant impact on productivity except EP5 (RE consumption) which was positive but insignificant. This means that a rise in energy poverty irrespective of the indicator boosts agricultural output. These findings tally with the findings of Amuakwa-Mensah and Surry (2021) and Chandio et al. (2018). For the case of the relationship between environmental degradation and agricultural productivity in East Africa, we noticed that ENDEG and labour significantly stimulate agricultural productivity in the region as shown in all the models. This implies that a rise in ecological footprint and labour will significantly increase the productivity of agriculture in the region. On the other hand, capital, and urbanization have a negative and significant influence on agricultural productivity. Financial development except for model 1 where the energy poverty index was used, exerts a positive and significant influence on agricultural productivity in the region.

Table VII: IV (2SLS) ESTIMATION FPR SUB-SAMPLE SOUTHERN AFRICA (DEPENDENT VARIABLE-LNAGRPROD)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lnENDEG	-0.4351	-3.4391**	-3.9532**	2.8794**	0.2465	-3.8272**	-2.4292***
	[2.0744]	[1.5700]	[1.7582]	[1.4240]	[0.6032]	[1.7961]	[0.8171]
lnCapital	-0.3392***	-0.4312**	-0.4124*	-0.4267**	-0.2294**	-0.3235*	-0.2836**
	[0.0800]	[0.2010]	[0.2252]	[0.1711]	[0.0951]	[0.1751]	[0.1333]
lnlabour	-0.0919	4.8488	-5.6685	-4.2686	1.1419	-3.2211	-2.2523
	[2.8281]	[3.1461]	[3.6282]	[2.7697]	[1.2770]	[2.3829]	[1.4777]
lnFD	0.1259	0.3537	0.3737	0.2994	-0.1306	-0.2331	0.2039
	[0.1211]	[0.2151]	[0.2438]	[0.1946]	[0.0964]	[0.2099]	[0.1392]
lnURB	-0.4176***	-0.1665	-0.12913	-0.2958	-0.5451***	-0.9869***	-0.6587***
	[0.1471]	[0.3980]	[0.4615]	[0.3631]	[0.1862]	[0.2977]	[0.2199]
EPINDEX	-0.1273						
	[0.1141]						
lnEP1		-0.1353					
		[0.2590]					
lnEP2			0.1644				
			[0.4820]				
lnEP3				-0.13479*			
				[0.0720]			
lnEP4					-0.3746***		
					[0.040]		
lnEP5						-1.4221	
						[0.9162]	
lnEP6							0.0651
							[0.068]
Constant	2.1461	10.938**	11.898**	9.9881**	0.5941	12.1221*	6.6699**
	[5.2433]	[5.3811]	[6.0104]	[4.7654]	[2.2243]	[6.716]6	[2.9211]
OBS	165	165	165	165	165	165	165
R2	0.9593	0.8353	0.7899	0.8792	0.9582	0.8546	0.9041
HJS	2.5531	0.1433	0.1823	0.2532	5.3442	2.2292	3.5361
P(HJS)	0.2791	0.9323	0.9129	0.8811	0.0691	0.3281	0.1707
ACLS	0.7771	4.6761	4.7921	4.1898	7.9859	5.7672	12.7241
P(ACLS)	0.8551	0.1971	0.1877	0.2471	0.0463	0.1235	0.0053
CDWF	0.2461	13.9111	1.5554	1.3555	2.6444	1.8836	4.3458

Source: Authors Computation

Note: Robust standard errors in parentheses. (HJS) represents the Hansen J-statistics of over-identification; p(HJS) is the p-value for Hansen J-statistics of over-identification; (ACLS) stands for the Anderson canon. corr. LM statistic of under-identification; p(ACLS) is the p-value of Anderson canon. corr. LM statistic of under-identification; (CDWF) represents Cragg-Donald Wald F statistic of robust weak instrument test. *p <0.10, **p <0.05, ***p <0.01.

Table VII is the IV two-stage least square output for the Southern African region. The outcome shows that the energy poverty index in model 1, has a negative but insignificant effect on agricultural productivity in the Southern African region. On disaggregated level, rural electrification (EP3) and access to clean fuels (EP4) are detrimental to agricultural productivity in the sub-region as the coefficients of both variables signs are negative and significant. However, national electricity access (EP1), urban electrification (EP2), RE consumption (EP5), and RE output (EP6) could not exert any significant influence on reducing agricultural output in the region. The outcome is in tandem with the findings of Ozturk (2017) who discovered that electricity access hampers agricultural sustainability in SSA.

Table VIII: IV (2SLS) ESTIMATION FOR SUB-SAMPLE WEST AFRICA (DEPENDENT VARIABLE-LNAGRPROD)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lnENDEG	-3.3142	-4.6170***	-2.9068***	-4.4787***	-1.6913***	-3.6796***	-2.2206***
	[2.1681]	[1.4371]	[0.6697]	[1.2697]	[0.5219]	[0.8792]	[0.3449]
lnCapital	0.4857	0.8148*	0.3801	8.2014**	0.0492	.48657**	0.19742
	[0.5876]	[0.4366]	[0.2359]	[0.4069]	[0.1871]	[0.2427]	[0.1522]
Lnlabour	4.5499*	6.2565***	4.0686***	5.9513***	2.3360***	4.8317***	3.2792***
	[2.7255]	[1.8524]	[0.8893]	[1.5921]	[0.7064]	[1.0436]	[0.4797]
lnFD	-0.3044	-0.3733***	-0.2644***	-0.3582***	0.0593	-0.3135***	-0.1883***
	[0.207]	[0.117]	[0.074]	[0.113]	[0.0701]	[0.0951]	[0.0571]
lnURB	0.3228	-0.0929	0.2795	-0.4682*	0.1512	0.3368*	0.0661
	[0.2687]	[0.2567]	[0.1800]	[0.2735]	[0.1491]	[0.2035]	[0.1479]
EPINDEX	0.0296						
	[0.0786]						
lnEP1		0.7238**					
		[0.3732]					
lnEP2			0.2551				
			[0.2661]				
lnEP3				0.1838*			
				[0.1021]			
lnEP4					0.1260***		
					[0.0366]		
lnEP5						0.4158	
						[0.2971]	
lnEP6							0.0537**
							[0.0218]
Constant	-7.2063	-10.9321***	-6.6985***	-10.3951***	-2.7738*	-6.9318***	4.4639***
	[5.5311]	[4.0989]	[2.3420]	[3.5618]	[1.5970]	[1.8937]	[1.1478]
OBS	180	180	180	180	180	180	180
R2	0.9774	0.9647	0.9811	0.9646	0.9898	0.9738	0.9863
HJS	7.9541	5.4154	9.7835	4.3935	11.4835	3.9157	10.4699
P(HJS)	0.0187	0.0665	0.0075	0.1112	0.0032	0.1412	0.0053
ACLS	3.1331	10.9242	24.5323	12.7855	20.6488	20.0581	55.7531
P(ACLS)	0.3715	0.0121	0	0.0051	0.0001	0.0002	0
CDWF	1.0111	3.6831	8.9945	4.3565	7.3866	7.1488	25.5781

Note: Robust standard errors in parentheses. (HJS) represents the Hansen J-statistics of over-identification; p(HJS) is the p-value for Hansen J-statistics of over-identification; (ACLS) stands for the Anderson canon. corr. LM statistic of under-identification; p(ACLS) is the p-value of Anderson canon. corr. LM statistic of under-identification; (CDWF) represents Cragg-Donald Wald F statistic of robust weak instrument test. *p <0.10, **p <0.05, ***p <0.01.

The association between environmental degradation and agricultural productivity in Southern Africa reveals a mixed result depending on the energy poverty mixture used in the model. For instance, in model 1, ENDEG has a positive but insignificant linkage with agricultural productivity. More so, capital and urbanization exert a negative and significant impact on agricultural productivity except for models 2, 3, and 4 where urbanization's coefficients are not significant. The result further indicates that financial development and labour did not contribute to agricultural productivity in the sub-region as their coefficients are not statistically insignificant.

Table VIII shows the IV 2SLS results for the Western African region. The estimated coefficient on the energy poverty index is positive but insignificant. This finding is related to the fact that access to energy is limited in West Africa, which makes it hard to achieve most of the SDGs. For example, several households in West Africa still use traditional fuels. This is because they do not have access to modern services. Another reason is that many people in this area live below the poverty line and do not have access to modern energy services. Instead, they rely on traditional energy sources like biomass because they cannot afford modern energy services. In this area, the cost of energy is higher than what people can afford, so they spend a larger portion of their income on energy. The output of the disaggregated energy poverty variables indicates that rural electrification (EP3), access to clean fuels (EP4), RE consumption (EP5), and RE output (EP6) have positive relationships with agricultural productivity but only national electricity access (EP1), rural electrification (EP3), access to clean fuels (EP4), and RE output (EP6) exert a significant impact on agricultural productivity in the Western African region. The result also indicates that environmental degradation (ENDEG) exhibits an inverse and significant impact on agricultural productivity in all the models except for the energy poverty index model. This implies that the rise in pollution via environmental degradation hampers the productivity of the agricultural sector in West Africa. The findings also align with the outcomes of Rayamajhee et al. (2020); Ehuitché (2015); Salahuddin et al. (2020); Nageye (2020); and Chandio et al. (2021). Capital has a positive association with agricultural productivity but was only significant in models 2, 4, and 6, while labour exerts a positive and significant impact on agricultural productivity in all the models. This implies that a rise in labour is essential for agricultural growth in the region. The coefficient of financial development (FD) on the other hand indicates that a rise in FD deteriorates agricultural productivity significantly in the region except for model 1 where the energy poverty index was incorporated. In addition, urbanization has a negative and significant impact on agricultural productivity in model 4 (rural electrification - EP3), while it exhibits a positive and significant influence on agricultural productivity in model 6 (RE Consumption - EP5 model).

4.3. Robust Check Using CO2 Emission on Full Sample

Table IX reports the robust check using the CO2 in place of ecological footprint with full sample size. The diagnostic tests are reported under the table are robust. Kleibergen-Paaprk LM statistic, Cragg-Donald Wald F statistic, and Kleibergen-Paaprk Wald F statistic measures the weak instrument with critical values ranges from 5.39 - 22.30, indicating that our research output above is free from an invalid instrument problem. Under the null hypothesis that our model is under-identified, the stock –Wright LM test depicts that the coefficient on the change in the independent is equal to zero, and over-identifying restrictions are valid across the model specifications. In addition, theHansen J statistic validates the instruments employed in the estimation. The R-squared, which captures the changes in the endogenous variable predicted by the independent variables, varies between 0.695 - 0.744. That is, between 69.5% to 74.4% of the changes in the agricultural productivity are collectively explained by independent variables. Furthermore, the coefficients are similar to the estimates obtained in the Table IV. For instance, environmental pollution proxied by carbon emission per capita has a negative significant influence on agricultural productivity. The energy poverty index has a positive significant influence on agricultural productivity. The various indicators of energy poverty have a diverse influence on agricultural productivity. For instance, except EP1 which has a significant positive influence on agricultural productivity, other components of energy poverty exert a significant negative effect on agricultural productivity in SSA.

Table IX: Robust check based on full sample size

Variables	1	2	3	4	5	6	7
Lnco2	-1.0251***	-0.9551***	-0.9070***	-0.8817***	-0.7187***	-0.7301***	-0.7973***
	(0.0450)	(0.0340)	(0.0300)	(0.0310)	(0.0401)	(0.0401)	(0.0310)
	[-22.6711]	[-28.3191]	[-30.2396]	[-28.6346]	[-17.9631]	[-18.2971]	[-25.3448]
Lncapital	-0.2951***	-0.2622***	-0.2691***	-0.2947***	-0.2609***	-0.2731***	-0.2872***
	(0.0511)	(0.0500)	(0.0490)	(0.0500)	(0.0570)	(0.0520)	(0.0561)
	[-5.7572]	[-5.1931]	[-5.4481]	[-5.834]	[-4.5721]	[-5.2093]	[-5.139]2
Lnlabour	-0.1871	-0.1942	-0.4041***	-0.1862	-0.545***	-0.5373***	-0.4814***
	(0.1444)	(0.1413)	(0.1371)	(0.1382)	(0.1251)	(0.126)	(0.1336)
	[-1.2975]	[-1.3743]	[-2.9622]	[-1.3492]	[-4.3641]	[-4.2673]	[-3.6251]
LnFD	0.0131	0.0524**	0.0696***	0.0541**	0.1631***	0.1583***	0.1290***
	(0.0292)	(0.0264)	(0.0234)	(0.0273)	(0.0294)	(0.0270)	(0.0270)
	[0.4551]	[1.9734]	[2.9384]	[2.0231]	[5.6937]	[5.9172]	[4.8450]
LnURN	-0.4561***	-0.2194***	-0.5223***	-0.5311***	-0.4748***	-0.4223***	-0.464***
	(0.0741)	(0.0752)	(0.0673)	(0.0696)	(0.0722)	(0.0743)	(0.0745)
	[6.1974]	[2.9302]	[7.7782]	[7.6652]	[6.5461]	[5.7336]	[6.2946]
LnEPINDEX	0.1064***						
	(0.0113)						
	[9.3475]						
LnEP1		0.6500***					
		(0.0510)					
		[12.6900]					
LnEP2			-0.9690***				
			(0.0816)				
			[11.9236]				
LnEP3				-0.1842***			
				(0.0200)			
				[9.2730]			
LnEP4					-0.0740***		
					(0.0260)		
					[-2.8070]		
LnEP5						-0.1375***	
						(0.0422)	
						[3.2452]	
LnEP6							-0.0354**
							(0.0160)
							[-2.1320]
Constant	0.7111**	0.0411	-0.8206**	0.4186	1.3058***	1.0849***	1.2340***
	(0.2761)	(0.2910)	(0.3238)	(0.2728)	(0.2463)	(0.2788)	(0.2546)
	[2.5721]	[0.141]	[-2.5372]	[1.5396]	[5.3086]	[3.9016]	[4.8576]
Observations	525	525	525	525	525	525	525
R-squared	0.6951	0.7281	0.7445	0.7250	0.7286	0.7232	0.7063
Diagnostic Test							
Kleibergen-Paaprk LM statistic	5.9431	5.9935	6.0436	6.0937	6.1434	6.1933	6.2430
P-val	0.1132	0.1111	0.1076	0.1046	0.10114	0.0983	0.1950
Cragg-Donald Wald F statistic	357.111	315.2193	273.3287	231.4371	189.5460	147.6559	105.7641
Kleibergen-Paaprk Wald F statistic	171.3411	152.9556	134.577	116.1859	97.822	79.4151	61.0380
Hansen J statistic	1.5000	1.3649	1.2281	1.0921	0.9563	0.8222	0.6848
P-val	0.2271	0.2429	0.2588	0.2747	0.2906	0.3065	0.3224

Sources: Authors compilation. Robust standard errors in ( ); t-statisics in [ ]; *** p<0.01, ** p<0.05, * p<0.1

5. Summary and Policy Direction

Agricultural productivity remains pivotal to the sustenance of the livelihoods of SSA economies. Given the established relevance of the sector, this study makes a foray into understanding the link among energy poverty, environmental degradation, and agricultural productivity in SSA in particular, and the nature of their impacts across the sub-region constituents namely; the central, eastern, western and southern sub-regional blocs. To achieve this, data from 35 SSA countries spanning from 2005 to 2020 was gathered from two major sources namely the World Development Indicators (WDI) database of the World Bank and the Global Footprint Network Database. Resultantly, our results showed evidence of cross-sectional dependency, prompting the rejection of the null hypothesis of no cross-sectional dependence. Accordingly, the instrumental variable generalized method of moment (IV-GMM) technique was implemented given its superiority over the ordinary least-squares which is plagued by distortion issues in the presence of endogeneity, omitted variable(s) bias, and autocorrelation. For the sub-regional estimations, the IV two-stage least square technique was adopted because its capability to deal with endogeneity.

The IV GMM results for the full aggregate sampleof Sub-Sahara Africa revealed that the index of energy poverty has a significant positive influence on agricultural productivity, while the disaggregated energy poverty models indicate that rural electrification (EP3) exerts a positive and significant effect on agricultural productivity, access to clean fuels (EP4), RE consumption (EP5), and RE output (EP6) exert a significant negative effect on agricultural productivity in SSA. The study further revealed that national electricity access (EP1) and urban electrification (EP2) have no significant influence on agricultural productivity in SSA.

The key policy implications emanating from each of the adopted measures of energy poverty provide interesting insights. According to the outcome of rural electrification (EP3), increased availability to electricity among rural population may encourage a rise in agricultural output, while national electricity access (EP1) and urban electrification (EP2) show no significant influence. The increase in agricultural productivity brought about by rural electrification demonstrates the complementing role of electrification in boosting the effectiveness of ongoing rural agricultural activities. As a result, prolonged efforts to energize rural areas with little access to electricity will improve agricultural yield. Our research also suggests that increasing access to electricity at the national level (EP1) and urban electrification (EP2) may be insufficient to increase agricultural output in SSA. Therefore, regional authorities in SSA should strengthen existing initiatives to intervene in the energy infrastructure in order to increase access to electricity that facilitates the whole value chain of agriculture in both urban and rural areas. Findings on access to clean fuels (EP4) indicate a negative impact on the agricultural sector, highlighting the need for coordinated measures to help rural communities in SSA obtain electricity from cleaner energy sources to support the expansion of agricultural production. Additionally, agricultural productivity in SSA is worsened by RE output (EP6) and RE consumption (EP5) as revealed by our findings, both of which have negative consequences. Given the vast amount of renewable resources for energy in SSA, coordinated regional efforts should be increased to enable each SSA bloc to utilize its own RE resources. Agricultural sector stakeholders in the region would better embrace renewable energy (RE) by engaging in more value-added agricultural processes which will ultimately increase RE output. Therefore, encouraging the use of renewable energy will help the agriculture industry grow increasingly competitive while emitting less pollution and aiding in the fight against global warming.

The result also shows that environmental degradation (ENDEG) proxied by ecological footprint exhibit an inverse and significant impact on agricultural productivity in all the models. Regarding the control variables, capital, labour and urbanization have a negative and significant influence on agricultural productivity except for capital in model two which was not significant. The coefficient of financial development (FD) on the other hand, indicates that a rise in FD enhances agricultural productivity.

For the sub-regional analysis, the findings of the IV two-stage least square output for Central Africa, East Africa, West Africa, and South Africa proved mixed results, this could be as a result of the complex nature economic activity and development in SSA. Climate change and energy poverty are lowering agriculture productivity globally, and without urgent corrective measures, the problem is predicted to get worse as an emerging energy crisis and global average temperatures escalate in the near future. Therefore, to prevent an agricultural emergency in the coming years, policymakers in SSA must move swiftly to tackle the issue of environmental degradation and energy poverty. Hence, from our study findings, the following policy directions are put forward, to combat the negative consequences of environmental destruction on agricultural productivity in the SSA region, more sophisticated agricultural practices that do not harm the land or emit CO2 will have to be encouraged. So far, digital technologies are helping farmers increase agricultural output and productivity because they enable the collection and analysis of massive volumes of en vironment-related data, enabling precision farming and efficiency. Also, a process-based strategy , comprised of a system of agro ecology initiatives is needed in the region to address climate change while maintaining agricultural productivity. This approach is considered to possess the greatest potential to reduce GHG emissions from agricultural practices and assist in developing a gainful and amenable agriculture framework. To decrease environmental effects on agriculture in the region, policymakers should support an eco-friendly system of agricultural management, improve access to organic and environmentally conscious agriculture production, expand forest cover to improve carbon absorption, and support renewable energy sources. Stakeholders (including farmers) that contribute to environmental deterioration should be subjected to a carbon tax and strict environmental rules and regulations across all sub-regions in SSA. Strong environmental legislative and regulatory systems must be emphasized with a focus on the agricultural industry especially. Expectedly, different environmental regulations are in place across the SSA region, but they are either not well enforced or do not have the requisite regulation and legal discipline to guarantee that the sector's operations are environmentally beneficial. Ther efore, good conceptualization, administration, and enforcement are crucial in this regard to foster favourable outcomes for agricultural productivity and bolster the chances of meeting the Paris climate accord. In this situation, farmers should be subjected to guidelines for ethical behaviour and helpful guidance on agricultural practices that are less detrimental to the environment. Consequently, agricultural activity-related air pollution would be reduced, and a decrease in atmospheric pollutants within the agriculture industry will consequently lead to an improvement in agricultural output.

Improvements in energy supply for agricultural activities have profited developed nations, but not so much for developing nations. A key aspect of agricultural progress in recent history came through "energizing" the agricultural production chain, which is a key component in attaining food security. From our findings, a deeper understanding of the agricultural sector's energy needs is necessary to ensure the sustainability of agricultural performance, particularly in SSA and among its subgroups. However, given their various energy endowments and other unique characteristics, domestic economic, ecological, and social concerns should serve as a guide for energy challenges and solutions for agricultural productivity in SSA. As a result, when developing policies and taking action to combat energy poverty in SSA, consideration should be given to country-specific needs as well as national energy policy measures. Although energy poverty is widespread throughout SSA, the severity of it varies considerably across the sub-region, which partially reflects the uneven economic and social advancement of these blocs. Specifically, regional governments should increase economic subsidies or undertake investments to deliberately encourage the improvement of existing energy infrastructure and supplies. While efforts should be made to implement a coordinated regional energy policy taking a cue from the Africa Renewable Energy Initiative (AREI), to pay more attention to renewable energy options to provide clean energy services for agriculture across the region in accordance with Goal 7 of the SDGs. Additionally, to increase economically viable output and reduce environmental degradation, the use of machinery and processes in the agricultural sector must be more energy-efficient. The determined adoption and general implementation of the African Union's energy efficiency policy will be a good place to start.

To address regional disparities in economic development and prevent the issue of economic underdevelopment, energy poverty, and environmental degradation from worsening into a problem of regional agricultural underperformance, SSA countries should generally intensify regional coordinated development. Particularly, large regional variations in agricultural productivity point to an imbalance of available resources. Overall, macroeconomic policies should prioritize energy and environmental concerns to adequately ensure financial development that deepens funding of energy projects and eco-friendly agribusiness, healthy and sustainable urbanization as well as rural energy provision and infrastructure, agricultural land acquisition and financing, improving capital availability and accessibility to enlarge the agricultural value chain and productivity. This will usher in favourable outcomes in the labour force participation rate and employment within the agricultural sector and beyond toward a prosperous and self-sufficient Africa we want ahead of agenda 2063.

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Appendix 1: List of Countries

Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Congo Dem. Rep, Congo Rep, Cote d'Ivoire, Equatorial Guinea, Eswatini, Ethiopia, Gabon, Ghana, Guinea, Kenya, Lesotho, Madagascar, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Tanzania, Togo, Uganda, Zambia, Zimbabwe