African Journal of
Agricultural and Resource Economics
Volume 20, Number 1 (2025), pp 44–70

Effects of climate change and agricultural productivity on poverty outcomes in Africa: A system GMM perspective

Chizoba G Okeke*
Department of Economics, Coal City University, Enugu, Nigeria. E-mail: gideon.okeke@ccu.edu.ng

Jonathan E Ogbuabor
Department of Economics, University of Nigeria, Nsukka, Nigeria. E-mail: jonathan.ogbuabor@unn.edu.ng

* Corresponding author

Received: January 2025
Published: March 2025

DOI: https://doi.org/10.53936/afjare.2025.20(1).4

Abstract

Climate change presents one of the most pressing challenges of the present time, with far-reaching implications for global economies and human socioeconomic well-being. Africa, in particular, remains susceptible to its effects. This study investigates the effects of climate change and agricultural productivity on selected poverty outcomes and the moderating role of governance institutions in these relationships *in Africa, using panel data of 36 African countries spanning a period of 20 years (2001 to 2020) and the system generalised method of moments (GMM) estimation framework. The findings indicate that climate change and agricultural productivity have a significant impact on poverty outcomes across Africa. Furthermore, the findings indicate that the continent's institutions for governance are not significantly improving the impact of climate change and agricultural productivity on poverty in Africa. This can be attributed to the prevalence of weak institutions in Africa, and their inability to effectively exploit the potential of the continent's institutions to their fullest. Based on the findings, the study makes some valid policy recommendations for African policy makers and heads of government.*

Key words: climate change, agricultural productivity, poverty, food security, system GMM, Africa

1. Introduction

Climate change poses one of the most pressing challenges in human history, with far-reaching consequence for global economies and human socioeconomic well-being. Among the most vulnerable to the impacts of climate change is Africa, where a significant portion of the population depends on agriculture for their livelihoods (Calderon *et al*. 2021; Salahuddin *et al*. 2023). The continent faces numerous challenges, which are exacerbated by climate change and poor agricultural productivity, including food insecurity, water scarcity and increased frequency of extreme weather events, all which put a strain on institutions. These challenges, in turn, have profound implications for poverty outcomes in the region. Taking cognisance of how these issues threaten global economies, global leaders came up with sets of 17 goals, widely known as the sustainable development goals (SDGs), with a deadline for achieving them fixed at 2030. Of these, goals 1, 13 and 16 focused on ending poverty in all its forms, ensuring concerted climate action and building effective, accountable and inclusive institutions respectively (United Nations 2015; World Bank 2018; Okeke & Amaechi 2021; Rana *et al*. 2023).

Agriculture is the backbone of many African economies, employing a large proportion of the population and contributing significantly to GDP. However, the sector is highly sensitive to climate variations, making it particularly vulnerable to the impacts of climate change (Singh *et al*. 2021; Zenebe *et al*. 2022). Changes in temperature and precipitation patterns, shifts in growing seasons, and the increased frequency and intensity of extreme weather events such as droughts and floods all pose significant threats to agricultural productivity in Africa (Food and Agricultural Organization [FAO] 2020). In addition to its direct impacts on agriculture, climate change can also have broader socio-economic effects that further exacerbate poverty. For example, increased frequency and intensity of extreme weather events can lead to a loss of infrastructure, displacement of populations, and the disruption of livelihoods, all of which can contribute to heightened poverty levels. Moreover, the impacts of climate change are not distributed evenly, with marginalised communities often bearing the brunt of its effects due to limited adaptive capacity and lack of access to resources and support systems (Kool *et al*. 2017; Traore *et al*. 2020).

Poverty remains one of the most pressing challenges facing Africa, with profound implications for the continent's development trajectory. Despite significant economic growth and progress, millions of Africans continue to live in poverty, struggling to meet their basic needs and access basic essential services. According to a World Bank 2021 report, over 400 million people in sub-Saharan Africa live on less than the international poverty line, which is $1.90. This represents more than 40% of the region's population (World Bank 2021). Furthermore, the COVID-19 pandemic exacerbated poverty levels, pushing an additional 27 million people into extreme poverty in Africa in 2020 alone (World Bank 2021). Compared to other countries of the world, African countries still rank very low across various poverty indicators, as shown in Table 1.

Table 1: Trends in poverty indicators across selected countries

Countries	Nigeria	South Africa	Germany	United States	Brazil	China
People living in slums	48.98	24.2	-	-	14.89	-
% people using basic sanitation	46.57	77.63	99.22	99.63	90.88	95.89
% people using basic drinking water	79.63	94.49	99.99	99.96	99.59	97.64
Children out of school	-	12.27	1.46	4.09	5.22	-
Households' consumption expenditure per capita growth	-	1.61	3.17	2.14	3.82	0.27
Multidimensional poverty headcount ratio (%)	39.7	21.7	0.2	0.6	6.1	-
HDI ranking	162	105	7	21	84	74

Note: Countries included in this table were selected because they recorded the highest nominal GDP in their respective regions in 2023. That is, Nigeria and South Africa for Africa, and Germany, the United States, Brazil and China are included because they recorded the highest nominal GDP in Europe, North America, South America and Asia respectively. - denotes data is not available.
Source: Authors, with data from the World Development Indicators (World Bank 2024) and the United Nations Development Programme ([UNDP] 2024)

Since the mid-1990s, Africa has witnessed relatively fast development – at a rate of 5% on average. However, Africa's growth rate has not been followed by a major decline in poverty. This is evident in Figure 1, which shows the poverty headcount ratio at $2.15 a day. While the figure depicts a downward trend in population, the rate of poverty reduction compared to Europe, Central Asia, Latin America and the USA is abysmally slow.

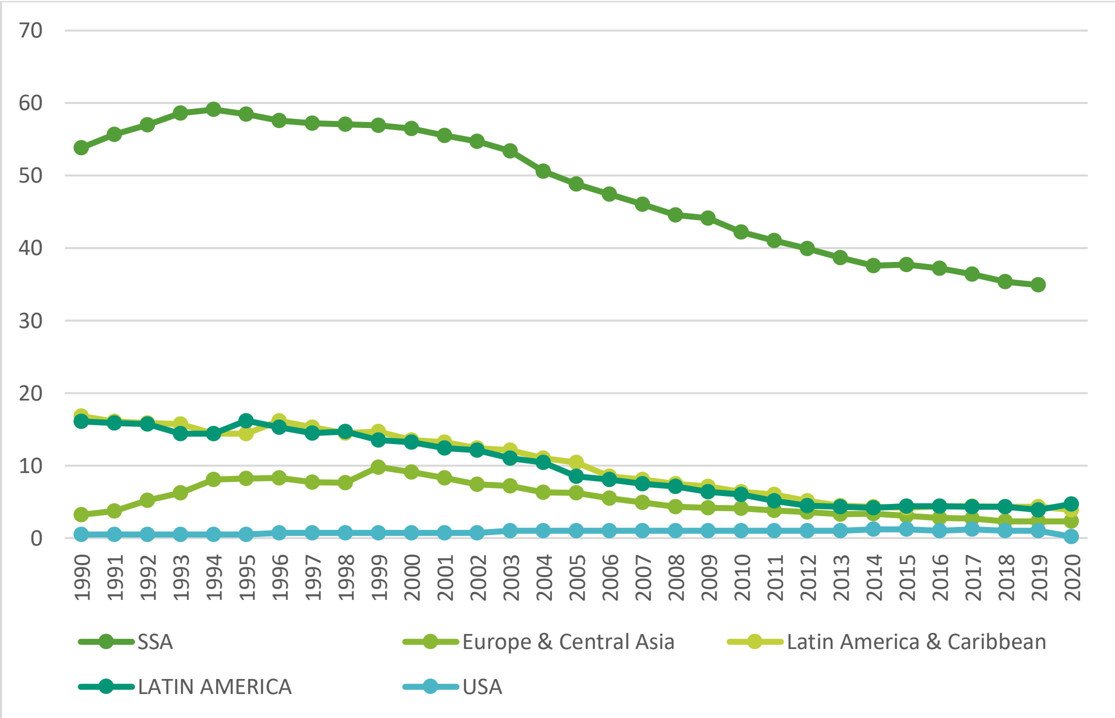

Figure 1: Trends in number of people living on less than $2.15 a day
Source: World Bank (2024)

Poverty levels in the region have remained relatively high (Kouadio & Gakpa 2022). The West African region has undergone substantial economic growth during the past 20 years. Coulibaly (2019) observed that six of Africa's 10 fastest-growing economies were in West Africa However, the outcomes of this exceptional economic expansion have benefitted only a few people in most countries. Regional inequality has reached high proportions in the region, as the wealthiest 1% of West Africans account for almost the entire sub-region's wealth (Lawson *et al*. 2019). While development statistics show tremendous progress, income disparity persists, and the disadvantaged population is increasing rapidly. West Africa has the biggest poor population in Africa, accounting for 30% of the total population. Poverty rates in Africa have decreased slightly since the 1990s, while the absolute number of impoverished people has increased (World Bank 2018).

Development and poverty reduction in Africa is mainly dependent on smallholder agriculture, and increases in the sector come from traditional inputs such as land, labour and livestock (Aweke *et al*. 2021; Djoumessi 2021). This has been identified as one of the major impediments to agricultural productivity on the continent, as the sector continues to perform below expectations when compared to other continents. For example, between 1990 and 2020, cereal yield increased by just 40% in Africa, but it increased four times more in East Asia, while increasing by about 69% in Chile, 81% in Brazil and over 164% in Latin America as a whole (Djoumessi 2021). While the average yield of cereals per hectare in the USA and Canada are above 10 tons per hectare, for countries in Africa the average is two tons (Matchaya *et al*. 2022).

While agriculture and its allied sectors contributed the least to global economic output, the marginal growth for the agricultural sector in Africa also declined between 2018 and 2019. For example, the level of crop yield for cereal – a staple in Africa – showed that the continent was lagging behind, in particular when considering its rapidly growing population.

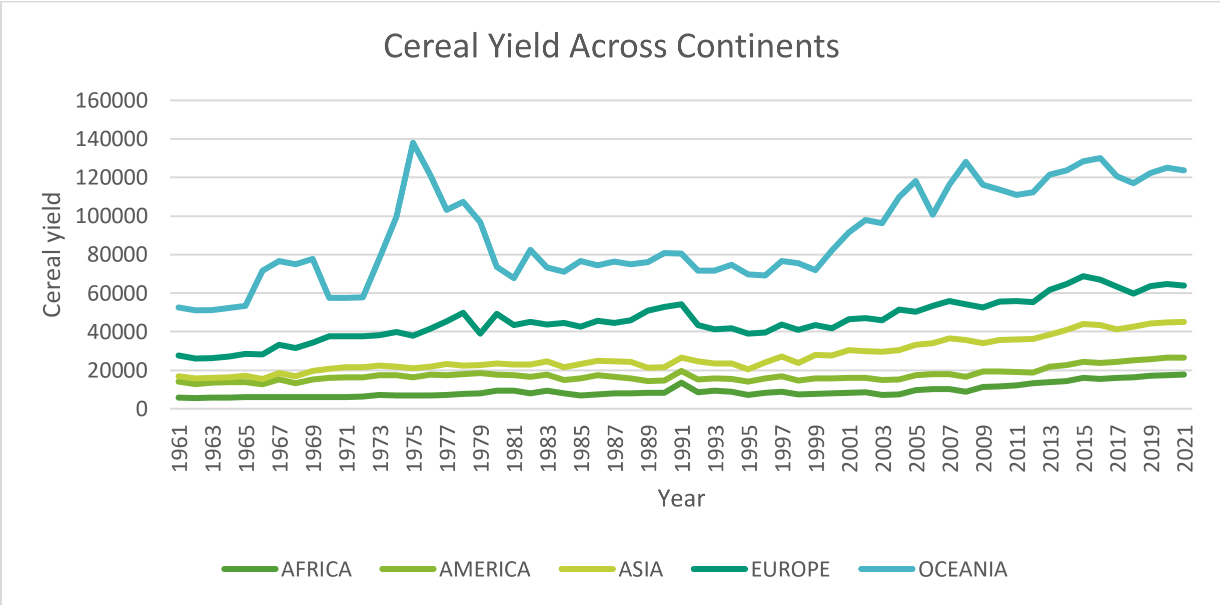

Figure 2: Trends in cereal yield across continents
Source: Food and Agricultural Organization (2023)

Furthermore, the quality of institutions in Africa significantly influences poverty dynamics across the continent. The nexus between institutional quality, climate change, agricultural productivity and poverty is intricate and consequential. Institutional deficiencies exacerbate the impacts of climate change on agriculture, consequently affecting poverty levels.

Institutional deficiencies, including weak governance structures, corruption and the inadequate rule of law, contribute to the persistence of poverty and hinder inclusive development (Kaufmann *et al*. 2011; Acemoglu & Robinson 2012; World Bank 2020). Inadequate institutional frameworks hinder effective responses to climate change in Africa, amplifying its adverse effects on agricultural productivity (Deressa *et al*. 2009; Intergovernmental Panel on Climate Change [IPCC] 2014). Weak governance, corruption and a lack of policy coherence impede the implementation of climate adaptation and mitigation strategies, leaving agricultural systems vulnerable to climate variability and extreme weather events. Furthermore, institutional failures in land tenure systems and resource management exacerbate land degradation and deforestation, undermining agricultural productivity and exacerbating poverty (World Bank 2016).

Against this background, this study investigates the effects of climate change and agricultural productivity on poverty outcomes in Africa. To guide the study we formulated four specific objectives: (i) to examine the effect of climate change on selected poverty outcomes in Africa, (ii) to determine the effect of agricultural productivity on selected poverty outcomes in Africa, (iii) to ascertain how institutional quality is moderating the effects of climate change and agricultural productivity on selected poverty outcomes in Africa, and (iv) determine the nature of causal relationship between climate change, agricultural productivity and poverty outcomes in Africa. We used data for 36 African countries covering a period of 20 years (2001 to 2020). The number of countries and time period were adopted based on the availability of data. The system generalised method of moments (GMM) estimator was adopted to avoid the problem of endogeneity that is usually associated with the ordinary least squares (OLS) estimator. The findings of our study show a significant positive relationship between climate change and the various poverty outcomes proxied by the number of people living in slums (without access to improved water, sanitation, sufficient living area, housing durability and affordability, and security of tenure) and infant mortality rate in Africa. This implies that, as climate change worsens, poverty outcomes also worsen. Also, the study found that, as agricultural productivity improves, food and poverty outcomes also improve. Furthermore, it also found a good causal relationship among the variables of interest. Interestingly, the findings of the study indicate that institutional quality moderates these effect; however, the effects are not highly significant across all six institutional quality indicators. This can be attributed to the prevalence of weak institutions in Africa and their inability to effectively exploit the continent's infrastructure potential to the fullest. The remainder of this paper is organised as follows: Section 2 offers a comprehensive review of the relevant empirical literature, and Section 3 presents the methodology adopted and data used. The research findings are presented and discussed in Section 4, and the study is concluded with policy recommendations in Section 5.

2. An overview of the literature

Agriculture remains the major contributor to the GDP of most African countries. Agriculture in Africa – though heavily fragmented – contributes significantly to global agricultural productivity. The continent is known for various cash and staple crops, such as rice, wheat, maize, cassava rice, soybean, potato, millet, sorghum, cotton, tea, sugar cane, banana, palms, teff, tobacco, cotton, etc. Tobacco, cotton, cocoa and tea remain the continent's major agricultural exports. The ability of agricultural productivity to link the supply and demand side makes it a major contributor towards economic development (Johnston & Mellor 1961). The agricultural sector provides raw materials to industries, while also serving as a ready market demanding the outputs from the industries.

AfDB-IFAD (2010) evaluated the results of greater agricultural output on outcomes related to food security in certain emerging economies. The study observed low levels of agricultural productivity among African economies compared to their developing counterparts in Asia and Latin America. AfDB-IFAD (2010) further observed that, while the average grain yield per hectare for Africa is two metric tons, for India, China and a developed economy like America, the metric tons of grain per hectare are double, four times more and five times more respectively. In a space of two decades, from 2000 to 2019, the value added generated by the global agricultural sector increased by close to 73%. With its 18% share of the world's farmland area, Africa's value added rose from USD 170 billion to USD 404 billion. However, the number of individuals employed in the agriculture sector decreased throughout this time (FAO 2020). The spending of government on agriculture has been on the increase, as many of the signatories of the Malabo Declaration of 2014 contribute a very large percentage of total government expenditure to agriculture. However, in order to effectively feed the growing population, the FAO (2018) estimates that food yield has to rise by about 50% before the year 2050. Despite these recent strides in agricultural productivity, the region's key agricultural yields continue to be below the global norm, with huge spatial variations across countries on the continent (Adhikari *et al*. 2015).

Djoumessi (2021), using the two-way fixed-effects approach and data covering the 18-year period from 1996 to 2014 in African countries, examined key factors that determine agricultural productivity on the continent. The study discovered a substantial connection between agricultural productivity and the various innovative characteristics (fertiliser constituents, pesticides, irrigations, crop diversification and cost-reducing innovations such as seeding, threshing and harvesting machines) that influence it, while using electricity and access to water as control variables. The study's findings indicate that fertiliser (nitrogen constituent) has a substantial positive effect on agricultural productivity. Furthermore, it also found a significant positive relationship between pesticide usage, irrigation patterns and agricultural productivity in all the countries studied. A point increase in pesticide usage and irrigation patterns will bring about 0.8% and 0.0005% increases in agricultural productivity. Furthermore, crop diversification and the use of various machines (tractors and threshing machines) further showed an extensive association with agricultural productivity, except for the threshing machine, which recorded low or no productivity in some Africa countries.

Sub-Saharan Africa is said to have missed out on this first 'Green Revolution', mainly because of the cost involved, its unreadiness and its lack of an enabling environment for such a novel programme to thrive. In the 1990s, low external input sustainable agriculture (LEISA) and the integrated nutrient management (INM) approaches began to gain more ground because of their combination of organic and mineral fertilisers, and for presenting a platform for farmers to have access to a modest amount of mineral fertiliser (Bado *et al*. 2022). Despite this, the intensity rate of fertiliser use in Africa is only 14.9 kg/ha, compared to a global average of 124 kg/ha and 322 kg/ha for East Asia and the Pacific (FAO 2015).

Using nationally diversified data from 2 160 Burkina Faso households and the conditional recursive mixed process (CMP) regression, Séogo and Zahonogo (2023) investigated the impacts of land property ownership on farm yield. The findings of the research revealed that land rights have a substantial impact on the output of agriculture. Ngango and Hong (2021) found that, in the eastern province of Rwanda, landowners compared to non-landowners enjoyed significantly higher yields and technical efficiency. Their study further observed that the elasticity of farm inputs for landowners was far higher when compared to that of non-landowners. Atwood (1990), Bambio and Bouayad Agha (2018), Asiama *et al*. (2019), Ajefu and Abiona (2020) and Séogo (2022) all found that food and land security are positively correlated, giving rise to productive agricultural investments and rural female empowerment, amongst other benefits.

Using a conditional mixed process (CMP) model and 366 randomly chosen small-scale maize farmers in the Trans-Mara East and Trans-Mara West sub-counties of Kenya's Narok County, Mbudzya (2022) found that not many of the household heads had land. Also, the study showed that the security of land tenure was greatly determined by educational levels, sex, marital status, fertility of the land, and other issues related to land disputes. The study also found that land tenure increases access to credit lines, which in turn leads to higher agricultural productivity (maize), by 2 001.902 kg/ha. However, this relationship in Africa is usually not straightforward, as land administration systems do not usually support agricultural policies because they often are riddled with huge land transaction costs, taxes, litigation, etc. (Singirankabo & Ertsen 2020; Singirankabo *et al*. 2020).

Over time, the role played by quality institutions in improving agricultural output has often been neglected. Fulginiti *et al*. (2004), Bates and Block (2013) and Lin *et al*. (2020) all investigated the role of institutional quality in the agricultural productivity of certain agro-products. Lin et al. (2020) used the structural gravity model to examine the effects of institutions on trade performance between the top 26 coconut-producing and the top 15 coconut-importing economies. This study found that efficiency in governance improves trade in agro-products, while accountability decreases trade in these products.

Infrastructure has also been proven to help improve agricultural productivity where it is available. The unavailability of basic infrastructure, such as electricity, roads, water, etc. has been proven over and again to be a major impediment to increasing agricultural output in Africa. Amuakwa-Mensah and Surry (2022), Ayhan *et al*. (2022) and Dimnwobi *et al*. (2022) have all examined the effect of electricity on agricultural productivity and its ability to improve rural economies. Amuakwa-Mensah and Surry (2022) used fully modified ordinary least squares (FMOLS) and panel data covering 43 Africa countries spanning a period of 26 years (1990 to 2016). Their study discovered a significant positive interaction between productivity in agriculture and electrification in rural areas in the light of quality institutions and strong input factors by the country. These findings are consistent with those of Kyriakarakos *et al*. (2020), who further proposed bridging the cost of rural electrification by the value of increased local products.

A number of researchers (Ogbuabor & Nwosu 2017; Matchaya 2020; Orji *et al*. 2020; Kassouri & Kacou 2022; Appiah-Twumasi *et al*. 2022) all examined how lending affected the productivity of agriculture in Africa. Agricultural finance can come in the form of direct investment in the sector, and as the purchase of input factors such as fertilisers, seedlings and machinery. Over time, studies have shown that productivity in the sector has been greatly affected by the lack of availability of credit. As evident in Abdulai *et al*. (2018), only 7.5% out of a sample of 360 maize farmers selected from the population in Northern Ghana had easy access to finance.

3. Data and methodology

3.1 The data

The thrust of this study is to understand the effects of climate change and agricultural productivity on poverty in Africa, along with the moderating role of institutional quality in this relationship, using a sample of 36 African economies covering a period of 20 years, from 2001 to 2020. Tables 2 and 3 show the list of countries and the variables of interest respectively.

Table 2: List of countries included in the study

S/N	Country	S/N	Country	S/N	Country	S/N	Country
1	Algeria	11	Congo Republic	21	Madagascar	31	Serria Leone
2	Angola	12	Ivory Coast	22	Mali	32	South Africa
3	Benin	13	Egypt	23	Mauritania	33	Sudan
4	Botswana	14	Eswatini	24	Mauritius	34	Tanzania
5	Burkina Faso	15	Ethiopia	25	Morocco	35	Togo
6	CAE	16	Gabon	26	Mozambique	36	Tunisia
7	Cameroun	17	Gambia	27	Namibia		
8	Cape Verde	18	Ghana	28	Nigeria		
9	Chad	19	Kenya	29	Rwanda		
10	Congo Dem. Rep.	20	Lesotho	30	Senegal		

Note: S/N – serial number
Source: Authors' compilation

The scope of the study was subject to data availability. The variables of interest were sourced from the World Bank database (World Development Indicators [WDI]; Worldwide Governance Indicators [WGI]). It was decided to use poverty outcomes variables, such as the number of people living in slums (without access to improved water, sanitation, sufficient living area, housing durability and affordability, and security of tenure) and the infant mortality rate in Africa.

To capture climate change, we adopted variables such as average annual temperature, average annual rainfall and CO_2 emissions, as used in Dube and Nhamo (2020). For agricultural productivity, the study adopted land under cereal cultivation (LUCP) and cereal yield (CRY) as proxies, rather than the use of technology in agriculture. Cereal yield (kg per hectare) was adjudged a better proxy for agricultural productivity in Africa, as it takes into account the per-hectare yield of selected cereals, all of which are staples in Africa. Following Adesete *et al*. (2022) and Affoh *et al*. (2022), the study adopted income proxied by GDP per capita and food price proxied by the consumer price index as control variables and major determinants of poverty in Africa.

Table 3: List of variables included in the study

S/N	Variable name	Symbol	Description/measurement	Unit	Source
	POVERTY VARIABLES				
1	Poverty	POV	(i) Population living in slums (PPLS) is the proportion of the urban population living in slum households. A slum household is defined as a group of individuals living under the same roof lacking one or more of the following conditions: access to improved water, access to improved sanitation, sufficient living area, housing durability, and security of tenure.	Percentage	WDI
			(ii) Infant mortality rate (IMR) is the proportion of newborns that pass away before turning one year old.	Infant deaths (per 1 000 live births)	WDI
	Climate change variables				
2	Climate change	CLC	(i) Average annual temperature (TEMP) (ii) Average annual rainfall (RAF)	Celsius millimetre	Climate Change Knowledge Portal of the WB
			(iii) Carbon dioxide emissions (COE), stemming mainly from the burning of fossil fuels and manufacturing activities.	Metric tons per capita	WDI
	Agricultural productivity variables				
3	Agricultural productivity	AGP	(i) Cereal yield is the amount of cereal yielded (CRY)	Kilograms per hectare	FAO
			(ii) Land under cereal production (LUCP). A region harvested for cereal is referred to as land under cereal cultivation.	Cereal harvested per hectare	WDI
	Control variables				
4	GDP per capita growth (annual %)	GDPPC	GDP per capita is gross domestic product divided by midyear population.	Percentage	WDI
5	Consumer price index	CPI	CPI is changes in the cost to the average consumer of acquiring a basket of goods and services.	Percentage	IMF
6	Institutional quality index	INQ	INQ is a measure of the quality and soundness of a nation's institutional framework.	Index	WGI

Notes: S/N = serial number; WDI = World Development Indicators; WGI = World Governance Indicators; FAO = Food and Agricultural Organization; WB = World Bank.
Source: Authors' compilation

With the exception of the consumer price index and the institutional quality index, all other variables were logged prior to estimation. The institutional quality index (INQ) was generated using six indices of institutional quality, namely control of corruption (COC), government effectiveness (GOE), political stability (POS), regulatory quality (REQ), rule of law (ROL), voice and accountability (VOA) and the principal component analysis (PCA) technique.

Tables 4 and 5 show the descriptive statistics and correlation matrix respectively of the variables used in the study. The variables of interest include climate change, measured by temperature (TEP), rainfall (RAF) and CO_2 emissions (COE); poverty outcomes are proxied by people living in slums (PPLS) and the infant mortality rate (IMR); agricultural productivity is measured by land under cereal cultivation (LUCP) and cereal yield (CRY), and finally the six indices of institutional quality. The results indicate a modest level of standard deviation and variance across all variables, except rainfall, consumer price index, cereal yield and land under cereal production. The mean, maximum and minimum values do not have very big differences between them, indicating the absence of outliers in the data.

Table 4: Descriptive statistics of the variables

Variables[1]	Observations	Mean	Minimum	Maximum	Standard deviation	Skewness
Temp	720	24.2696	11.99	29.75	3.6388	-0.9123
RAF	720	929.6364	10.88	3 061.66	623.0973	0.7041
COE	720	1.1006	0.0162	9.9794	1.6509	3.2076
CPI	720	116.9971	7.3472	3 364.82	142.7546	17.8117
GDPPC	720	1.7179	-36.7777	27.8310	4.4675	-1.2245
CRY	720	1 577.966	0.1	9 453.7	1 462.408	2.9405
LUCP	720	2 476	14	1.9407	3 475 564	2.6462
PPLS	720	53.8043	43.635	67.0416	7.7967	0.2504
IMR	720	54.1826	12.2	136.1	24.6884	0.4458
COC	720	-0.5250	-1.5746	1.2449	0.6091	0.5126
GOE	720	-0.6239	-1.8873	1.1609	0.5948	0.4188
POS	720	-0.5376	-2.6991	1.2010	0.8821	-0.2355
REQ	720	-0.5380	-1.7050	1.1969	0.5489	0.5189
ROL	720	-0.5657	-1.8502	1.0239	0.6051	0.2585
VOA	720	-0.5204	-1.8510	0.9741	0.7144	0.3535

Note: See footnote for explanation for abbreviations, also in relation to other tables.
Source: Authors' computation

Table 4 further shows a negative mean value for all the institutional quality variables (COC, GOE, POS, REQ, ROL, VOA), corroborating the age-long assertion that African economies possess weak institutions. Generally, the descriptive statistics show less sufficient differences among climate change variables due to the number of observations in various samples.

The result shows that, except for the institutional quality variables, which show signs of correlation, the other variables show weak or no correlations in the matrix. This indicates that the variables are free of multicollinearity issues. To test for multicollinearity in the institutional quality model, the variance inflation factor was used to check for the degree of multicollinearity among the variables, which revealed that multicollinearity is not a problem in our model.

3.2 Model specification

This study estimates the connection between climate change, agricultural productivity and selected poverty outcomes in Africa, as well as the moderating role of institutional quality in this relationship using the system generalised method of moments (SGMM) estimator.

[1] Temp = Temperature; RAF = Rainfall; COE = CO_2 emissions; CPI = Consumer price index; GDPPC = Gross domestic product per capita; CRY = Cereal yield; LUCP = Land under cereal cultivation; PPLS = People living in slums; IMR = Infant mortality rate; COC = Control of corruption; GOE = Government effectiveness; POS = Political stability; REQ = Regulatory quality; ROL = Rule of law; VOA = Voice and accountability.

Table 5: Correlation matrix of the variables

	RAF	TEP	COE	IMR	GDPPC	CRY	CPI	LUCP	PPLS	COC	GOE	POS	REQ	ROL	VOA
RAF	1.0														
TEP	0.1	1.0													
COE	-0.2	-0.4	1.0												
IMR	0.3	0.2	-0.4	1.0											
GDPPC	0.004	0.004	-0.06	-0.02	1.0										
CRY	0.08	-0.07	0.41	-0.36	0.03	1.0									
CPI	-0.05	0.07	-0.02	-0.10	-0.15	-0.02	1.0								
LUCP	-0.1	0.17	-0.02	0.19	0.08	0.04	0.19	1.0							
PPLS	-0.02	-0.07	0.0017	0.31	0.20	-0.00	-0.29	-0.07	1.0						
COC	-0.2	-0.43	0.34	-0.49	0.11	0.10	-0.11	-0.29	0.03	1.0					
GOE	-0.2	-0.4	0.52	-0.63	0.14	0.31	-0.13	-0.20	0.08	0.85	1.0				
POS	0.03	-0.2	0.24	-0.32	0.06	0.01	-0.15	-0.51	0.16	0.70	0.67	1.0			
REQ	-0.1	-0.3	0.46	-0.49	0.11	0.28	-0.16	-0.23	0.11	0.81	0.89	0.70	1.0		
ROL	-0.2	-0.3	0.41	-0.61	0.09	0.30	-0.07	-0.24	0.03	0.88	0.91	0.75	0.87	1.0	
VOA	-0.04	-0.1	0.34	-0.25	0.05	0.10	-0.10	-0.15	-0.007	0.66	0.66	0.62	0.70	0.73	1.0

The choice of the SGMM model was inspired by the number of cross-sections (N) and time periods (T) that make up the proposed panel data that were used for the current study. There were a total 36 cross-sections (countries), while the time period used was 20 years (2001 to 2020). There was a functional relationship among the variables to be estimated. The dependent variables are dynamic and depend on their past values. Furthermore, the GMM techniques account for endogeneity, and address heteroscedasticity and autocorrelation within individual cross-sections. The GMM is particularly useful when dealing with models that have endogeneity or when the assumptions of other estimation methods, such as maximum likelihood, are violated. GMM provides a flexible framework for estimating parameters in these cases. Endogeneity in regression occurs when an explanatory variable correlates with the error term, or when two error terms correlate dealing with structural equation modelling. Endogeneity bias can cause errors in estimates, inaccurate inferences, and incorrect conclusions and interpretations. Such bias can occasionally result in coefficients with the wrong sign, magnitude or standard error. Endogeneity bias is corrected by GMM (Ketokivi & McIntosh 2017).

The difference and system GMM estimators are the two main distinct types of GMM estimators, and were developed by Arellano and Bond (1991). Difference GMM exclusively estimates difference equations using the lag of the differenced variables as an instrument. To eliminate individual effects, the first differenced are widely adopted. However, a major flaw of the first differenced GMM is that the lagged values of a variable at level are relatively poor instruments for the variable in its first-differenced form (Arellano & Bover 1995; Blundell & Bond 1998). To address this problem, the system GMM estimator, which uses both lagged levels and differences as instruments, was created. Furthermore, the system GMM estimator possesses superior small sample bias features. The choice of the system GMM estimator for this study was based on the result of the Bond (2002) test for all the models. This test shows whether the system GMM estimator is indeed preferred to the difference GMM estimator in all cases.

Following Adesete *et al*. (2022), we specified the following equation:

$$POV_{i,t} = \varphi_0 + \varphi_1 POV_{i,t-1} + \varphi_2 CLC_{i,t} + \varphi_3 INQ_{i,t} + \varphi_4 CLC * INQ_{i,t} + \sum_{k=1}^{3} \varphi_k Z_{k,i,t} + \pi_i + \xi_t + \varepsilon_{i,t} \quad (1)$$

Still following Adesete *et al*. (2022), we highlight the effect of agricultural productivity on poverty outcomes as follows:

$$POV_{i,t} = \varphi_0 + \varphi_1 POV_{i,t-1} + \varphi_2 AGP_{i,t} + \varphi_3 INQ_{i,t} + \varphi_4 AGP * INQ_{i,t} + \sum_{k=1}^{3} \varphi_k Z_{k,i,t} + \pi_i + \xi_t + \varepsilon_{i,t} \quad (2)$$

POV represents poverty outcomes proxied by people living in slums (PPLS) and infant mortality rate, where φ are parameters to be estimated, while φ_0 is a constant. CLC is climate change proxied by average annual temperature (degrees Celsius), average annual rainfall and CO_2 emissions, as used in Dube and Nhamo (2020). This study adopts average annual temperature (degrees Celsius) and average annual rainfall (millimetres) as proxies for climate change, which is adjudged a better proxy for climate change than the conventional carbon dioxide (CO_2) emissions or other greenhouse gas emissions. This is because, aside from CO_2 emissions, there are other factors that cause changes in the climate, but a change in the average temperature and amount of rainfall are clear consequences of climate variability.

For agricultural productivity (AGP), the study adopted land under cereal cultivation (LUCP) and cereal yield (kg per hectare) as proxies, against the use of technology in agriculture. The food production index has been used in Djoumessi (2021) and many other studies. Cereal yield (kg per hectare) is adjudged a better proxy for agricultural productivity in Africa, as it takes into account the per-hectare yield of selected cereals. Following Adesete *et al*. (2022) and Affoh *et al*. (2022), the study adopted income, proxied by GDP per capita, and food price, proxied by the consumer price index, as control variables and major determinants of poverty in Africa. INQ is the institutional quality index, while $CLC * INQ$ and $AGP * INQ$ are interaction terms. *r* represents tau; Z represents all control variables; π_i is the country-specific impact; ξ_t is the time-specific constant and $\varepsilon_{i,t}$ is the error term. The stochastic error term is assumed to be independently and identically distributed.

The dependent variables are dynamic and depend on their past values. Furthermore, the GMM techniques account for endogeneity, and address heteroscedasticity and autocorrelation within individual cross-sections. The GMM method is particularly useful when dealing with models that have endogeneity or when the assumptions of other estimation methods, such as maximum likelihood, are violated. GMM provides a flexible framework for estimating parameters in such cases. Following Ogbuabor *et al*. (2023), the estimates were tested for serial correlation using the Arellano-Bond second-order (AR2) test and the Hansen test of over-identifying limitations, as suggested by Arellano and Bond (1991) and Hansen (1982).

Furthermore, the study took into account the problems of identification, simultaneity and exclusion restrictions within the framework of the system GMM. Following Asongu and Odhiambo (2020) and Ogbuabor *et al*. (2023) in the underlying model, all explanatory variables are absolutely exogenous, with the exception of the time-invariant indicators, which are all predetermined to be endogenous. This strategy conforms to Roodman (2009), who clarified why it is unlikely that time-invariant variables will become endogenous following the first difference. On the other hand, the difference in Hansen test (DHT) is utilised to evaluate the exogeneity of the instrument and determine the statistical reliability of the exclusion restriction. The DHT null hypothesis should not be rejected in order for the exclusion restriction hypothesis to be valid. The results of this study demonstrate that our exclusion restrictions are validated.

4. Empirical results

4.1 Bonds test and cross-sectional dependence test

The main objective of this study was to investigate the effects of climate change and agricultural productivity on poverty in Africa, as well as the moderating role of institutional quality using the system generalised method of moments (SGMM) estimator. We conducted the Bonds test to help decide on the choice of system GMM, and the cross-sectional dependence test as proposed by Friedman (1937), Frees (1995) and Pesaran *et al*. (2004), before estimating the system GMM models for this investigation. SGMM becomes a better choice of estimator over the differenced GMM if the first- and second-step difference GMM point estimates of the lagged coefficient matrix in the underlying equations are less than or close to the fixed-effects model estimates, implying a downward bias in the difference GMM estimates, or if they are less than or close to pooled OLS estimates, implying an upward bias in difference GMM estimators. The system GMM estimator is preferred over the difference GMM estimator according to the findings of the Bond (2002) test, and our panel exhibits cross-sectional independence according to the cross-sectional dependence tests. We are not presenting the results of these preliminary tests here to save space, but they are obtainable upon request. Consequently, this study used the system GMM estimator throughout.

4.2 Modelling the effect of climate on poverty outcomes in Africa

The primary objective of this study was to examine the effect of climate change on poverty in Africa using the system GMM framework. The results for these estimates of the underlying model in Equation (1) are presented in Table 6. Since each measure of governance institution (COC, GOE, POS, REQ, ROL, VOA) is employed in a separate regression to prevent the issue of collinearity, this table comprises six panels. We used the number of people living in slums (PPLS) without access to improved water, to improved sanitation, to a sufficient living area and housing durability, and to security of tenure as the measure of poverty. The results in Table 6 show the following: the initial level of poverty (i.e. the lag of the dependent variables) has a positive and significant effect, at 1%, on the current levels of poverty in all models. This implies that previous levels of poverty significantly influence current poverty outcomes in Africa and, if left unchecked, could keep various African economies trapped in the vicious circle of poverty. This finding is consistent with the findings of Adesete *et al*. (2022).

The results further indicate that, in the absence of institutional quality effects, there is a positive relationship between climate change and poverty across Africa. This implies that, as temperature, rainfall and CO_2 emissions rise, poverty outcomes worsen. A unit rise in temperature and CO_2 emissions will lead to an increase in the number of people living in slums and in the level of infant mortality. However, this finding is not significant, at 5%. This finding is consistent with the findings of Adesete *et al*. (2022), Anser *et al*. (2023) and Rana *et al*. (2023). Furthermore, the results show a positive relationship between poverty and food prices (CPI), as evident in panels 3, 4 and 6. An increase in food prices will cause poverty to rise as well. Interestingly, our results further indicate a negative relationship with gross domestic product per capita poverty in Africa, and the results are statistically significant across all panels except panel 2. The outcome of this result conforms to the economic theoretical underpinning of the current study, the a priori expectations and the findings of previous studies, such as those by Anser *et al*. (2023), Mondal *et al*. (2023), Phuong *et al*. (2023) and Rana *et al*. (2023). This is because extreme weather events, rising temperatures and altered precipitation patterns pose a direct threat to the livelihoods of many poor communities. Subsistence farmers, for example, are highly dependent on predictable weather patterns for successful crop yields. Climate change-induced disruptions can lead to crop failures, loss of livestock and diminished fisheries, directly affecting income.

Extreme climatic events such as floods, drought, extreme heat, rising sea levels, storms, wildfires, increasing carbon emissions and other natural disasters sometimes cause heat stress, heat cramps, heat exhaustion, heatstroke, dehydration, respiratory infections, malaria, cholera, asthma and many more. High temperatures cause extreme heat which can lead to a number of problems in pregnancy, including antenatal distress, preterm birth, low birth weight and, in some cases, infant death. These finding are consistent with the findings of the United Nations Development Programme Zimbabwe (2017), Anderko and Pennea (2022), Baba *et al*. (2023) and Lykins *et al*. (2024). Empirical findings have shown that access to quality healthcare and nutritious food decrease infant mortality. Schady and Smitz (2010), Testoni Costa-Nobre *et al*. (2021) and Doerr and Hofmann (2022) found that, in years when GDP and GDPPC fell, death rates, particularly infant mortality rates, rose in emerging market and developing countries (EMDEs), while they remained unchanged in established economies.

The results in Table 6 further show the moderating role of governance institutions on the effect of agricultural productivity on poverty in Africa. The results indicate that institutional quality plays a significant role in moderating the effect of climate change on poverty outcomes across Africa. In the majority of the models estimated, the effects of the interactions of climate change and institutional quality variables remained very valid and significant, at the 5% level of significance. The individual effects of the institutional quality variables are significant for control of corruption (COC, panel 1), government effectiveness (GOE, panel 2) and political stability (POS, panel 3). For the robustness check, we used infant mortality as a proxy for poverty and, interestingly, the results reported in Appendix 3 show that our findings are consistent. Overall, these findings indicate that institutional quality contributes significantly towards improving poverty outcomes in Africa.

Table 6: Climate change and poverty in Africa

Regressors	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5	Panel 6
People living in slums	0.95461*** (0.000)	0.9239*** (0.000)	0.9643*** (0.000)	0.9548*** (0.000)	0.9547*** (0.000)	0.96741*** (0.000)
Temperature (TEMP)	8.2191 (0.387)	34.056 (0.298)	-4.0485 (0.308)	1.4567 (0.801)	4.6212 (0.347)	-3.8843 (0.503)
Rainfall (RAF)	0.1228 (0.924)	4.379 (0.288)	0.4671 (0.402)	0.9297 (0.132)	-1.1369 (0.304)	0.1378 (0.887)
CO_2 emissions (COE)	0.2186 (0.718)	0.2698 (0.930)	0.1436 (0.701)	0.1014 (0.760)	-0.34369 (0.584)	0.0926 (0.850)
Consumer price index	0.00025 (0.354)	0.0020 (0.271)	0.00043* (0.062)	0.00038* (0.079)	0.00046 (0.102)	0.00051* (0.059)
GDP per capita	-0.0289** (0.045)	-0.0010 (0.961)	-0.0186** (0.013)	-0.0169** (0.043)	-0.0190** (0.020)	-0.0203** (0.005)
COC	-19.769** (0.010)					
COE*COC	0.6669 (0.119)					
TEMP*COC	12.558** (0.013)					
RAF*COC	1.1288 (0.385)					
GOE		-78.3395** (0.020)				
COE*GOE		3.1534 (0.301)				
RAF*GOE		-0.5344 (0.840)				
TEMP*GOE		59.394** (0.019)				
POS			5.0117 (0.123)			
COE*POS			-0.02633 (0.866)			
RAF*POS			-1.0207** (0.011)			
TEMP*POS			-1.7087 (0.378)			
REQ				-1.7366 (0.808)		
COE*REQ				0.64931** (0.006)		
RAF*REQ				-0.74722 (0.252)		
TEMP*REQ				2.7758 (0.600)		
ROL					6.0757 (0.497)	
COE*ROL					0.1868 (0.678)	

Regressors	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5	Panel 6
TEMP*ROL					-1.7516 (0.155)	
RAF*ROL					-1.2945 (0.205)	
VOA						-0.99757 (0.870)
COE*VOA						0.16583 (0.462)
TEMP*VOA						0.75860 (0.854)
RAF*VOA						0.0343 (0.967)
Constant	-9.7123 (0.474)	-32.9991 (0.530)	7.3796 (0.226)	-5.4048 (0.492)	10.2558 (0.205)	5.4951 (0.479)
Diagnostics	**Panel 1**	**Panel 2**	**Panel 3**	**Panel 4**	**Panel 5**	**Panel 6**
Observations	678	678	678	678	678	678
AR (1) *P value*	0.030	0.097	0.012	0.089	0.004	0.002
AR (2) *P value*	0.205	0.353	0.917	0.406	0.751	0.653
Hansen prob	0.472	0.579	0.280	0.857	0.269	0.085
H excluding group	0.305	0.094	0.224	0.800	0.560	0.493
Diff (null, H = exogenous	0.522	0.731	1.000	0.745	0.203	0.057
H excluding group	0.498	0.545	0.460	0.747	0.569	0.093
Diff (null, H = exogenous)	0.436	0.459	0.957	0.892	0.058	0.255
Instruments	19	17	27	27	27	27
F stat	11 832.77*** (0.000)	2 193.17*** (0.000)	81 068.02*** (0.000)	46 281.3*** (0.000)	36 164.37*** (0.000)	164 934.80*** (0.000)

Notes: Dependent variable is number of people living in slums without basic needs; estimated coefficients are reported, and the p values are in parentheses. Abbreviations: DHT = difference in Hansen test for exogeneity of instruments' subsets. Diff = difference. * = p < 0.1, ** = p < 0.05 and *** = p < 0.01. VIF result shows that the model is free from any multicollinearity problem.
Source: Authors

It is possible to summarise the findings from Table 6 as follows: (i) climate change worsens poverty in Africa; (ii) governance institutions in the region mitigate the negative effects of climate change on poverty in Africa; and (iii) rising food prices exacerbate poverty in Africa, whereas rising income significantly improves poverty in Africa. As demonstrated in Appendix 1, we tested these findings for robustness by using infant mortality as a poverty outcome, rather than the number of individuals living in slums, and the results were consistent.

4.3 Modelling the effect of agricultural productivity on poverty in Africa

The second specific objective of the study was to investigate the effects of agricultural productivity on poverty outcomes. Table 7 shows the results for this objective and contains the effects of the core variables, such as land under cereal production and cereal yield, and the control variables, namely consumer price index and GDP per capita, on the dependent variable poverty outcomes (PPLS and IMR). In order to accomplish this objective, we used the system GMM estimator to estimate the underlying model in Equation (2). Since the governance institution variables are included in distinct estimations to prevent the issue of collinearity, Table 7 follows our established pattern and includes six panels.

It can be observed that the impact of agricultural productivity on poverty is negligible, at the 5% level, irrespective of whether agricultural productivity is measured using cereal yield or land under cereal cultivation. This indicates that the region's agricultural productivity is not making a major difference in reducing African poverty. Our paper accurately depicts the situation in many African nations, where increased food imports and declining agricultural output have always being major problems. This could be attributed to small farm holdings and the fragmented nature of African agriculture. For instance, Amankwah and Gwatidzo (2024) and Islam and Farjana (2024) observed that the joint use of technology in production, e-agriculture, smart agriculture and access to extension services improves agricultural productivity and the general standard of living. Interestingly, our results in Table 7 show that a rise in food prices (consumer price index) will give rise to more people living in slums. This is partly because a rise in the consumer price index is an indication of an increase in the general price level, which will cause a decrease in consumers' real income and thereby reduce the percentage of their income spent on maximising their welfare and improving their socioeconomic status.

Furthermore, the study found that income (GDPPC) has a negative effect on poverty. As individual or household incomes improve, poverty decreases. The outcome of this result conforms to the economic theoretical underpinning of this study, a priori expectations and the findings of previous studies (Anser *et al*. 2023; Li *et al*. 2023; Mgomezulu *et al*. 2023; Mondal *et al*. 2023; Phuong *et al*. 2023; Zheng & Ma 2023). This is because, as observed by Li *et al*. (2023) in China and Mgomezulu *et al*. (2023) in Malawi, most rural household depend mainly on agriculture for survival. Improvements in agricultural productivity will invariably lead to rise in income for farming households as well as in the general food supply, while also decreasing the general food prices. A fall in food prices will increase the real income of consuming households, thereby reducing the percentage of their income to be spent on maximising their welfare and improving their socioeconomic status. Our findings indicate that the governing institutions have a generally beneficial, but statistically significant, effect only in panel 5 (rule of law). This indicates that African poverty is made worse by the governance institutions in the region. This is in line with research that has drawn attention to the issue of Africa's poor governance institutions, such as that by Anser *et al*. (2023), Li *et al*. (2023), Ogbuabor *et al*. (2023), Zheng and Ma (2023) and Ojonta and Ogbuabor (2024a, 2024b). For the robustness check we used infant mortality as a proxy for poverty. What is interesting is that the results as reported in Appendix 4 show that our findings are consistent

Table 7: Agricultural productivity and poverty in Africa

Regressors	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5	Panel 6
People living in slums	.98712*** (0.000)	0.9641*** (0.000)	0.9685*** (0.000)	0.9668*** (0.000)	0.9598*** (0.000)	0.9666*** (0.000)
Land under cereal cultivation (LUCP)	0.3072 (0.180)	0.1221 (0.459)	-0.0993 (0.456)	-0.0099 (0.949)	1.3581** (0.025)	-0.01222 (0.929)
Cereal yield (CRY)	0.6783 (0.287)	-0.2981 (0.477)	-0.1589 (0.357)	0.1281 (0.654)	1.4218 (0.328)	0.2176 (0.271)
Consumer price index	0.00008 (0.902)	0.00037** (0.044)	0.00037** (0.040)	0.00029** (0.016)	-0.0011 (0.362)	0.00039** (0.019)
GDP per capita	-0.1855** (0.029)	-0.0223** (0.025)	-0.0234** (0.033)	-0.0232** (0.024)	-0.1782 (0.210)	-0.0244** (0.041)
COC	-0.8447 (0.880)					
LUCP*COC	0.03183 (0.659)					
CRY*COC	0.0637 (0.945)					

Regressors	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5	Panel 6
GOE		-2.8323 (0.382)				
LUCP*GOE		0.2416 (0.251)				
CRY*GOE		0.2264 (0.473)				
POS			0.2369 (0.841)			
LUCP*POS			0.0898 (0.552)			
CRY*POS			-0.1355 (0.214)			
REQ				1.977 (0.607)		
LUCP*REQ				-0.0805 (0.711)		
CRY*REQ				-0.2267 (0.561)		
ROL					-38.615** (0.013)	
LUCP*ROL					1.5760 (0.177)	
CRY*ROL					4.4096** (0.004)	
VOA						0.5298 (0.674)
LUCP*VOA						0.0836 (0.553)
CRY*VOA						-0.1596 (0.238)
Constant	-6.5541 (0.28)	-1.9754 (0.618)	-0.1519 (0.929)	-0.344 (0.90)	-15.5728 (0.230)	-0.9559 (0.615)
Diagnostics	**Panel 1**	**Panel 2**	**Panel 3**	**Panel 4**	**Panel 5**	**Panel 6**
Observations	639	639	639	639	639	639
AR (1) *P value*	0.029	0.106	0.011	0.013	0.090	0.007
AR (2) *P value*	0.179	0.462	0.759	0.443	0.201	0.550
Hansen prob	0.252	0.272	0.162	0.879	0.198	0.788
DHT for instruments						
H excluding group	0.446	0.267	0.084	0.388	0.127	0.709
Diff (null, H = exogenous	0.371	0.986	0.998	0.877	0.272	0.735
(b) IV (years, eq. [diff])						
H excluding group	0.392	1.000	0.461	0.864	0.107	0.777
Diff (null, H = exogenous)	0.627	0.873	0.888	0.476	0.742	0.405
Instruments	17	24	17	24	17	24
F stat	67 862.15*** (0.000)	547 993.61*** (0.000)	413 162.14*** (0.000)	685 639.98*** (0.000)	9 037.93*** (0.000)	365 416.2*** (0.000)

Notes: Dependent variable is people living in slums. Estimated coefficients are reported, while the p values are in parentheses. Abbreviations: DHT = difference in Hansen test for exogeneity of instruments' subsets; Diff = difference. * = p < 0.1, ** = p < 0.05 and *** = p < 0.01. VIF result shows that the model is free from multicollinearity problem.
Source: Authors

The following is a summary of the findings in Table 7: (i) the region's agricultural productivity is not significantly reducing poverty in Africa; (ii) the continent's institutions for governance are not significantly improving the impact of agricultural productivity on poverty; and (iii) rising food prices make poverty in Africa worse, while rising income dramatically reduces it. We also tested the robustness of these results using infant mortality as a proxy for poverty, as indicated in Appendix 2, and the results held constant. In all models estimated, the Arellano-Bond tests for second-order serial correlation indicate that all the models are free from the problem of serial correlation. The Hansen tests of over-identifying restrictions shows that the hypothesis of jointly valid instruments cannot be rejected in all cases, implying that the set of instruments employed in the estimations satisfied the exogeneity condition required for obtaining valid regression estimates. Hence, there are valid over-identifying restrictions in all cases, and our models are robust enough for policy formulation. The difference-in-Hansen test (DHT) was conducted to assess the validity of the instruments used in the system GMM estimation by testing the exogeneity of instrument subsets. Across all model specifications (panels 1 to 6), the DHT p-values generally support the validity of the instruments. For instance, panels 1 to 4 recorded high DHT p-values, indicating that the null hypothesis of instrument exogeneity could not be rejected at conventional levels of significance. These results confirm the validity of the additional moment conditions and support the robustness of the instrument specification. Overall, the DHT results confirm that the instruments used are valid and that the exclusion restrictions hold in most cases, strengthening the credibility of the GMM estimates.

5. Concluding remarks and some policy recommendations

Using panel data of 36 African countries spanning a period of 20 years (2001 to 2020) and the system GMM estimation technique, the study investigated the effects of climate change and agricultural productivity on poverty in Africa. The findings indicate that climate change and agricultural productivity worsen poverty outcomes across the continent. Furthermore, the study examined if institutional quality has the ability to significantly moderate the effects of climate change and agricultural productivity on the selected poverty outcomes in Africa. The findings indicate that the continent's institutions for governance are not significantly improving the impact of agricultural productivity on poverty in Africa. This has been attributed to the prevalence of weak institutions on the continent and their inability to effectively exploit the existing potential to its fullest. Furthermore, our results indicate that rising food prices worsen poverty in Africa, while rising income significantly improves poverty in the region.

Based on the findings, the study recommends the following: First, given how negatively climate change affects poverty, it is necessary for African governments to prioritise policies that support climate-resilient livelihoods and social protection programmes for vulnerable populations, including smallholder farmers, pastoralists, and those dependent on agriculture for their income. This can include investments in climate-smart agricultural practices, such as drought-resistant crops, sustainable land management, and livestock management techniques.

It is imperative that policymakers and African leaders adopt and execute institutional reforms in the light of governance institutions' inability to mitigate the negative effects of climate change or markedly increase agricultural productivity. Establishing and strengthening governance frameworks and policies that support climate resilience, sustainable agriculture and poverty alleviation should be given top priority in such reforms. This includes developing and implementing national strategies and action plans that integrate climate change adaptation and mitigation measures into agricultural policies and programmes.

In conclusion, the present study has investigated the effects of climate change and agricultural productivity on selected poverty outcomes in Africa, as well as the moderating role of institutional quality on these relationships. Future studies can investigate the effect of climate change and agricultural productivity on other poverty outcomes and dimensions of poverty. A comparative study on the subject matter could be carried out to examine if and how this relationship varies across regions, time and space.

References

Abdulai S, Nkegbe PK & Donkoh SA, 2018. Assessing the technical efficiency of maize production in northern Ghana: The data envelopment analysis approach. Cogent Food & Agriculture 4(1): 1512390.

Acemoglu D & Robinson JA, 2012. Why nations fail: The origins of power, prosperity, and poverty. New York, NY: Crown Business.

Adesete AA, Olanubi OE & Dauda RO, 2022. Climate change and food security in selected Sub-Saharan African countries. Environment, Development and Sustainability 25: 14623–41.

Adhikari U, Nejadhashemi AP & Woznicki SA, 2015. Climate change and eastern Africa: A review of impact on major crops. Food and Energy Security 4(2): 110–32. https://doi.org/10.1002/fes3.61.

AfDB-IFAD, 2010. Towards purposeful partnerships in African agriculture: African Development Bank and the International Fund for Agricultural Development (ADB-IFAD) joint evaluation on agriculture and rural development in Africa. Tunis: AfDB-IFAD.

Affoh R, Zheng H, Dangui K & Dissani BM, 2022. The impact of climate variability and change on food security in sub-Saharan Africa: Perspective from panel data analysis. Sustainability 14(2): 759.

Ajefu JB & Abiona O, 2020. The mitigating impact of land tenure security on drought-induced food insecurity: Evidence from rural Malawi. The Journal of Development Studies 56(12): 2169–93.

Amankwah A & Gwatidzo T, 2024. Food security and poverty reduction effects of agricultural technologies adoption – A multinomial endogenous switching regression application in rural Zimbabwe. Food Policy 125: 102629.

Amuakwa-Mensah S & Surry Y, 2022. Association between rural electrification and agricultural output: Evidence from Sub-Saharan Africa. World Development Perspectives 25: 100392.

Anderko L & Pennea E, 2022. Climate changes children's health: Improving clinical practice to address changing health needs. The Journal for Nurse Practitioners 18(4): 395–8.

Anser MK, Yousaf SU, Usman B, Azam K, Bandar NFA, Jambari H, Sriyanto S & Zaman K, 2023. Beyond climate change: Examining the role of environmental justice, agricultural mechanization, and social expenditures in alleviating rural poverty. Sustainable Futures 6: 100130.

Appiah-Twumasi M, Donkoh SA & Ansah IGK, 2022. Innovations in smallholder agricultural financing and economic efficiency of maize production in Ghana's northern region. Heliyon 8(12): e12087.

Arellano M & Bond S, 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The Review of Economic Studies 58(2): 277–97.

Arellano M & Bover O, 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68(1): 29–51.

Asiama KO, Bennett RM, Zevenbergen JA & Mano ADS, 2019. Responsible consolidation of customary lands: A framework for land reallocation. Land Use Policy 83(2): 412–23.

Asongu SA & Odhiambo NM, 2020. Foreign direct investment, information technology and economic growth dynamics in Sub-Saharan Africa. Telecommunications Policy 44(1): 101838

Atwood DA, 1990. Land registration in Africa: The impact on agricultural production. World Development 18(5): 659–71.

Aweke CS, Hassen JY, Wordofa MG, Moges DK, Endris GS & Rorisa DT, 2021. Impact assessment of agricultural technologies on household food consumption and dietary diversity in eastern Ethiopia. Journal of Agriculture and Food Research 4: 100141.

Ayhan SH, Falchetta G & Steckel JC, 2022. Evaluating the impacts of minigrid electrification in Sub-Saharan Africa. IZA Institute of Labor Economics Discussion Paper No. 15466, IZA, Bonn.

Baba FM, Hussein MH, Saleh S, Baba M & Awad J, 2023. Mitigating undercooling and overheating risk in existing desert schools under current and future climate using validated building simulation model. Building and Environment 245: 110871

Bado BV, Bationo A, Whitbread A, Tabo R & Manzo MLS, 2022. Improving the productivity of millet based cropping systems in the West African Sahel: Experiences from a long-term experiment in Niger. Agriculture, Ecosystems & Environment 335: 107992.

Bambio Y & Agha SB, 2018. Land tenure security and investment: Does strength of land right really matter in rural Burkina Faso? World Development 111, 130-147.

Bates RH & Block SA, 2013. Revisiting African agriculture: Institutional change and productivity growth. The Journal of Politics 75(2): 372–84.

Blundell R & Bond S, 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87(1): 115–43.

Bond SR, 2002. Dynamic panel data models: A guide to micro data methods and practice. Portuguese Economic Journal 1: 141–62.

Calderon C, Zeufack AG, Kambou G, Kubota M, Korman V, Cantu Canales C & Aviomoh HE, 2021. Africa's Pulse, No. 23, April 2021: An analysis of issues shaping Africa's economic future. Washington, DC: World Bank.

Coulibaly BS, 2019. Foresight Africa: Top priorities for the continent in 2019. Brookings. https://www.brookings.edu/articles/foresight-africa-top-priorities-for-the-continent-in-2019/

Deressa TT, Hassan RM, Ringler C, Alemu T & Yesuf M, 2009. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. Global Environmental Change 19(2): 248–55.

Dimnwobi SK, Okere KI, Onuoha FC & Ekesiobi C, 2023. Energy poverty, environmental degradation and agricultural productivity in Sub-Saharan Africa. International Journal of Sustainable Development & World Ecology 30(4): 428–44.

Djoumessi YF, 2021. What innovations impact agricultural productivity in Sub-Saharan Africa? Journal of Agriculture and Food Research 6: 100228.

Doerr S & Hofmann B, 2022. Recessions and mortality: A global perspective. Economics Letters 220: 110860.

Dube K & Nhamo G, 2020. Evidence and impact of climate change on South African national parks. Potential implications for tourism in the Kruger National Park. Environmental Development 33: 100485.

Food and Agriculture Organization (FAO), 2015. Regional overview of food insecurity in Africa: African food security prospects brighter than ever. Accra: FAO. https://openknowledge.fao.org/server/api/core/bitstreams/7333f34a-b229-409f-adfd-baa16ab465c1/content

Food and Agriculture Organization (FAO), 2018. Food and Agriculture Organization corporate statistical database. www.fao.org/faostat/en/#home

Food and Agriculture Organization (FAO), 2020. The state of food security and nutrition in the world 2020: Transforming food systems for affordable healthy diets. Rome: FAO.

Food and Agriculture Organization (FAO), 2023. The state of food and agriculture 2023 – Revealing the true cost of food to transform agrifood systems. Rome: FAO.

Frees EW, 1995. Assessing cross-sectional correlation in panel data. Journal of Econometrics 69(2): 393–414. https://doi.org/10.1016/0304-4076(94)01658-M

Friedman M, 1937. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32(200): 675–701.
Fulginiti LE, Perrin RK & Yu B, 2004. Institutions and agricultural productivity in Sub-Saharan Africa. Agricultural Economics 31(2–3): 169–80.
Hansen LP, 1982. Large sample properties of generalized method of moments estimators. Econometrica 50(4): 1029–54. https://doi.org/10.2307/1912775
Intergovernmental Panel on Climate Change (IPCC), 2014. Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.
Islam MK & Farjana F, 2024. Does e-agriculture practice matter for poverty reduction among coastal farm households? Journal of Agriculture and Food Research 17: 101212.
Johnston BF & Mellor JW, 1961. The role of agriculture in economic development. The American Economic Review 51(4): 566–93.
Kassouri Y & Kacou KYT, 2022. Does the structure of credit markets affect agricultural development in West African countries? Economic Analysis and Policy 73: 588–601.
Kaufmann D, Kraay A & Mastruzzi M, 2011. The worldwide governance indicators: Methodology and analytical issues. Hague Journal on the Rule of Law 3(2): 220–46.
Ketokivi M & McIntosh CN, 2017. Addressing the endogeneity dilemma in operations management research: Theoretical, empirical, and pragmatic considerations. Journal of Operations Management 52: 1–14.
Kool M, Van Steenbergen F, Mehari Haile A, Abbas YM & Hagos E, 2018. The promise of flood-based farming systems in arid and semi-arid areas. In Wuta M, Nyamadwazo G, Nyamasoka B, Matayaya G, Nazare R, Madyiwa S & Tsoka J (eds.), Rainwater-smart agriculture in arid and semi-arid areas. Cham: Springer.
Kouadio HK & Gakpa LL, 2022. Do economic growth and institutional quality reduce poverty and inequality in West Africa? Journal of Policy Modeling 44(1): 41–63.
Kyriakarakos G, Balafoutis AT & Bochtis D, 2020. Proposing a paradigm shift in rural electrification investments in Sub-Saharan Africa through agriculture. Sustainability 12(8): 3096.
Lawson M, Chan MK, Rhodes F, Butt AP, Marriott A, Ehmke E, Jacobs D, Seghers J, Atienza J & Gowland R, 2019. Public good or private wealth? Oxford: Oxfam International.
Li X, Peng X & Peng Y, 2023. Unravelling the influence and mechanism of agricultural inputs on rural poverty vulnerability: Evidence from China. Heliyon 9(12): e22851.
Lin J, Flachsbarth I & Von Cramon-Taubadel S, 2020. The role of institutional quality on the performance in the export of coconut products. Agricultural Economics 51(2): 237–58.
Lykins AD, Bonich M, Sundaraja C & Cosh S, 2024. Climate change anxiety positively predicts antenatal distress in expectant female parents. Journal of Anxiety Disorders 101: 102801.
Matchaya GC, 2020. Public spending on agriculture in Southern Africa: Sectoral and intra-sectoral impact and policy implications. Journal of Policy Modeling 42(6): 1228–47.
Mbudzya JJ, Gido EO & Owuor G, 2022. Effect of land tenure security on agricultural productivity among small scale farmers in Kenya: A conditional mixed processes analysis. Cogent Food & Agriculture 8(1): 2139805.
Mgomezulu WR, Edriss AK, Machira K & Pangapanga-Phiri I, 2023. Towards sustainability in the adoption of sustainable agricultural practices: Implications on household poverty, food and nutrition security. Innovation and Green Development 2(3): 100054.
Mondal M, Paul S, Mukhopadhyay A, Mandal P, Chatterjee U, Santra S, Bhattacharya S & Paul S, 2023. Evaluating rural poverty and livelihood diversification in the context of climate-induced extreme events in coastal area: Insights from Indian Sundarban. Regional Studies in Marine Science 67: 103191.

Ngango J & Hong S, 2021. Impacts of land tenure security on yield and technical efficiency of maize farmers in Rwanda. Land Use Policy 107: 105488.
Ogbuabor JE & Nwosu CA, 2017. The impact of deposit money bank's agricultural credit on agricultural productivity in Nigeria: Evidence from an error correction model. International Journal of Economics and Financial Issues 7(2): 513–7.
Ogbuabor JE, Emeka ET & Nwosu EO, 2023. Effects of terrorism and economic policy uncertainty on economic complexity in Africa: A study of the moderating role of governance institutions. South African Journal of Economics 91(4): 528–57. https://doi.org/10.1111/saje.12353
Ojonta OI & Ogbuabor JE, 2024a. Effects of international tourism on environmental quality and renewable energy use in Africa: A study of the moderating role of governance institutions. Economic Change and Restructuring 57: 149. https://doi.org/10.1007/s10644-024-09731-9
Ojonta OI & Ogbuabor JE, 2024b. Effects of tourism and institutional quality on infrastructural development in Africa: New evidence from the system GMM technique. Business Economics 59: 101–17. https://doi.org/10.1057/s11369-024-00355-5
Okeke CG & Amaechi OC, 2021. Investigating the impact of agricultural development on food security in Nigeria: An econometric synthesis. University of Nigeria Journal of Political Economy 11(2): 492–511.
Orji A, Ogbuabor JE, Anthony-Orji OI & Nkechi Alisigwe J, 2020. Agricultural financing and agricultural output growth in developing economies: Any causal linkage in Nigeria? International Journal of Finance, Insurance and Risk Management 10(2): 34–43.
Pesaran MH, Shin Y & Smith RJ, 2004. Bounds testing approaches to the analysis of long-run relationships. https://doi.org/10.17863/CAM.5093
Phuong TT, Tan NQ, Dinh NC, Van Chuong H, Ha HD & Hung HT, 2023. Livelihood vulnerability to climate change: Indexes and insights from two ethnic minority communities in Central Vietnam. Environmental Challenges 10: 100666.
Rana IA, Khan MM, Lodhi RH, Altaf S, Nawaz A & Najam FA, 2023. Multidimensional poverty vis-à-vis climate change vulnerability: Empirical evidence from flood-prone rural communities of Charsadda and Nowshera districts in Pakistan. World Development Sustainability 2: 100064.
Roodman D, 2009. How to do xtabond2: An introduction to difference and system GMM in Stata. Stata Journal 9(1): 86–136. https://doi.org/10.1177/1536867X0900900106
Salahuddin M, Gow J & Vink N, 2020. Effects of environmental quality on agricultural productivity in sub Saharan African countries: A second generation panel based empirical assessment. Science of the Total Environment 741: 140520.
Schady N & Smitz MF, 2010. Aggregate economic shocks and infant mortality: New evidence for middle-income countries. Economics Letters 108(2): 145–8.
Séogo W, 2022. Enhancing food production to prevent households from food insecurity in rural Burkina Faso: Does land ownership matter? International Journal of Social Economics 49(11): 1569–88. https://doi.org/10.1108/IJSE-11-2021-0658
Séogo W & Zahonogo P, 2023. Do land property rights matter for stimulating agricultural productivity? Empirical evidence from Burkina Faso. Land Use Policy 125: 106475.
Singh R, Patel SK, Tiwari AK & Singh GS, 2021. Assessment of flood recession farming for livelihood provision, food security and environmental sustainability in the Ganga River Basin. Current Research in Environmental Sustainability 3: 100038.
Singirankabo UA & Ertsen MW, 2020. Relations between land tenure security and agricultural productivity: Exploring the effect of land registration. Land 9(5): 138.
Singirankabo UA, Ertsen MW & Van de Giesen N, 2022. The relations between farmers' land tenure security and agriculture production. An assessment in the perspective of smallholder farmers in Rwanda. Land Use Policy 118: 106122.
Testoni Costa-Nobre D, Kawakami MD, Areco KCN, Sanudo A, Balda RCX, Marinonio ASS, Miyoshi MH, Konstantyner T, Bandiera-Paiva P *et al*., 2021. Clusters of cause specific neonatal

mortality and its association with per capita gross domestic product: A structured spatial analytical approach. PLoS One 16(8): e0255882.
Traore K, Traore B, Synnevåg G & Aune JB, 2020. Intensification of sorghum production in flood recession agriculture in Yelimane, Western Mali. Agronomy 10(5): 726.
United Nations, 2015. Transforming our world: The 2030 agenda for sustainable development. New York: United Nations.
United Nations Development Programme (UNDP), 2024. Human Development Index (HDI). https://hdr.undp.org/data-center/human-development-index#/indicies/HDI
United Nations Development Programme Zimbabwe, 2017. Zimbabwe Human Development Report 2017. Climate change and human development: Towards building a climate resilient nation. Harare, Zimbabwe: United Nations Development Programme.
World Bank, 2016. Shock waves: Managing the impacts of climate change on poverty. Washington, DC: World Bank.
World Bank, 2018. Poverty and shared prosperity 2018: Piecing together the poverty puzzle. Washington, DC: World Bank.
World Bank, 2020. Africa development indicators 2020. Washington, DC: World Bank.
World Bank, 2021. Global economic prospects, June 2021. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1665-9
World Bank, 2024. World Development Indicators. https://databank.worldbank.org/source/world-development-indicators
Zenebe MG, Fleskens L, Ritsema C & Steenbergen F, 2022. Basin-wide productivity and livelihood analysis of flood-based agricultural systems in African drylands: A case study in the Fogera floodplain. Agricultural Water Management 261: 107379.
Zheng H & Ma W, 2023. Impact of agricultural commercialization on dietary diversity and vulnerability to poverty: Insights from Chinese rural households. Economic Analysis and Policy 80: 558–69.

Appendix 1

Bond (2002) test result for choice of GMM estimator

BOND1	**PPLSL1**	**IMRL1**
FE	0.95835*	0.94078*
OLS	0.97916*	1.00538*
FIRST DIFF	0.95880*	0.79252*
SECOND DIFF	0.95881*	0.81755*
BOND2	**PPLSL1**	**IMRL1**
FE	0.96671*	0.9574*
OLS	0.97490*	1.0131*
FIRST DIFF	0.96682*	0.8950*
SECOND DIFF	0.96675*	0.9078*

Source: Authors' computation

Appendix 2

Results of tests for cross-sectional independence

	PPPLS	**IMR**
Pesaran - Fe	97.213 (0.3142)	-1.871 (1.9386)
Pesaran - Fe	94.828 (0.6218)	-1.192 (1.7666)
Friedman - Fe	255.942 (0.2715)	2.692 (1.0000)
Friedman - Fe	267.70 (0.3145)	3.566 (1.0000)
Frees' – Fe	19.302 (0.3826)	1.677 (0.3826)
Frees' – Fe	26.742 (0.4325)	2.907 (0.4325)
Decision	**CID**	**CID**

Notes: Fe = Friedman; probability values are reported for the tests based on Pesaran and Friedman, while the alpha values are reported for the Frees' tests. Absolute values are reported in parentheses in all cases. CID denotes cross-sectional independence.
Source: Authors' computation using STATA 15.

Appendix 3

Climate change and poverty in Africa

Regressors	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5	Panel 6
Infant mortality (IMR)	0.9537*** (0.000)	0.94667*** (0.000)	0.98574*** (0.000)	0.9649*** (0.000)	0.9590*** (0.000)	0.9606*** (0.000)
Temperature (TEMP)	11.7488 (0.282)	-47.6861** (0.045)	29.3749* (0.061)	-10.758 (0.341)	-22.11** (0.026)	-6.5711 (0.562)
Rainfall (RAF)	2.16306 (0.326)	0.7514 (0.739)	0.04923 (0.973)	2.0699** (0.010)	0.93454 (0.445)	1.83317* (0.074)
CO_2 emissions (COE)	0.5348 (0.456)	-0.03480 (0.969)	1.85724* (0.078)	0.2679 (0.715)	0.4177 (0.510)	0.00227 (0.997)
Consumer price index	0.00016 (0.537)	-0.00047 (0.494)	-0.0000105 (0.652)	-0.00024 (0.529)	-0.00006 (0.692)	0.00047 (0.419)
GDP per capital	-0.0192** (0.040)	-0.00993 (0.574)	-0.01288 (0.354)	-0.0228 (0.233)	0.0181 (0.245)	0.00244 (0.856)
COC	32.790** (0.001)					
COE*COC	1.2479* (0.072)					
TEMP*COC	-24.7526** (0.005)					
RAF*COC	0.9759 (0.667)					
GOE		136.286* (0.064)				
COE*GOE		-0.3000 (0.794)				
RAF*GOE		-4.2634 (0.144)				
TEMP*GOE		-89.4844* (0.066)				
POS			-1.8817 (0.837)			
COE*POS			0.13206 (0.700)			
RAF*POS			-0.48515 (0.572)			
TEMP*POS			2.7964 (0.663)			
REQ				47.058** (0.008)		
COE*REQ				-1.4579* (0.064)		
RAF*REQ				0.18315 (0.869)		
TEMP*REQ				-33.912** (0.005)		
ROL					59.713** (0.003)	
COE*ROL					-1.1734* (0.094)	
TEMP*ROL					-41.638** (0.002)	
RAF*ROL					-0.6856 (0.647)	
VOA						25.8135 (0.100)
COE*VOA						-0.6311 (0.252)
TEMP*VOA						-21.3914* (0.076)
RAF*VOA						1.3562 (0.297)

Regressors	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5	Panel 6
Constant	10.9236 (0.395)	68.288* (0.060)	-39.8700* (0.071)	10.3099 (0.534)	28.5884** (0.047)	4.7023 (0.751)
Diagnostics	**Panel 1**	**Panel 2**	**Panel 3**	**Panel 4**	**Panel 5**	**Panel 6**
Observations	678	678	678	678	678	678
AR (1) *P value*	0.084	0.088	0.080	0.050	0.067	0.079
AR (2) *P value*	0.290	0.667	0.227	0.394	0.278	0.224
Hansen prob	0.682	0.235	0.530	0.143	0.175	0.215
H excluding group	-	0.297	-	0.034	0.041	0.206
Diff (null, H = exogenous)	0.682	0.252	0.530	0.715	0.761	0.327
H excluding group	0.805	0.216	0.450	0.087	0.109	0.339
Diff (null, H = exogenous)	0.265	0.375	0.523	0.818	0.827	0.104
Instruments	19	24	19	27	27	27
F stat	13 435.39*** (0.000)	4 625.23*** (0.000)	41 302.05*** (0.000)	8 751.09*** (0.000)	30 853.58*** (0.000)	12 226.38*** (0.000)

Notes: Dependent variable is child mortality. Estimated coefficients are reported, while the p values are in parentheses. Abbreviations: DHT = difference in Hansen test for exogeneity of instruments' subsets; Diff = difference. * = p < 0.1, ** = p < 0.05, and *** = p < 0.01. VIF result shows that the model is free from the multicollinearity problem.
Source: Authors

Appendix 4

Agricultural productivity and poverty in Africa (Dependent variable is Infant Mortality)

Regressors	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5	Panel 6
Infant mortality	0.9630*** (0.000)	0.9433*** (0.000)	0.9675*** (0.000)	0.9541*** (0.000)	0.9533*** (0.000)	0.97423*** (0.000)
Land under cereal cultivation (LUCP)	0.010 (0.977)	-1.7005 (0.121)	-0.65047* (0.089)	-0.7063** (0.339)	-0.9169 (0.350)	-0.0313 (0.929)
Cereal yield (CRY)	0.4366 (0.661)	3.0714** (0.032)	-0.5681 (0.392)	-2.1494** (0.045)	-0.7452 (0.512)	0.3070 (0.271)
Consumer price index	.00029 (0.781)	0.00037 (0.820)	0.00043 (0.673)	0.00026 (0.806)	0.0012 (0.474)	0.00013** (0.019)
GDP per capita	-0.0314** (0.004)	-0.00283 (0.955)	0.0072 (0.767)	-0.0022 (0.968)	0.0029 (0.866)	-0.0340** (0.041)
COC	2.1140 (0.704)					
LUCP*COC	0.0366 (0.644)					
CRY*COC	-0.47027 (0.628)					
GOE		14.7813 (0.192)				
LUCP*GOE		-0.675218 (0.353)				
CRY*GOE		-1.6539 (0.210)				
POS			0.6364 (0.872)			
LUCP*POS			0.2145 (0.449)			
CRY*POS			-0.3672 (0.374)			
REQ				4.6054 (0.730)		
LUCP*REQ				-0.3938 (0.509)		

Regressors	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5	Panel 6
CRY*REQ				-0.24652 (0.877)		
ROL					8.3648 (0.251)	
LUCP*ROL					0.2668 (0.688)	
CRY*ROL					-1.531* (0.054)	
VOA						3.9979 (0.674)
LUCP*VOA						-0.4105 (0.553)
CRY*VOA						-0.1497 (0.238)
Constant	-2.8234 (0.75)	32.84577** (0.028)	7.777 (0.220)	20.7402* (0.059)	11.1684 (0.360)	-1.8428 (0.615)
Diagnostics	**Panel 1**	**Panel 2**	**Panel 3**	**Panel 4**	**Panel 5**	**Panel 6**
Observations	639	639	639	639	639	639
AR (1) *P value*	0.094	0.151	0.051	0.070	0.073	0.086
AR (2) *P value*	0.185	0.205	0.210	0.207	0.136	0.222
Hansen prob	0.177	0.988	0.438	0.901	0.349	0.159
DHT for instruments						
H excluding group	0.081	0.638	0.330	0.607	0.195	0.699
Diff (null, H = exogenous	0.560	0.982	0.535	0.865	0.614	0.111
H excluding group	0.248	0.989	0.329	0.994	0.604	0.258
Diff (null, H = exogenous)	0.145	0.664	0.766	0.253	0.066	0.129
Instruments	24	17	24	17	24	17
F stat	27 765.03*** (0.000)	5 582.86*** (0.000)	33 463.34*** (0.000)	10 556.00*** (0.000)	7 019.54*** (0.000)	22 956.63*** (0.000)

Notes: Dependent variable is infant mortality. Estimated coefficients are reported, while the p values are in parentheses. Abbreviations: DHT = difference in Hansen test for exogeneity of instruments' subsets; Diff = difference. * = $p < 0.1$, ** = $p < 0.05$, and *** = $p < 0.01$. VIF result shows that the model is free from the multicollinearity problem.
Source: Authors