A G D I Working Paper

WP/22/065

Climate Change and Agricultural Productivity in West Africa

Chimere O. Iheonu
Research Analyst, Kwakol, Abuja, Nigeria
E-mail: iheonuchimere@yahoo.com

Simplice A. Asongu
(Corresponding author)
African Governance and Development Institute,
P. O. 8413, Yaoundé, Cameroon
E-mail: asongusimplice@yahoo.com

Ekene T. Emeka
Department of Economics, University of Nigeria, Nsukka, Nigeria
E-mail:ekenekeynes101@gmail.com

Ebuka C. Orjiakor
Department of Economics, University of Nigeria, Nsukka, Nigeria
E-mail: orjiakorebuka@yahoo.com

2022 African Governance and Development Institute WP/22/065

Research Department

Climate Change and Agricultural Productivity in West Africa

Chimere O. Iheonu, Simplice A. Asongu, Ekene T. Emeka & Ebuka C. Orjiakor

January 2022

Abstract

Agriculture remains one of the major sources of livelihood in West Africa. The sector accounts for a significant share of output and employment in the sub-region. However, extreme weather events have been signaled to affect the sector's productivity in recent times. In this study, we investigate the heterogeneous long-run relationship between climate change and agricultural productivity in West Africa from 1990 to 2020. Using the Augmented Mean Group (AMG) and the Common Correlated Effect Mean Group (CCEMG) estimators, we show that rising temperatures significantly reduce agricultural productivity in Gambia, Mali, Niger, and Togo. However, after accounting for endogeneity, we find that the negative relationship between temperature and agricultural productivity becomes insignificant for Niger while the positive relationship between rising temperature and agricultural productivity becomes significant for Ghana. Also, the results show that temperature Granger cause agricultural productivity in West Africa. We discussed some policy implications based on these findings.

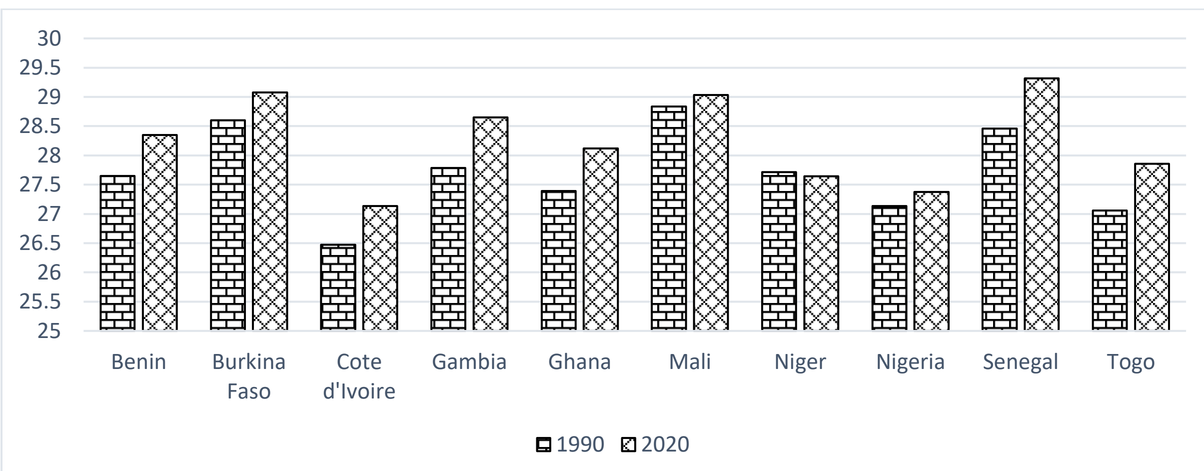
Keywords: Climate Change, Temperature, Agricultural Productivity, West Africa, Augmented Mean Group, Common Correlated Effect Mean Group.

Introduction

The intrinsic relationship between climate change and agricultural productivity has been well amplified by several studies (e.g., Rao et al. 2015; Serdeczny et al. 2017; Amankwah 2019; Zakari et al 2022). Several agricultural and sustainability conferences, such as the International Conference on Forestry Food and Sustainable Agriculture (2022), the United Nations Climate Change Conference (2015), and the Intergovernmental Panel on Climate Change report (IPCC, 2007; 2010; 2019), have raised concerns about the susceptibility of agriculture to climate change.

The vulnerability of agricultural productivity to climate change in West Africa has in recent times become not only an environmental concern but also an economic concern due to its negative effect on the survival of the region's ever increasing human population. Overtime, there have been a rise in average yearly temperature across almost all countries within West Africa. This has led to environmental issues such as drought, heatwaves, lower levels of rainfall among other issues.

Figure 1: Average Yearly Temperature in Celsius, 1990 and 2020.



Source: World Bank (2021)

Since climatic change events can directly alter economic outcomes such as gross domestic product (GDP), the level of agricultural productivity, investment, price level, pattern and composition of imports and exports, thereby worsening social inequality, several programmes and policies have been put in place to mitigate the effect of climate change. Among these programs are the West Africa Agricultural Productivity Program (WAAPP), the Global

Environment Facility (GEF), the Reducing Emissions from Deforestation and Forest Degradation (REDD+), and the Action Against Desertification (AAD) Program. However, these programs have not yielded the desired results as extreme weather events have been noted to influence the productivity of the agricultural sector, and many other subsets of the economy in West Africa.

Climate change affects agriculture through various means, such as low or excessive rainfall (drought and flooding), climate extremes (e.g., heat waves), and changes in average temperatures (IPCC 2007; Heltberg et al. 2009; Ayanlade et al. 2018). Climate change is a threat to both agricultural and non-agricultural development in any economy, but more so to food production in developing countries due to heavy reliance on agriculture (Binuometa et al. 2012; Koudahe 2018). In West Africa, the vulnerability of the agricultural sector to climate change is of particular interest to policy makers because agriculture is considered a major growth driver in the region. According to a World Bank report on the role of agriculture in West Africa, 50%–60% of the total workforce in the region and 40% of the region's GDP are accounted for by the agricultural sector (World Bank 2015). Effort in literature has been made by (Heltberg et al. 2009; Oluoko-Odingo 2011; Seaman et al. 2014; Amobi & Onyishi 2015; Adenle et al. 2017; Morton 2017; Serdeczny et al. 2017; Batten, 2018; Akuwudike & Mac-Ozigbo 2020; Molua 2020) in studying the relationship between climatic conditions and agricultural productivities. However, previous studies are often country-specific and they focused most on the effect of climatic change on specific agricultural outputs (e.g., yam, coffee, cocoa, sorghum, oil palm, maize, etc.). Since there is a dearth of literature on the intrinsic relationship between climate change and agricultural productivity in West Africa, this study fills this gap by using data that covers most West African countries and accounting for issues such as cross-sectional dependence and endogeneity, which is more accurate in delineating climate change effects on total agricultural productivity. The study leans on the agricultural system analysis framework of Smith et al. (1988), which goes beyond crop yield and spatial analysis to examining the impact of climate change on the overall productivity of the agricultural sector.

As the global economy strives to promote sustainable economic stability and growth, which is one of the Sustainable Development Goals of the United Nations, there is a need to understand the long run impact of climate change on agricultural productivities, especially in West Africa, a region heavily dependent on the agricultural sector. Our findings show heterogeneity in the impact of temperature on agricultural productivity in West Africa. In particular, we find that rising temperatures significantly dampen agricultural productivity in Gambia, Mali, and Togo when endogeneity is accounted for. The policy information from this study will be useful to the government and key stakeholders in the agricultural sector of the different economies that make up the region.

Literature Review

A considerable number of studies have found links between climate change variables and the productivity of the agricultural sector. In Nigeria, Zakari et al. (2022) used data from 1783 households to confirm that changes in rain patterns (93.21%) have a negative impact on food security. However, encouraging adaptation strategies to climate change awareness has a positive and significant impact on both household income and food security. The study by Koudahe et al. (2018) in Togo investigating the trend in monthly and annual precipitation, minimum and maximum air temperature using multiple regression analysis also revealed that adaptation strategies for agricultural productivity are necessary for stable agricultural production, especially in locations where crops are affected by climatic variability. Furthermore, Oluwatayo and Ojo (2016) find that Nigerian crops are more susceptible to variable weather and precipitation changes and suggest awareness amongst farmers and general households of the impeding effect of climate change on agricultural yield.

In the Ashanti region of Ghana, Dwamena, Tawiah, and Akuoko (2022) found that a reduction in maize of 74.3% and a reduction in cassava of 62.4% is attributed to variations in minimum temperature, maximum temperature, relative humidity, and rainfall. Molua and Lambi (2006) find that a 3.5% increase in temperature is associated with a 4.5% increase in precipitation, which is detrimental to Cameroon's agriculture, leading to a loss of almost 46.7% in output value. They further suggested that the decrease in agricultural output has led to a 30% decline in the economy's national GDP growth, which comes from agriculture. Soviadan et al. (2019) confirmed that climate change has a significant negative impact on cotton production. From the sample of 172 cotton farmers used in the study, they further confirmed that climate change reduces the level of soil fertility in northern Togo. The study by Fonta et al. (2017) further reveals that annual increases in temperature and decreasing precipitation are associated with declining productivity levels of cocoa farms.

After applying the dynamic general equilibrium model to examine the shock to the economy effect of climate change in Benin, Hounnou et al. (2019) found that climate change has a significant effect on crop losses by 4.4% and non-agricultural output by 0.9% on average by 2025. They further confirm that climate change is associated with a decrease in exports (25.5%), imports (4.9%), and the price of labor and capital. Ezin, Kochoni, and Ahanchede (2018) also revealed that an increase in temperature negatively affects crop production. This finding is further collaborated by Ayanlade et al. (2020) on the negative relationship between temperature and crop yields in Nigeria. In three northern states in Ghana, Amankwah (2019) used data on rainfall and temperature ranging from 1961–2010 to examine the effect of the climate on agriculture productivity in the three states. The results showed that climate change is accompanied by increasing temperatures and decreasing rainfall trends across the three regions, with a significant impact on agricultural productivity. Adams (2019) confirmed that climate change remains the dominant influence on the variety of crops cultivated and the types of agriculture practiced in Nigeria. The author also suggested that an increase in sustained agricultural productivity will require constant adaptation mechanisms and agricultural sensitive technologies and innovations that can prevent climate fluctuation should be encouraged.

In Bangladesh, Kazi and Abu (2014) employed the Fixed Effects regression to examine the impact of climate change on agricultural productivity. The study finds that fluctuations in rainfall in dry and wet seasons have a positive impact on agricultural productivity, but fluctuations in humidity in the wet season have a negative impact on rice productivity. Sultan et al. (2014) also confirms that crops in Senegal, South-West Mali, Burkina Faso, and South-West Niger are more responsive to climate stresses and impact negatively on crop production in the four regions. The study by Bagbohouna et al. (2020) revealed that an increase in maximum temperature (Tmax) and a variation in minimum temperature (Tmin) have a negative impact on crop yields. Grüter et al. (2022) confirm that climate change in the form of high temperatures and flooding impedes the growth of coffee, cashew, and avocado in Guinea Bissau.

The reviewed literature has generally confirmed the detrimental effect of climate change on the productivity of the agricultural sector. Our study deviates from these studies in three ways: (1)

this study takes into consideration total agricultural productivity as against specification crop yields; (2) the study focuses on the West African sub-region where climate change has become pronounced; and lastly, (3) we utilize an updated panel data, taking into consideration cross-sectional dependence in our long run estimates.

Methodology and Data

Pre-Estimation Tests

In analyzing the impact of climate change on agricultural productivity in West Africa, this study employs four different statistical procedures as a justification of the estimation strategies to be employed in the study. They include the test for cross-sectional dependence, the test for stationarity, also known as the unit root test, the test for cointegration, and the test for slope homogeneity. Regarding testing for cross-sectional dependence, the study utilizes the Breusch-Pagan Lagrangian Multiplier (LM) test, the Pesaran scaled LM test, the Bias-corrected scaled LM test, and the Pesaran Cross-sectional Dependence (CD) test. According to Iheonu et al. (2020) and Iheonu et al. (2021), cross-sectional dependence mirrors the correlation between individual error terms among cross-sectional units. Neglecting the presence of cross-sectional dependence in an econometric procedure will result in biased standard errors.

The general null hypothesis for cross-sectional dependence is such that:

$$\tau_{ij} = corr(\tau_{it}, \tau_{jt}) = 0 \ \forall i \neq j \tag{1}$$

here, i and j are two cross-sectional units.

In regards to the test for stationarity of the variables in the model, the study utilizes the augmented Dicker Fuller (ADF) unit root test proposed by Maddala and Wu (1999) and Choi (2001), and the cross-sectional ADF (CADF) unit root test proposed by Pesaran (2003). While the ADF test does not account for cross-sectional dependence, the CADF unit root test accounts for cross-sectional dependence. The ADF test also assumes variation of the autoregressive parameter for all cross-sections in analyzing stationarity properties. The Pesaran (2003) procedure eliminates cross-sectional dependence by augmenting the standard ADF regressions with the cross-sectional averages of lagged levels and first difference of the individual series.

The study further progresses to test for cointegration. In particular, three cointegration tests are utilized. They include the Johansen Fisher panel cointegration test proposed by Maddala and Wu (1999), the Kao (1999) cointegration test, and the Westerlund panel cointegration test proposed by Westerlund (2007) and Persyn and Westerlund (2008). Both the Johansen Fisher test and the Kao test assume cross-sectional independence, while the Westerlund test accounts for cross-sectional dependence. According to Nathaniel and Iheonu (2019), the Westerlund test is an error-correction based test that deals with cross-sectional dependence by utilizing robust critical values via bootstrapping. The final pre-estimation procedure involves the slope homogeneity test of Pesaran and Yamagata (2008) in testing for homogeneous slope coefficients. The null hypothesis of the test is slope homogeneity, while the alternate hypothesis is the presence of a heterogeneous slope. We utilize the test statistics of Blomquist and Westerlund (2013) to account for heteroskedasticity and autocorrelation.

Estimation Techniques

Augmented Mean Group (AMG)

This study utilizes the AMG estimation procedure proposed by Eberhardt and Teal (2010) for three reasons, (1) it is suitable for the examination of long run analysis, (2) it accounts for cross-sectional dependence and country-specific heterogeneity, and (3) it is suitable for a moderate number of cross sections. The AMG is specified such that:

$$agric_{i,t} = \alpha_1 temp_{i,t} + \alpha_2 fert_{i,t} + \alpha_3 land_{i,t} + \alpha_4 dc_{i,t} + v_{i,t} \quad (2)$$

where $v_{i,t} = \theta_{1i} + \vartheta_i f_t + u_{i,t}$ (3)

In equation (2), $\alpha_1, \alpha_2, \alpha_3, and\ \alpha_4$ represent country-specific slope parameters. $v_{i,t}$ consist of the unobservables and the error term $u_{i,t}$. The unobservables are made up of group fixed effects θ_{1i} that capture the time-invariant heterogeneity across groups and the unobserved common factor f_t with heterogeneous factor loadings $\vartheta_i$which captures time-invariant heterogeneity and cross-sectional dependence. $agric$ is the dependent variable which measures agricultural productivity; $temp$ represents average annual temperature; $fert$ stands for fertilizer consumption; $land$ represents arable land; and dc is domestic credit to the private sector. i represents the cross-sectional index and t represents the time period.

Common Correlated Effect Mean Group (CCEMG)

For robustness purpose, the study further applies the CCEMG estimation procedure which further accounts for endogeneity. The CCEMG as is the AMG is a long run estimation procedure which accounts for cross-sectional dependence and country-specific heterogeneity. The CCEMG proposed by Pesaran (2006) accounts for cross-sectional dependence and time-variant unobservables by augmenting the group-specific regression via the inclusion of cross-sectional averages of the dependent and independent variables as additional regressors. The CCEMG equation is specified as:

$$agric_{i,t} = \alpha_i + \alpha_1 temp_{i,t} + \alpha_2 fert_{i,t} + \alpha_3 land_{i,t} + \alpha_4 dc_{i,t} + \alpha_{i0}\overline{agric}_{i,t} + \alpha_{i1}\overline{temp}_{i,t} + \alpha_{i2}\overline{fert}_{i,t} + \alpha_{i3}\overline{land}_{i,t} + \alpha_{i4}\overline{dc}_{i,t} + v_{i,t} \quad (4)$$

here, $\overline{agric}$, $\overline{temp}$, $\overline{fert}$, $\overline{land}$, and $\overline{dc}$ are proxies for the common factors which have no interpretable meaning (Pesaran, 2006).

According to Eberhardt and Bond (2009), the AMG and the CCEMG perform similarly well in panels with non-stationary variables and cross-sectional dependence.

Data

Annual data from 1990 to 2020 is utilized in this study for 10 West African countries. The study employs agriculture, forestry, and fishing value added (% of GDP) as a proxy for agricultural productivity. Average annual temperature is utilized to as a measure of climate change. Fertilizer consumption is proxied by fertilizer consumption (kilograms per hectare of arable land), land is arable land (hectares), and domestic credit to the private sector (% of GDP). All the data is sourced from the World Development Indicator (WDI) database except temperature data which is sourced from the World Bank Climate Change Knowledge Portal.

Table 1: Description and Source of Variables

Variables	Description	Source
Agric	Agriculture, forestry, and fishing value added (% of GDP)	WDI (2021)
Temperature	Temperature in degree Celsius	World Bank Climate Change Knowledge Portal (2021)
Fertilizer consumption	Fertilizer consumption (kilograms per hectare of arable land).	WDI (2021)
Land	Arable land (hectares)	WDI (2021)
Domestic Credit	Domestic credit to the private sector (% of GDP)	WDI (2021)

Source: Authors' compilation.

For ease of interpretation, the study converts temperature, fertilizer consumption, and land to their natural logarithms. Countries involved in this study include Benin, Burkina Faso, Cote d'Ivoire, Gambia, Ghana, Mali, Niger, Nigeria, Senegal, and Togo.

Presentation and Discussion of Results

The presentation of the results begins with discussions on the summary statistics and the correlation matrix of the variables. We show that the mean value of agricultural productivity is 27.17. This reveals that, on average, agriculture contributes 27.17 percent to GDP in West Africa- an indication of the importance of agriculture to the West African economy. We further find that the average temperature in West Africa is 27.86 degrees Celsius. The average fertilizer consumption per hectare of arable land is 9.81, while the average arable land is 252,149. The average domestic credit to the private sector (as a share of GDP) is 13.9. This signifies the low state of financial development in the region.

Table 2: Summary Statistics and Correlation Matrix

Variables	Agric	Temp	Fert	Land	DC
Mean	27.1765	27.8694	9.8118	252149.8	13.9020
Standard Deviation	7.8947	0.8479	8.6934	211924.4	7.2128
Minimum	12.2459	20.05	0	4950	2.6609
Maximum	45.5104	29.3667	44.1182	697542.5	40.1630
No. of Observations	310	310	310	310	310
	Agric	Temp	Fert	Land	DC
Agric	1.0000				
Temp	-0.0355	1.0000			
Fert	-0.2844	-0.0061	1.0000		
Land	0.2527	-0.0699	-0.0072	1.0000	
DC	-0.1364	0.1785	0.2832	0.2266	1.0000

Source: Author’s consumption. Note: Fert is Fertilizer Consumption, DC is Domestic Credit.

Table 2 further reveals the correlation among the variables in the model. It is revealed that there is no strong correlation among the variables in the model. This is an indication of the absence of multicollinearity in the model. However, it is found that agricultural productivity has a negative correlation with temperature, fertilizer consumption and domestic credit while a negative correlation exist between agricultural productivity and arable land area. In table 3, we test for cross-sectional dependence in the model using four different tests. The results show the presence of cross-sectional dependence in the model apart from the Pesaran CD test, which indicates no cross-sectional dependence. However, the data structure where the number of time periods is greater than the number of cross-sectionals is an indication that the Pesaran CD test is invalid. We, therefore, accept the presence of cross-sectional dependence in the model.

Table 3: Cross-Sectional Dependence Test

Test	Statistics	Probability
Breusch-Pagan LM	210.7565***	0.0000
Pesaran scaled LM	16.4181***	0.0000
Bias-corrected scaled LM	16.2515***	0.0000
Pesaran CD	1.3416	0.1797

Source: Authors' computation.

Note: Null hypothesis: No cross-section dependence in residuals.

In table 4, the ADF and the CADF unit root tests are presented. We find differing levels of variable stationarity across tests and across specifications. We discover, however, that all of the variables in the model are stationarity at the first difference and at the 1% level of statistical significance. This then means we can test for a long run cointegrating relationship among the variables in the model.

Table 4: Panel Unit Root Tests

Variables	ADF				CADF			
	Intercept		Intercept/trend		Intercept		Intercept/trend	
	Levels	First diff.	Levels	First diff.	Levels	First diff.	Levels	First diff.
Agric	25.6216	132.013***	22.6861	108.760***	-1.951	-3.238***	-1.791	-3.416***
Temp	36.6605**	200.852***	66.1719***	163.417***	-2.212*	-3.552***	-2.384	-3.546***
Fert	36.9801**	122.819***	36.0852**	90.3988***	-1.934	-3.122***	-2.833**	-3.149***
Land	31.5328**	115.693***	27.6949	114.841***	-2.069	-2.952***	-2.316	-3.442***
DC	22.3809	96.4297***	33.4041**	77.9902***	-2.872***	-3.301***	-2.904**	-3.432***

Source: Author's computation.

Note: ***, **, and * represents statistical significance at 1 percent, 5 percent and 10 percent respectively. Fert is Fertilizer Consumption, DC is Domestic Credit.

Table 5: Panel Cointegration Test

Panel A: Johansen-Fisher		
Hypothesized No. of CE(s)	Fisher Stat (Trace Test)	Fisher Stat (Maximum Eigen Test)
None	305.7***	173.9***
At most 1	158.6***	106.5***
At most 2	73.80***	54.66***
At most 3	34.34**	28.48
At most 4	21.35	21.35
Panel B: Kao		
ADF t-Statistic		P-value
-3.1412***		0.0008

Source: Authors' computation.

Note: ***, and ** represents statistical significance at 1 percent and 5 percent. Johansen Fisher: Trend Assumption: Linear deterministic trend. Kao: Null hypothesis: No cointegration. Trend assumption: No deterministic trend.

Table 5 shows the test results from the Johansen-Fisher cointegration test and the Kao cointegration test. The results of the Johansen-Fisher test show that for the trace test, there are at most three cointegrating equations, and for the maximum eigen test, there are at least two cointegrating equations. The Kao test validates the result of the Johansen-Fisher test and reveals the presence of cointegration at a 1 percent level of statistical significance.

Table 6: Panel Cointegration Test (Westerlund)

Statistic	Value	Z-value	p-value	Robust p-value
Gt	-2.233	0.702	0.759	0.280
Ga	-1.882	4.571	1.000	0.780
Pt	-9.940	-2.904	0.002	0.000
Pa	-11.920	-1.090	0.138	0.000

Source: Author's computation. Note: Null hypothesis: No cointegration.

In table 6, the result of the Westerlund test for cointegration is examined. The results show cointegration among the variables in the model, utilizing two tests within the Westerlund framework—Pt and Pa. Both tests are representations of the panel mean test that pools information across cross-sectional units and tests for cointegration for the panel as a whole. To avoid spurious regression and biased conclusions, the study proceeds to the test for slope heterogeneity using the Pesaran and Yamagata (2008) test. The findings reveal the presence of slope heterogeneity. This denotes the importance of utilizing estimation procedures that produce country-specific estimates.

Table 7: Pesaran and Yamagata (2008) Slope Heterogeneity Test

Test	p-value
Delta	11.066***
Adjusted Delta	12.322***

Source: Author's cointegration. Note: Test values are computed using HAC standard errors. *** denotes statistical significance at 1 percent.

In table 8, country-specific long run estimates are presented using the AMG procedure. The findings clearly show slope heterogeneity and the differing impacts of temperature on agricultural productivity in West Africa. The results reveal that rising temperatures significantly reduce agricultural productivity in the Gambia, Mali, Niger, and Togo. These countries are revealed to be some of the worst hit in terms of climate change in West Africa. These findings support the conclusions of Fonta et al. (2017), Ezin, Kochoni and Ahanchede (2018), Amankwah (2019), and Ayanlade et al. (2020) regarding the negative relationship between rising temperatures and agricultural productivity. In particular, we find that rising temperatures have a more adverse effect on agricultural productivity in Mali and Togo. Further findings reveal that in the long run, fertilizer consumption reduces agricultural productivity in Mali, Nigeria, and Togo. This is intuitive in the sense that fertilizer consumption may be significant in the short run but will not have a positive impact on agricultural productivity in the long run. Endale (2011) reveals that the magnitude at which the value of production responds to a change in fertilizer use is low, suggesting that the positive influence fertilizers can have on agricultural productivity is in the short run. We also reveal that increasing arable land increases agricultural productivity in Cote d'Ivoire, Niger, and Nigeria but reduces agricultural productivity in Ghana and Mali. The negative impact of agricultural land area on agricultural productivity in Ghana and Mali might be as a result of land sustainability management issues as revealed by the World Bank (2021). Demographic effects and thresholds are also factors that might lead to declining productivity as a result of an increase in agricultural land area. The positive and significant impact of arable land area on agricultural productivity supports the study Alemu (2017).

Table 8: AMG Estimation Results

Variables	Benin	Burkina Faso	Cote D'Ivoire	Gambia	Ghana	Mali	Niger	Nigeria	Senegal	Togo
Temperature	0.4329	-0.3552	-0.0782	-0.3458**	0.3478	-1.9675***	-0.8469*	0.7728	-0.2418	-2.3357***
	(0.651)	(0.526)	(0.889)	(0.020)	(0.618)	(0.000)	(0.074)	(0.163)	(0.299)	(0.000)
Fertilizer	0.000003	0.0076	0.0096	0.0007	0.0072	-0.0267**	-0.0022	-0.0267***	0.0067	-0.0071**
	(0.988)	(0.181)	(0.571)	(0.944)	(0.113)	(0.043)	(0.758)	(0.000)	(0.129)	(0.048)
Land	-0.0935	-0.0906	0.3790***	0.1441	-1.7432***	-0.1600**	0.4691***	0.6631***	0.0560	0.0097
	(0.111)	(0.249)	(0.007)	(0.337)	(0.000)	(0.014)	(0.000)	(0.009)	(0.560)	(0.541)
Domestic Credit	0.0052**	-0.0002	0.0070***	0.0175***	0.0130***	0.0119***	-0.0038	-0.0006	0.0030***	0.0014
	(0.000)	(0.836)	(0.000)	(0.000)	(0.000)	(0.000)	(0.103)	(0.755)	(0.000)	(0.186)
Constant	-0.2230	2.5160	-4.2971**	0.0292	19.6865***	8.9191***	-2.8386**	-11.1197***	0.2816	7.9208***
	(0.934)	(0.131)	(0.025)	(0.982)	(0.000)	(0.000)	(0.000)	(0.000)	(0.848)	(0.000)

Source: Authors' computation. Note: ***, ** and * represents statistical significance at 1 percent, 5 percent and 10 percent.

The findings also revealed the importance of domestic credit to the private sector in enhancing agricultural productivity in Benin, Cote d'Ivoire, Gambia, Ghana, Mali, and Senegal. This supports the findings of Ngog et al. (2022), who found that domestic credit improves agricultural productivity in the Central African Economic and Monetary Community. This has revealed the importance of accessing credits for farmers in West Africa.

In table 9, the CCEMG results are presented. An advantage of the CCEMG is its ability to account for endogeneity in a long run relationship. The findings slightly differ from those of the AMG in terms of the statistical significance of the coefficients. The results find that rising temperatures reduce agricultural productivity in Gambia, Mali, and Togo. The results further indicate that rising temperatures lead to higher agricultural productivity in Ghana. The positive impact of temperature on agricultural productivity in Ghana could be as a result of threshold levels and non-linearity in the impact of temperature on agricultural productivity, which are not captured in this study. Furthermore, we find that fertilizer consumption improves agricultural productivity in Gambia but reduces agricultural productivity in Mali.

Table 9: CCEMG Estimation Results

Variables	Benin	Burkina Faso	Cote D'Ivoire	Gambia	Ghana	Mali	Niger	Nigeria	Senegal	Togo
Temperature	0.2601	-1.2006	0.4184	-0.4818***	1.9003*	-1.5680***	-0.7295	0.5510	-0.2804	-3.7088***
	(0.887)	(0.118)	(0.514)	(0.000)	(0.053)	(0.002)	(0.185)	(0.485)	(0.434)	(0.004)
Fertilizer	-0.0019	0.0066	-0.0061	0.0149*	0.0052	-0.0278***	-0.0079	-0.0200	0.0069	-0.0027
	(0.679)	(0.227)	(0.685)	(0.064)	(0.348)	(0.009)	(0.377)	(0.235)	(0.244)	(0.518)
Land	-0.2293**	-0.2386*	-0.3918	0.3838**	-1.3054***	-0.1938*	0.3414	2.3105**	0.0857	-0.1578***
	(0.044)	(0.062)	(0.205)	(0.032)	(0.001)	(0.064)	(0.106)	(0.016)	(0.424)	(0.000)
Domestic Credit	-0.0022	0.0006	0.0071***	0.0118***	0.0104***	0.0055***	0.0048	0.0006	0.0016	0.0071***
	(0.540)	(0.750)	(0.000)	(0.000)	(0.001)	(0.004)	(0.493)	(0.779)	(0.444)	(0.000)
Constant	-1.9941	-0.4914	3.4382	-9.1393***	14.3073***	4.9115***	-2.9345	-29.3797***	-0.2080	-3.6867
	(0.569)	(0.795)	(0.355)	(0.002)	(0.000)	(0.000)	(0.147)	(0.005)	(0.895)	(0.131)

Source: Author's computation.Note: ***, ** and * represents statistical significance at 1 percent, 5 percent and 10 percent.

We further find that increasing arable land reduces agricultural productivity in Benin, Burkina Faso, Ghana, Mali, and Togo but increases agricultural productivity in Gambia and Nigeria. Furthermore, domestic credit to the private sector increases agricultural productivity in Cote d'Ivoire, Gambia, Ghana, Mali, and Togo, thus raising awareness of the need to increase domestic credit for agricultural productivity.

Table 10: Dumitrescu and Hurlin (2012) Panel Granger Non-Causality Test

Null hypothesis	W-bar	Z-bar	Probability
Temperature ≠>Agric	2.6610	3.7140	0.0400
Fertilizer ≠> Agric	0.6876	-0.6986	0.5500
Land ≠> Agric	2.4532	3,2496	0.2000
Domestic Credit ≠> Agric	1.9397	2.1012	0.3900

Source: Author's computation. Note: Null hypothesis: No cointegration. Bootstrap: 50.

In table 10, we test for causality in the model using the Dumitrescu and Hurlin procedure. Our findings show that temperature Granger cause agricultural productivity in West Africa. This means that temperatures can be used to forecast future levels of agricultural productivity in West Africa. This is important for policymakers in the agricultural sector in their construct of agricultural policies in West Africa. We further do not find causality running from the control variables to the dependent variable in the model irrespective of the level of statistical significance.

Conclusion

This study examined the impact of rising temperatures on agricultural productivity in 10 West African countries from 1990 to 2020 in a panel data framework. The study utilized the AMG procedure of Eberhardt and Teal (2010) and the CCEMG procedure of Pesaran (2006). The findings show heterogeneity in the impact of rising temperatures on agricultural productivity in West Africa. In particular, we find that rising temperatures have a more adverse effect on Togo and Mali. We also find that rising temperature is detrimental to agricultural productivity in Gambia. These findings are robust irrespective of the choice of estimator. We further find the importance of temperature in predicting future values of agricultural productivity in West Africa. The study recommends the adoption of green energy in West Africa as extant literature has noted that green energy reduces climate change. Furthermore, it is also recommended that Gambia, Mali, and Togo adopt climate adaptation strategies in order to boost agricultural productivity.

Such strategies can include the use of drought-resistant crop varieties, improving the efficiency of irrigation, diversification of crops, and changing cropping patterns, among other strategies. It is also important that policymakers always take climate change into consideration when forecasting future levels of agricultural productivity. The limitation of this study is such that thresholds were not taking into account. Future studies can this examine the threshold effect of climate change on agricultural productivity in West Africa.

Ethical Approval: Not applicable

Consent to Participate: Not applicable

Consent to Publish: Not applicable

Authors' Contribution: COI conceptualized the study and estimated the model. ETE wrote the introduction and literature review, ECO reviewed the introduction and literature review. SAA contributed to all the sections through comprehensive proofreading.

Funding: This research paper received no funding

Competing Interest: There is no competing interest

Availability of Data and Materials: Data for this study is available on request

References

Adejuwon JO (2012). An assessment of the effect of climate variability on selected agricultural practices and yieldsin Sokoto-Rima River Basin, Nigeria. PhD thesis, Obafemi Awolowo University, Ile-Ife.

Adenle A, Ford J, Morton J, Twomlow S, Alverson K, Cattaneo A, Cervigni R, Kurukulasuriya P, Huq S, &Helfgott, A. (2017). Managing climate change risks in Africa – a global perspective. Ecol Econ 141:190–201.

Adams OK (2019). Impact of climate change on agricultural production in Nigeria. International Journal of Scientific & Engineering Research 10(3):2229–5518.

Alemu GT (2017). Effect of land fragmentation on productivity in Northwestern Ethiopia. Advances in Agriculture 2017.https://doi.org/10.1155/2017/4509605

Amankwah E (2019). Impact of climate variability and change on agricultural productivity in the three northern regions of Ghana. American Journal of Environmental Science & Technology 3(1):30–41.

AyanladeA, Oluwatimilehin I, Oladimeji A, Atai G, &Agbalajobi D (2021). Climate change adaptation options in farming communities of selected Nigerian ecological zones. African Handbook of Climate Change Adaptation 1–17.

Bagbohouna M, Ragatoa D, Simon S, &Edjame I (2020). Rainfall and temperature predictions: Implications for rice production in the lower river region of the Gambia. Universal Journal of Agricultural Research 8(4):97–123.

Blomquist J & Westerlund J (2013). Testing slope homogeneity in large panels with serial correlation. Economics Letters121(3):374–378.

Choi I (2001). Unit root tests for panel data. J Int Money Finance 20(2):249–272.

Dwamena H, Tawiah K, &AkuokoKodua A (2022). The effect of rainfall, temperature, and relative humidity on the yield of cassava, yam, and maize in the Ashanti region of Ghana. International Journal of Agronomy1–12. https://doi.org/10.1155/2022/90773831

Eberhardt M & Bond S (2009). Cross-section dependence in nonstationary panel models: A novel estimator. *MPRA Paper* No. 17692.http://mpra.ub.uni-muenchen.de/17692/1/MPRA_paper_17692.pdf.

Eberhardt M & Teal F (2010). Productivity analysis in global manufacturing production. Department of Economics, University of Oxford, Discussion Paper 515, retrieved fromwww.economics.ox.ac.uk/research/WP/pdf/paper515.pdf

Endale K (2011). Fertilizer consumption and agricultural productivity in Ethiopia. *Ethiopian Development Research Institute Working Paper* No. 003.

Ezin V, Kochoni E, &Ahanchede A (2018). Agriculture and food security under threat of change climate in Benin. African Journal of Agricultural Research 13(27):1389-1399.

Fonta W, Bossa A, Sylla M, Urama N &Edame G (2017). The Economic impact of climate change on plantation agriculture in Nigeria: Implication for enhanced productivity. African Economic Research Consortium Research Paper No. 342.

Grüter R, Trachsel T, Laube P, &Jaisli I (2022). Expected global suitability of coffee, cashew and avocado due to climate change. PloS one, 17(1): e0261976.

Heltberg R. Siegel P, & Jorgensen S (2009). Addressing human vulnerability to climate change: Toward a 'no-regrets' approach. Glob Environ Chang 19:89–99.

Hounnou FE, Dedehouanou H, Zannou A, Agbahey J &Biaou G (2019). Economy-Wide Effects of Climate Change in Benin: An Applied General Equilibrium Analysis. Sustainability 11(23):6569.

Iheonu CO, Anyanwu, C.O, Odo KO & Nathaniel SP (2021). Does Economic Growth, International Trade and Urbanization uphold Environmental Sustainability in sub-Saharan Africa? Insights from Quantile and Causality Procedures. Environmental Science and Pollution Research 28:28222-28233.

Iheonu CO, Anyanwu SA, OdoKO &Ojiem PK (2020). Financial Sector Development and Investment in selected Countries of Economic Community of West African States: empirical evidence using heterogeneous panel data method.Financial Innovation6(1):1-15.

Iheonu C, & Nwachukwu T (2020). Macroeconomic determinants of householdconsumption in selected West African countries. Econ Bull 40(2):1596–1606.

Intergovernmental Panel on Climate Change (IPCC) (2010). The physical science basis. Summary for Policymakers (2010). Contribution of Working Group I to the third assessment report of the IPCC. Geneva, Switzerland; 2001: IPCC Secretariat.

IPCC (2007). Climate change 2007 – impacts, adaptation and vulnerability. Contribution of working group ii to the fourth assessment report of the IPCC (eds: Parry ML, Canziani OF, Palukitof JP, Van der Linden PJ, Hanson CE). Cambridge University Press, Cambridge.

IPCC (2019). Climate Change 2019 – impacts, adaptation and vulnerability. Contribution of working group ii to the fourth assessment report of the IPCC (eds: Parry ML, Canziani OF, Palukitof JP, Van der Linden PJ, Hanson CE). Cambridge University Press, Cambridge.

Kao C (1999). Spurious regression and residual based tests for cointegration in panel data. *J Econ* 90(1):1–44.

Koudahe K, Koffi D, Kayode J, Awokola S & Adebola A (2018). Impact of climate variability on crop yields in southern Togo. Environment Pollution and Climate Change 2(1):1-9.

Lemi T, & Hailu F (2019). Effects of climate change variability on agricultural productivity. Int. J. Environ. Sci. Nat. Resour, 17:14-20.

Maddala G, & Wu S (1999). A comparative study of unit root tests with panel data and a new simple test. Oxf Bull Econ Stat 61(0):631–652

Morton J (2017). Climate change and African agriculture: unlocking the potential of research and advisory services. In: Nunan, F. (ed) Making climate compatible development happen (pp 109–135). Routledge.

Molua E (2002). Climate variability, vulnerability and effectiveness of farm-level adaptation options: The challenges and implications for food security in Southwestern Cameroon. Environment and Development Economics 7:529- 45.

Molua E (2020). Africa in a changing climate: redefining Africa's agrarian development policies. In: Climate variability and change in Africa (pp 171–181). Springer, Cham.

Nathaniel S & Iheonu C (2019). Carbon dioxide abatement in Africa: The role of renewable and non-renewable energy consumption. Sci Total Environ 679:337–345.

Ngog C, Onyejiaku C, Fonchamnyo D, &Onwumere J (2022). Has Bank Credit really impacted Agricultural Productivity in the Central African Economic and Monetary Community? Asian Journal of Economics and Banking.https://doi.org/10.1108/AJEB-12-2021-0133

Oluoko-Odingo A (2011). Vulnerability and adaptation to food insecurity and poverty in Kenya. Ann Assoc Am Geogr 101:1–20.

Oluwatayo I & Ayodeji O (2016). Awareness and adaptation to climate change among Yam-Based farmers in rural Oyo State, Nigeria. Journal of Developing Areas50(2):97–108.

Park S (2012). World Bank Group interactions with environmentalists: Changing International Organization Identities. Manchester University Press.

Pesaran M (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica* 74 (4):967–1012.

Pesaran M (2007). A simple unit root test in the presence of cross-section dependence. *J Appl Econ* 22(2):265–312

Pesaran M & Yamagata T (2008). Testing slope homogeneity in large panels. Journal of Econometrics142 (1):50–93.

Persyn D & Westerlund J (2008). Error-correction-based cointegration tests for panel data. Stata J 8(2):232–241.

Seaman J, Sawdon G, Acidri J & Petty C (2014). The household economy approach. Managing the impact of climate change on poverty and food security in developing countries. Clim Risk Management 4:59–68.

Serdeczny O, Adams S, Baarsch F, Coumou D, Robinson A, Hare W, Schaeffer M, Perrette M, & Reinhardt J (2017). Climate change impacts in sub-Saharan Africa: from physical changes to their social repercussions. Regional Environmental Change 17(16):1585–1600.

Smith B, Ludlow L, &Brklacich M (1988). Implications of a global climatic warming for agriculture: A review and appraisal. Journal of Environmental Quality17(4):519-27.

SoviadanM, Koffi-Tessio E, Enete A, &Nweze N (2019). Impact of climate change on cotton production: Case of Savannah Region, Northern Togo. Agricultural Sciences10(07):927-947.

Sultan B, Guan K, Kouressy M, Biasutti M, Piani, C, Hammer, GL & Lobell, D. (2014). Robust features of future climate change impacts on sorghum yields in West Africa. Environmental Research Letters 9(10): 104006.

Westerlund J (2007). Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics 69(6):709–748.

World Bank. (2015). Investment Climate Reforms: An independent evaluation of World Bank Group Support to Reforms of Business Regulations. World Bank Group, Washington, DC: World Bank.

World Bank (2021). Mali: Climate Change Overview. Climate Change Knowledge Portal. https://climateknowledgeportal.worldbank.org/country/mali

Zakari S, Ibro G, Moussa B, & Abdoulaye T (2022). Adaptation Strategies to Climate Change and Impacts on Household Income and Food Security: Evidence from Sahelian Region of Niger. Sustainability, 14(5):2847.