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CLIMATE CHANGE IN WEST AFRICA: ESTIMATING TEMPERATURE THRESHOLD FOR AGRICULTURAL PRODUCTIVITY

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Abstract

This study aims to estimate the temperature threshold for agricultural productivity in West Africa, as little is known about the temperature threshold for agricultural production. The study utilized the Driscoll and Kraay regression, the Prais-Winsten regression, and the Quantile Regression as estimation strategies for 16 West African countries between 1990 and 2021. The findings reveal a threshold value of 24.39 degrees Celsius, above which temperature reduces agricultural productivity. Moreover, the result from the quantile regression reveals a threshold value of 25.27 degrees Celsius in countries where the existing level of agricultural productivity is low. These findings carry significant policy implications for the West African region, as the mean annual temperature is above these threshold values, emphasizing the importance of adopting a comprehensive approach that integrates climate change adaptation and mitigation strategies. The findings call for proactive measures to enhance climate resilience and reduce vulnerability by governments in West Africa and stakeholders. Climate-resilient agricultural practices should be adopted, including the use of drought-resistant crop varieties, the development of efficient irrigation systems, the implementation of early warning systems for extreme weather events, and the provision of agricultural extension services to support farmers in adopting sustainable practices.

Keywords: Climate Change, Temperature, Agricultural Productivity, West Africa, Panel Data Regression

Introduction

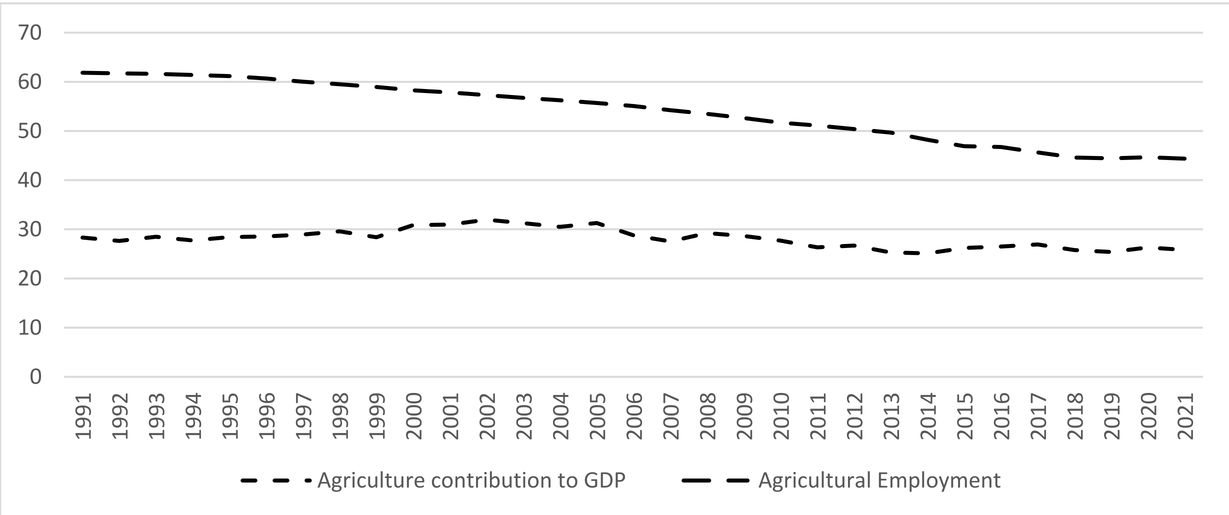
The intrinsic relationship between climate change and agricultural productivity has been well amplified by several studies (e.g., Serdeczny et al., 2017; Amankwah, 2019; Zakari et al., 2022). Several scholarly and policy standpoints on agriculture and sustainability, such as those in the 2022 International Conference on Forestry Food and Sustainable Agriculture, the 2015 United Nations Climate Change Conference (2015), and the Intergovernmental Panel on Climate Change report (2007, 2010, 2019), have raised concerns about the susceptibility of agriculture to climate change. Factors such as rising temperatures, altered precipitation patterns, rising sea levels, and even a shift in pests and diseases as a result of changes in temperature can influence agricultural outputs. Globally, understanding the nexus between climate change and agricultural productivity is essential to achieving two key United Nations Sustainable Development Goals (SDGs): Goal 1 (poverty reduction) and Goal 2 (zero hunger).

In this study, an attempt is made to estimate the temperature threshold for agricultural productivity in West Africa, which is justifiable for several reasons and holds significant implications for food security in the region. Firstly, understanding the temperature threshold for agricultural productivity is key to informing policy interventions that are aimed at mitigating the adverse effects of climate change on agricultural productivity. Through the identification of the point at which rising temperatures begin to adversely affect agriculture, policymakers can implement targeted interventions to adapt farming practices and minimize potential losses. Though significant variability exists in temperature both day and night, identifying the threshold value is essential to understanding how far the mean temperature deviates from the threshold for agricultural productivity. Secondly, estimating the temperature threshold can inform agricultural stakeholders on decisions regarding crop selection, planting schedules, and investment in climate-resilient agricultural practices.

In West Africa, rising temperatures have become an economic concern due to their negative effect on agriculture and food security. According to Jalloh et al. (2013), rising temperatures are exacerbating existing problems for farmers and those in the agriculture-related sectors in the sub-region. Von Braun (2021) has further revealed that extreme weather events amplified by climate change contribute significantly to food insecurity. For West Africa, climate change poses additional threats to socioeconomic conditions due to the high poverty numbers in the sub-region (Trameau, 2022). The region has witnessed substantial changes to the surface temperature in some countries, growing by almost a degree Celsius in Gambia, Ghana, and Togo (World Bank, 2021). Temperature changes such as this can affect the ecosystem and biodiversity, with warmer climates associated with extreme weather events such as heatwaves, storms, floods, and droughts that precipitate lower agricultural productivity levels (IPCC, 2007; Heltberg et al., 2009; Ayanlade et al., 2021).

According to the Food and Agriculture Organization (FAO, 2018), the agricultural sector holds significant importance in West Africa, contributing approximately 66% to total employment in the region. This statistic aligns with findings from the World Bank (2024a), which indicate that more than 50% of the overall workforce in West Africa was engaged in agriculture in 2021, as revealed in Figure 1. Moreover, the agricultural sector accounted for 25.8% of the region's gross domestic product (GDP) in that year (World Bank, 2024b). The heavy reliance on agriculture as a source of employment and economic output in West Africa underscores the critical need to address the challenges posed by climate change. The increase in temperature can significantly impact crop yields, livestock productivity, and overall food security in the region. As a result, effective adaptation and mitigation strategies are imperative to safeguard both the livelihoods of those dependent on agriculture and the broader economic stability of West African countries.

Figure 1: Agriculture (%) of GDP and Employment in agriculture (% of total employment)



Source: World Bank World Development Indicators. Note: The data are average values across West African countries.

An initial step in developing adaptation and mitigation strategies is to comprehend the temperature dynamics in the region. Understanding these dynamics is crucial to assessing the mean temperature in relation to the level of temperature needed for optimal agricultural productivity. Schlenker and Roberts (2009), Dell et al. (2009), Burke, Hsiang, and Miguel (2015), Ibrahim and Ajide (2021), Ibrahim (2022), and Ortiz-Bobea et al. (2021) have all demonstrated that temperature has a significant influence on agricultural productivity and that there is a non-linear impact on both agricultural productivity and economic production. They have observed an inverted U-shaped relationship between temperature and agricultural productivity, indicating that as temperatures rise, agricultural productivity increases up to a certain threshold. However, beyond this threshold, a negative relationship emerges, leading to decreased agricultural productivity.

This study contributes to the existing literature by applying panel data from 16 West African countries from 1990 to 2021 to examine the threshold temperature for agricultural productivity. To the best of our knowledge, this is the first study that attempts to estimate the temperature threshold for the region. Furthermore, while this study focuses on total agricultural productivity, previous studies on the implications of climate change on agricultural productivity have often focused on selected crops (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; Molua, 2020). The study follows the three-factor agricultural production function of Echevarria (1998) as a theoretical framework. Driscoll and Kraay Ordinary Least Square (OLS) and Prais-Winsten regressions with standard errors that are robust to conventional biases in econometric modeling are used as empirical strategies. The robustness of the results is further examined using Quantile Regression (QR) to ascertain whether existing levels of agricultural productivity influence temperature and agricultural productivity dynamics. The potential findings also have implications for the 13th sustainable development goal (i.e., SDG13) on climate change, especially as it pertains to the corresponding findings showing the relevance of a multi-faceted approach that integrates adaptation and mitigation climate change strategies and taking proactive measures to build climate resilience and vulnerability.

Climate Change and Agricultural Productivity

This section provides some theoretical considerations and an empirical review that are relevant to this study. The theoretical underpinning of the nexus between climate change and agricultural productivity is consistent with the theory of change in the agricultural literature (Thornton et al., 2017), especially as it pertains to agricultural research for development (AR4D) being a key mechanism to economic development in the sampled countries. According to the existing theoretical insight (i.e., the theory of change in the agricultural literature), massive obstacles are ahead for AR4D, and methods for overcoming them more quickly and effectively are required (Thornton et al., 2017). Here, we describe one AR4D strategy based on impact pathway thinking and the theory of change that may be able to address effectiveness and efficiency concerns.

This is articulated in the present study in terms of understanding the temperature levels at which climate change negatively affects agricultural productivity. Additionally, within the context of ecological and environmental economics, the environmental stress hypothesis and the cognitive stress theory (Lazarus, 1966) suggest that environmental stressors, such as those induced by climate change, can have significant impacts on ecological systems, including agricultural ecosystems, thereby affecting productivity. Earlier studies, including those by Mendelsohn, Nordhaus, and Shaw (1994) and Fischer, Shah, and van Velthuizen (2002), have highlighted the impact of rising temperatures on agricultural productivity.

In consonance with the environmental stress hypothesis, a considerable number of studies have found inverse links between climate change variables and agricultural productivity. For instance, 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. The study further found that encouraging adaptation strategies to raise awareness of climate change has a positive and significant impact on food security. 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% are attributed to variations in minimum temperature, maximum temperature, relative humidity, and rainfall. From the sample of 172 cotton farmers, Soviadan et al. (2019) confirmed that climate change has a significant negative impact on cotton production. They further confirmed that climate change reduces the level of soil fertility in northern Togo. The study by Fonta et al. (2017) and Ezin, Kochoni, and Ahanchede (2018) further reveals that annual increases in temperature and decreasing precipitation are associated with declining crop production.

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 of 4.4% and non-agricultural output of 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. This finding is further supported 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 agricultural 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 climate change's dominant role in shaping crop variety and farming practices in Nigeria. To sustainably boost agricultural productivity, the study recommends constant adaptation and the promotion of climate-resilient technologies.

The study by Bagbohouna et al. (2020) revealed that an increase in maximum temperature and a variation in minimum temperature 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. Ortiz-Bobea et al. (2021) found that anthropogenic climate change (ACC) has slowed global agricultural productivity growth. Their study shows ACC has reduced global agricultural total factor productivity (TFP) by approximately 21% since 1961, equivalent to losing seven years of productivity growth. The impact is more severe (a reduction of 26–34%) in warmer regions like Africa, Latin America, and the Caribbean. They also discovered that global agriculture has become more vulnerable to ongoing climate change. Dell et al. (2009) explored the inverse association between temperature and income, analyzing cross-country data and subnational data at the municipal level across 12 countries in the Americas. They observed a consistent negative correlation between income and temperature, irrespective of whether it was within-country cross-sectional or cross-country correlation analysis. The reviewed literature has generally confirmed the detrimental effect of climate change on the productivity of the agricultural sector. Addressing the discrepancy between micro- and macro-level observations concerning the influence of wealth on coupled human-natural systems and the worldwide ramifications of climate change, Burke, Hsiang, and Miguel (2015) discovered that economic productivity exhibits a non-linear relationship with temperature across all nations. They noted that productivity reaches its peak at an annual average temperature of 13 °C and experiences a significant decline at higher temperatures.

Our study deviates from these studies in three ways: (1) this study takes into consideration total agricultural productivity as against specified crop yields, providing a much broader perspective on the nexus between temperature and agriculture; (2) the study focuses on the West African subregion where climate change has become pronounced; and lastly, (3) the study utilizes updated panel data, taking into consideration cross-sectional dependence in our long-run estimates. The need to consider cross-sectional dependence in the estimation procedure is key to addressing the interdependence of the error term across West African countries, ensuring inference validity.

Model Specification, Methodology and Data

Model Specification

This study follows the three-factor agricultural production function of Echevarria (1998). The production function captures agricultural productivity using agricultural land, labor, and capital, thus allowing for neutral technological change. This framework is straightforward to operationalize in econometric modeling and can examine the dynamics of agricultural productivity while accounting for structural change. The production function, which allows us to demonstrate the direct effect of the explanatory variables, can be expressed as:

$$Y_t = A_t f(K_t, L_t, N_t) \qquad (1)$$

where Y_t is agricultural output in year t. K_t, L_t and N_t are capital in year t, labor in year t, and land in year t, respectively. A_t represents the level of technology. The production function is assumed to be constant in its return to scale. More explicitly, equation (1) can be re-written as an econometric specification of the form:

$$Y_t = a_0 + a_1 K_t + a_2 L_t + a_3 N_t + u_t \qquad (2)$$

here, u_t is the error term assumed to be normally distributed. We introduce three variables into equation (2). The first is materials (M), which include fertilizers and feed, which are essential for agricultural productivity. Secondly, we introduce our temperature and its squared term to capture the non-linear effect temperature on agricultural productivity. Equation (2) can hence be written in a panel data framework as:

$$Y_{it} = a_0 + a_1 K_{it} + a_2 L_{it} + a_3 N_{it} + a_4 M_{it} + a_5 temp_{it} + a_6 temp_{it}^2 + u_t \qquad (3)$$

According to Echevarria (1998), the coefficients of capital, labor, land, and materials should add up to one and represents the share of value added from these factors of production. The study assumes that rising temperature increases agricultural productivity to a certain threshold beyond which agricultural productivity starts declining. Temperature is treated as an exogenous variable in this study because it is influenced by broader climatic and atmospheric conditions. In computing the threshold value, the study follows Asongu and Odhiambo (2021).

Methodology

This study utilized three estimation procedures for robustness purposes. They include the Prais-Winsten regression, the Driscoll and Kraay (1998) OLS regression, and the QR estimator. According to Iheonu and Oladipupo (2023), the Prais-Winsten regression with panel-corrected standard errors (PCSE) was developed by Beck and Katz (1995) and is robust to small sample sizes and finite sample bias (Elheddad, 2018; Lu et al., 2020). The estimator is robust to cross-sectional dependence, heteroskedasticity, and serial correlation, which bias econometric models. Moreover, the Driscoll and Kraay regression OLS is also robust to conventional econometric biases such as cross-sectional dependence, heteroskedasticity, and serial correlation (Adeniran, Ekeruche, & Iheonu, 2022). To take into consideration existing levels of agricultural productivity, the study utilizes QR. Following Asongu and Eita (2023) and Asongu and Odhiambo (2021), by employing QR, the study can assess how temperature affects agricultural productivity throughout the conditional distribution of agricultural productivity. While the OLS assumes a normally distributed error term, the quantile regression assumes the non-normality of the error terms, and the estimated parameters in QR are examined throughout the conditional distribution of the dependent variable (Koenker & Bassett, 1978; Iheonu, Obumneke, & Agbutun, 2023; Iheonu et al., 2023).

Essentially, the θ^{th} quantile estimator of agricultural productivity is obtained by solving the optimization problem in equation (4). Following Asongu & Odhiambo (2021), for simplicity, the equation is presented without subscripts.

$$\min_{\beta \epsilon R^k} \left[\underset{i \epsilon \{i: y_i \geq x_i \beta\}}{\Sigma \theta |y_i - x_i \beta|} + \underset{i \epsilon \{i: y_i < x_i \beta\}}{\Sigma (1-\theta) |y_i - x_i \beta|} \right] \quad (4)$$

where $\theta \epsilon (0,1)$. While the OLS is premised on reducing the error sum of square, QR is premised on assessing the sum of absolute deviations for all quantiles. In light of this, the conditional quantile of agricultural productivity or y_i given x_i is:

$$Q_y \left(\frac{\theta}{x_i} \right) = x_i' \beta \theta \quad (5)$$

In equation (5), for the respective θ^{th} examined quantiles, parameters that are characterized by unique slops are examined. The dependent variable y_i is the agricultural productivity indicator and x_i contains a constant term, temperature, and the control variables adopted in the model.

Prior to the estimation of the models, the study examines the characteristics of each of the variables in the model to justify the utilization of the regression strategy. Firstly, the study tests for cross-sectional dependence using the Breusch-Pagan Lagrangian Multiplier (LM) procedure. It should also be highlighted that the major reason for using the Breusch-Pagan LM test is due to the characteristics of the dataset, where the number of time periods is greater than the number of cross-sections, i.e. $T > N$. 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:

$$\tau_{ij} = corr(\tau_{it}, \tau_{jt}) = 0 \ \forall i \neq j \qquad (6)$$

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

With regards to the test for stationarity of the variables, the study employed the cross-sectional augmented Dickey-Fuller (CADF) unit root test proposed by Pesaran (2003), which accounts for cross-sectional dependence in the testing procedure. The Pesaran (2003) procedure eliminates cross-sectional dependence by augmenting the standard ADF regressions with the cross-sectional averages of lagged levels and the first difference of the individual series. Additionally, the existence of long-run relationships was ascertained using three panel cointegration techniques. They include the Kao (1999) cointegration test, the Pedroni (1999) cointegration test, and the Westerlund test proposed by Westerlund (2007) and Persyn and Westerlund (2008). While the Kao and Pedroni tests assume cross-sectional independence, 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 through bootstrapping.

The slope homogeneity test of Pesaran and Yamagata (2008) is further used to test for slope homogeneity. The null hypothesis of the test is that the regression slope is homogeneous, while the alternate hypothesis is the presence of a heterogeneous slope. The study utilizes the test statistics of Blomquist and Westerlund (2013) to account for heteroskedasticity and autocorrelation. The presence of slope heterogeneity adds more credence to the use of QR due to its ability to estimate regression parameters based on existing levels of the dependent variable. Due to the number of countries in the sample, we estimate only three quantiles of agricultural productivity to avoid computation complexity and bias.

Data

This study utilizes data from 16 West African countries from 1990 to 2021 to estimate the threshold value of temperature for agricultural productivity. The study employed the index gross value of agricultural output as the dependent variable to capture agricultural productivity. The index for quality-adjusted agricultural area is used to measure land, and the index for the number of economically active adults employed in agriculture is used as a proxy for labor. Capital is the index of the value of net capital stock; materials is the index of crop and animal intermediate inputs; and temperature is measured in degrees Celsius.

Table 1: Description and Source of Variables

Variables	Description	Source
Output (Y)	Gross value of agricultural output from crops, livestock, and aquaculture, constant 2015 prices index.	Economic Research Service, US Department of Agriculture (2024)
Land (N)	Quality-adjusted agricultural area, 1000 hectares of "rainfed-equivalent cropland" index	Economic Research Service, US Department of Agriculture (2024)
Labor (L)	Number of economically active adults primarily employed in agriculture index.	Economic Research Service, US Department of Agriculture (2024)
Capital (K)	Value of net capital stock, constant 2015 prices index.	Economic Research Service, US Department of Agriculture (2024)
Materials (M)	Index of crop and animal intermediate inputs, 2015.	Economic Research Service, US Department of Agriculture (2024)
Temperature	Temperature in degree Celsius.	World Bank Climate Change Knowledge Portal (2023)

Source: Authors' compilation. Note: US is the United States.

We use the natural log index of the agriculture indicators for ease of interpretation and data consistency, with a base year of 2015. Thus, the value of these variables in any year is the level of that variable relative to 2015. As an example, the agricultural output value for Nigeria in 2021 is 110, meaning that agricultural productivity increased from 100 to 110, or by 10%, between 2015 and 2021. This example is similar to the agricultural inputs in the model. The countries in this study include Benin, Burkina Faso, Cabo Verde, Cote d'Ivoire, Ghana, Gambia, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, and Togo.

Presentation and Discussion of Results

In this section, the results of the empirical analysis are presented and discussed. However, prior to the discussion of results, the correlation matrix of the variables in the model is examined to ascertain the degree of relationship among the variables in the model in a bid to avoid multicollinearity. The findings revealed in Table 2 show that agricultural output has a positive correlation with agricultural land, labor, capital, and materials. However, the results show agricultural output to have a negative correlation with temperature. Moreover, it is revealed that multicollinearity might not be a major econometric issue in the modeling. This is because the highest correlation, i.e., the correlation between land and material, is below the threshold of Kennedy (2008), i.e., 0.700, and around the threshold of Asongu and Odhiambo (2021), i.e., 0.600, used in literature to assess evidence of multicollinearity (Iheonu & Asongu, 2024). Furthermore, it can be revealed that our key variable, which is temperature, has very little correlation with other variables in the model, revealing that the coefficients and the standard errors of the temperature variable will be unbiased with regards to the problem of multicollinearity.

Table 2: Correlation Matrix

	Output	Land	Labor	Capita	Material	Temperature
Output	1.0000					
Land	0.8405	1.0000				
Labor	0.5165	0.5706	1.0000			
Capital	0.6615	0.6015	0.4499	1.0000		
Material	0.7257	0.6447	0.3166	0.5753	1.0000	
Temperature	-0.0290	0.0115	-0.0042	0.1013	0.0911	1.0000

Source: Authors' computation.

In Table 3, we test for cross-sectional dependence in the model using the Breusch-Pagan LM test. The result shows the presence of cross-sectional dependence as indicated by the probability value, which is less than conventional levels of statistical significance. This finding reveals the importance of utilizing estimation procedures that can account for cross-sectional dependence due to the interdependence of the error term across countries.

Table 3: Cross-Sectional Dependence Test

Test	Statistics	Probability
Breusch-Pagan LM	674.429***	0.0000

Source: Authors' computation. Note: Null hypothesis: No cross-section dependence in residuals.

In Table 4, the results of the CADF unit root test are presented. The results are presented in both the intercept and the intercept with trend specifications. The findings reveal that under the intercept specification, land and temperature are stationary at levels at the 10% level of statistical significance. However, under the intercept with trend specification, it is revealed that these variables are not stationary in levels. Moreover, all the variables are revealed to be stationary after first differencing.

Table 4: CADF Panel Unit Root Tests

Variables	Intercept		Intercept/trend	
	Levels	First diff.	Levels	First diff.
Output	-2.069	-2.707***	-2.221	-2.888***
Land	-2.153*	-2.606***	-2.043	-2.768**
Labor	-0.919	-2.819***	-2.492	-2.775**
Capital	-0.847	-3.565***	-1.839	-3.550***
Material	-1.700	-2.699***	-2.291	-2.877***
Temperature	-2,103*	-3.566***	-2.125	-3.610***

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

This finding indicates the necessity of estimating whether long-run relationships exist in the model. As previously revealed, the study utilizes three cointegrating techniques: the Kao test, the Pedroni test, and the Westerlund test. The findings are presented in Table 5 and Table 6. The result reveals the presence of a long-run relationship among the variables in the model. Under the Kao test, it is revealed that the augmented Dickey-Fuller probability value, the unadjusted modified Dickey-Fuller probability value, and the unadjusted Dickey-Fuller probability value are less than 5% levels of statistical significance, indicating cointegration. In the Pedroni test, the Phillips-Perron and the

Augmented Dickey-Fuller probability values are also less than 5% levels of statistical significance, indicating cointegration.

Table 5: Panel Cointegration Test

Panel A: Kao			Panel B: Pedroni		
Test	Statistic	P-value	Test	Statistic	P-value
Modified Dickey-Fuller	-0.0037	0.4985	Modified Phillips-Perron	0.9421	0.1731
Dickey-Fuller	-0.0590	0.4765	Phillips-Perron	-6.8985***	0.0000
Augmented Dickey-Fuller	2.1493**	0.0158	Augmented Dickey-Fuller	-4.4228***	0.0000
Unadjusted Modified Dickey-Fuller	-3.9443***	0.0000			
Unadjusted Dickey-Fuller	-2.4222***	0.0077			

Source: Authors' computation. Note: H_0: No cointegration. H_1: All panels are cointegrated. *** and ** represents statistical significance at 1% and 5%, respectively. P-value is probability value.

Table 6: Westerlund Cointegration Test and Pesaran and Yamagata Slope Homogeneity Test

Statistic	Value	Z-value	p-value	Robust p-value
Gt	-3.173***	-3.832	0.000	0.000
Ga	-8.237***	1.817	0.965	0.000
Pt	-11.827***	-3.520	0.000	0.000
Pa	-8.500***	-0.236	0.407	0.000

Pesaran and Yamagata Test	Statistic	
Delta	21.282***	0.000
Adjusted Delta	24.078***	0.000

Source: Authors' computation. Note: Null hypothesis: No cointegration. *** denotes statistical significance at 1% in the presence of cross-sectional dependence. Pesaran and Yamagata test values are computed using HAC standard errors.

In Table 6, the result of the Westerlund test for cointegration is examined. The results show cointegration among the variables in the model. According to Persyn and Westerlund (2008), to ascertain cointegration for the panel as a whole, the Pa and Pt test statistics are relevant because they pool information over all the cross-sectional units. The emphasis should also be placed on the robust probability value due to the presence of cross-sectional dependence. Accordingly, all four cointegration test results are indicative of cointegration. Providing similar conclusions to the Kao and Pedroni test results. More so, the findings of the Pesaran and Yamagata tests reveal slope heterogeneity. This is revealed by the probability value, which is less than conventional levels of statistical significance.

Table 7: Driscoll and Kraay OLS and Prais-Winsten Regression

Variables	OLS Driscoll and Kraay Regression	Prais-Winsten Regression
Land	0.6819***	0.6819***
	(0.000)	(0.000)
Labor	0.0908**	0.0908***
	(0.017)	(0.005)
Capital	0.1100***	0.1100***
	(0.000)	(0.000)
Materials	0.1205***	0.1205***
	(0.000)	(0.000)
Temperature	0.2000*	0.2000*
	(0.088)	(0.080)
Temperature^2	-0.0041*	-0.0041*
	(0.067)	(0.057)
Constant	-2.4189	-2.4189

	(0.131)	(0.101)
Threshold	24.39	24.39
R^2	0.7893	0.7893
F-statistic	575.93***	
	(0.0000)	
Wald		1749.74***
		(0.0000)
Observations	512	512

Source: Authors' computation. Note: ***, ** and * represent statistical significance at 1 percent, 5 percent, and 10 percent. Probability values are in parentheses.

In Table 7, the Prais-Winsten regression and the Driscoll and Kraay OLS regressions are presented. Firstly, both estimates reveal similar findings in terms of the coefficients, statistical significance, and signs of the regressions. It is revealed that agricultural inputs—land, labor, capital, and materials—are all statistically significant in pushing up agricultural productivity in the region, signifying the validity of the agricultural production function. Additionally, as revealed by Echevarria (1998), the result revealed that the coefficients of capital, labor, land, and material add up to one. It is further revealed that land and materials are the most important factors among the four inputs, as revealed by their coefficient values. Additionally, our core variable for this study, temperature, is revealed to have an inverted U-shaped relationship with agricultural productivity. It reveals that increasing temperatures increase agricultural productivity up to a threshold, after which higher temperature values reduce agricultural productivity. This finding is consistent with the studies of Sclenker and Roberts (2009), Burke, Hsiang, and Miguel (2015), and Ortiz-Bobea et al. (2021). These studies have highlighted the importance of non-linearity in the temperature and agricultural productivity nexus studies. Following Asongu and Odhiambo (2021), the temperature threshold at which the overall effect of temperature on agricultural productivity changes from positive to negative is $24.39 = [\frac{0.2000}{2\times 0.0041}]$. It follows that at a critical mass of 24.39, the overall net effect is 0 $[2 \times (24.3902 \times -0.0041) + 0.2000]$. Therefore, above the threshold of 24.3902 of mean annual temperature, the net effect on agricultural productivity becomes negative.

Table 8: Quantile Regression

Variables	Q.20	Q.50	Q.80
Land	0.6851***	0.6804***	0.6064***
	(0.000)	(0.000)	(0.000)
Labor	0.2650***	0.0544	-0.0070

	(0.000)	(0.510)	(0.900)
Capital	0.1211***	0.1295***	0.1054***
	(0.000)	(0.000)	(0.000)
Materials	0.1607***	0.1203***	0.1313***
	(0.000)	(0.000)	(0.000)
Temperature	0.9605***	0.1709	-0.1097
	(0.000)	(0.284)	(0.402)
Temperature^2	-0.0190***	-0.0034	0.0021
	(0.000)	(0.259)	(0.399)
Threshold	25.2763	n/a	n/a
Constant	-13.2224***	-2.0274	2.2089
	(0.000)	(0.370)	(0.228)
Pseudo R^2	0.5680	0.5916	0.5935
Observations	512	512	512

Source: Authors' computation. Note: ***, ** and * represents statistical significance at 1 percent, 5 percent, and 10 percent. Probability values are in parentheses. n/a represents not available.

In Table 8, the quantile regression estimates are presented across two quantiles and the median. The application of just two quantiles, i.e., 0.20 and 0.80, is based on the sample size but has implications for policy. The findings revealed that the inverted U-shaped relationship between temperature and agricultural productivity in West Africa is only significant in countries where the existing level of agricultural productivity is low. Further, it is revealed that the estimated threshold for agricultural productivity in the 20^{th} quantile is 25.2763, above which temperature has a negative effect on agricultural productivity. It then follows that at a critical mass of 25.2763, the overall net effect is 0 $[2 \times (25.2763 \times -0.0190) + 0.9605]$. Above the threshold of 25.2763 of the mean annual temperature, the net effect on agricultural productivity becomes negative. Additional findings further reveal that the coefficients of agricultural inputs are positive and statistically significant. Moreover, an increasing return to scale is observed in the 20^{th} quantile, i.e., in countries where the existing level of agricultural productivity is low. This is identified because the sum of the agricultural inputs' coefficients is greater than unity—an indication of increasing returns to scale in West African countries where agricultural productivity is low. For the median and the 80^{th} quantile, the threshold values cannot be estimated because the variables (temperature and its square) used in the computation are not statistically significant.

Conclusion

In this study, the temperature threshold for agricultural productivity in 16 West African countries from 1990 to 2021 is estimated utilizing the Prais-Winsten regression, the Driscoll and Kraay OLS regression, and QR. Understanding the non-linear nexus between temperature and agricultural productivity is not only relevant for West Africa but also relevant for developing economies that rely heavily on agriculture. The results reveal that an inverted U-shaped relationship exists between temperature and agricultural productivity. The result revealed that the increase in temperature increases agricultural productivity up to a critical mass, above which rising temperatures will lead to a decline in agricultural productivity. The findings estimated a threshold value for temperature to be about 24.39 degrees Celsius. Moreover, in countries where the existing level of agricultural productivity is low, the estimated temperature threshold is revealed to be around 25.27 degrees Celsius.

These findings hold significance for the West African region. For most countries in the region, the mean surface temperature is greater than the threshold values (World Bank, 2024d) and rising in a significant number of countries in the region, signifying the need to promote climate-resilient crop varieties that are adaptable to rising temperature levels. These crop varieties should have traits such as early maturity, drought resistance, and heat tolerance to withstand temperature extremes. The governments in West Africa, in collaboration with agricultural stakeholders, must also invest in irrigation infrastructure at scale to ensure reliable access to water for agriculture.

Efforts must also be made to build the capacity of farmers via various stakeholder engagements to adapt to rising temperatures. These engagements should build capacity for farmers through climate-smart innovations such as agroforestry, carbon farming, and crop diversification, ensuring that farmers have the knowledge and skills needed to implement these practices effectively. Additionally, access to extension services and technical support provided by the government and stakeholders should be improved to provide farmers with ongoing assistance and guidance in adopting climate-smart innovations. Moreover, agricultural agencies can invest in seasonal climate forecasting systems that provide farmers with timely information about anticipated temperature rises. This will enable farmers to adjust their planting schedules, crop selection, and water management practices accordingly.

This study however has some limitations. One of which is the assumption of exogeneity of temperature. Future studies can hence, account for endogeneity in the temperature and agricultural productivity nexus. Future studies can also consider Sub-Saharan Africa, expanding the understanding of the nexus. The study has contributed to the theory of change in the agriculture literature by establishing critical levels of temperature above which climate change negatively affects agricultural productivity. Accordingly, the theory of change assumes that agricultural research for development (AR4D) is a key mechanism for economic development in the sampled countries, and we have shown that understanding the critical levels at which temperature rise is detrimental to agricultural productivity contributes modestly to the extant theoretical literature.

These findings obviously leave room for further research, especially in view of considering whether the established findings withstand empirical scrutiny in other regions of Africa. This future research direction is motivated by the limitation that the findings in this study cannot be generalized to the entire African continent. Furthermore, future research should also focus on other United Nations' sustainable development goals (SDGs) that are relevant to addressing concerns related to climate change.

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Appendix A1: Descriptive Statistics

Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
Output	512	76.8164	25.8280	25	163
Land	512	82.5976	21.9682	39	146
Labour	512	92.7753	17.0143	46	134
Capital	512	74.4179	32.0343	12	188
Material	512	86.5136	63.0934	4	470
Temperature	512	27.2571	1.4371	20.05	29.3667

Source: Authors' computation.