Investigating the Effect of Climate Change on Agricultural Productivity and Food Inflation in Ghana

Eric Atanga Ayamga

Department of Economics

Texas Tech University, P. O. Box 4104, Lubbock-Texas 79409-1014, United States of America

eayamga@ttu.edu

Millicent Nimakoh

Department of Agriculture and Applied Economics

Texas Tech University, P. O. Box 4104, Lubbock-Texas 79409-1014, United States of America

millcenimakoh@gmail.com

Abstract

Recent incidence of flooding, droughts, erratic changes in rainfall patterns, rising temperatures, and low humidity levels as a result of climate change have a potential impact on agricultural performance. The study investigates the impact of climate change on agricultural performance and food inflation in Ghana using time series that from 1970 to 2022. Using data from the Ghana Statistical Service and World Bank Indicators and applying the Autoregressive Distributed Lag model (ARDL), the study found a significant negative impact of climate change (proxied by carbon emissions, precipitation, and changes in temperature) on overall agricultural performance and cereal production in Ghana. We also found that temperature increases food inflation, however food inflation reduces with precipitation up to some optimum level of precipitation and begin to increase. The study concludes that climate change affects Ghana's agricultural performance negatively, hence governments, stakeholders and farmers should take pragmatic steps in addressing the issue of climate change in the country.

Keywords: Climate change, agricultural productivity, food inflation, sustainable development goals, food security, Ghana.

JEL Classification Codes: A1, A12, B4, C01, C5.

1. Introduction

The recent rise in global temperatures, erratic rainfalls, droughts, and frequent flooding as a result of carbon emissions and forest depletion has raised concerns among policymakers and researchers. Among these concerns is the role of climate change and variability in economic activities. The dependence of agricultural (food) production on climatic features coupled with global rises in population raises concerns regarding food security, especially in the future (Kariuki et al., 2022). These concerns led to the World Summit on food security in 2009. It was declared during the summit that in order to catch up with global population growth, there is the need to increase crop production by about 70% by 2050 (Tester and Langridge, 2010). However, this expected increase in agricultural production will have to battle with a series of limitations and challenges caused by changes in the global environment expected to occur in the subsequent years. Meanwhile, these climatic features continue to worsen as global temperatures are likely to rise further to 0.3 to 1.7 degree Celsius in moderate scenario and 2.6 to 4.8 degree Celsius in extreme case depending on greenhouse gases emissions and mitigation strategies (IPCC, 1990 & 2013). The rise in temperature has a dire consequence including global food insecurity, water scarcity, infectious diseases, economic losses, and displacements (WHO, 2015). The adverse effects of climate change on agricultural activities led to the inclusion of food security features in the Paris Agreement as a part of a global climate change accord (UNFCCC, 2015). The inclusion of food security features in the Paris Agreement not only confirms climate change impacts on food productivity but also presents a challenge for maintaining food supply and demand, especially in the over-populated part of the world (UNFCCC, 2015).

Following the consequences of climate change outlined above, especially regarding food security, there is now growing interest among policymakers and researchers regarding the possible relationship between agricultural productivity and global environmental changes. This is to identify possible ways of curtailing food insecurity, which is anticipated in the near future, which is also in line with the achievement of some of the sustainable development goals (SDGs) such as zero hunger. According to Nicklin and Cornwell (2012), sectors of economies (such as agriculture and health) are expected to be affected severely by climate change. However, among these sectors, the agriculture sector suffers the most from the climate change especially in sub-Saharan Africa; this is because the sector is directly affected by climate change and variability given the minimal technological input (Mendelsohn et al., 2006; Abubakari et al., 2016). Given the importance of agriculture in Ghana; employing more than 30% of the working force and a source of livelihoods to many rural communities (GSS Report, 2017), any loss in agricultural productivity as a result of climate change and variability gives cause to worry.

Although the agricultural sector employs about 30% of the working force, its contribution to gross domestic product (GDP) has been declining overtime; 30.4% in 2006, 20.3% in 2015 and 18.3% in 2017. The service and industry sectors contribute 56.2% and 25.5% to gross domestic product. However, according to Kormawa and Jerome (2014), unlike the developed countries like Asia, Africa cannot grow or develop faster when it focuses more on the manufacturing and the service sectors. Therefore, it is important for Africa to exploit growth opportunities outside manufacturing and service sectors in order to expedite the economic growth process. The only promising sector is the agricultural sector since it is the dominant employer with growing markets at both national and international levels. The world demand for food is fast growing as a result of the growth in population, rising income, rapid urbanization and more open inter-regional trade policies and it is projected to more than double by 2050 (Badiane and Ulimwengu, 2017). Therefore, it is paramount that issues pertaining to food production be given much attention by policymakers, and the role of research in this regard cannot be overemphasized.

Consequently, considering the importance of agriculture in Ghana, it is therefore imperative to ascertain the impact of climate change on agricultural productivity. Studies (such as Sarpong & Anyidoho, 2012; Mohan et al., 2014; Mulungu & Ng'ombe, 2019; Naab et al., 2019; Etwire, 2020; allude that agriculture in Africa is still in a devastating state due to high carbon concentration, forest loss, prolong droughts, anomalous floods, frequent and severe bushfires. Climate change imposes a threat to households' income and consumption through many other economic sectors apart from agriculture (IPCC, 2013). The dependence of the poor on climate-sensitive natural resources further accelerates their vulnerabilities thereby worsening the social welfare system of the poor (Chalise et al., 2017).

Inflation in Ghana reached a two-decade high due to increases in food prices, transportation costs, and the cost of other items. According to the Ghana Statistical Service (January 2023), in December 2022, the yearly inflation rose for the 19th successive month, reaching 54.1%, a rise from the prior month's 50.3%. This marked the highest rate since April 2001. The inflation figure surpasses the upper boundary of the central bank's target range of 6% to 10%, with the depreciation of the cedi contributing to elevated food costs and the cost associated with imported commodities. Food prices are one of the primary drivers of inflation. Ghana's economic conditions have deteriorated as a result of the country's persistent price increases, which have had devastating effects on individuals' and households' livelihoods, as well as high costs for businesses. Consequently, rising prices erode individuals' and households' purchasing power, raise business costs, and stifle growth.

Farming, fisheries, and forestry, on the other hand, are diminishing due to the effects of climate change and extreme weather incidents like elevated temperatures and the rising of sea levels., prolonged dry seasons, rainfall variations, floods, and more. These extreme weather events have a negative impact on food production and, as a result, food supply. Food shortage drives up food prices significantly. Given the weight of food in the consumer price index, food price volatility as a result of unpredictable agricultural production implies food and headline inflation volatility. High and unpredictable price levels make it harder for monetary policy officials to manage inflation in the economy.

Although there is clear evidence that agriculture sector of Ghana is vulnerable to climate change amidst the sector's importance, there are only few studies with respect to the impact of climate change on agricultural productivity (see, for example, Mohan et al., 2014; Amankwah, 2019; Naab et al., 2019; Etwire, 2020). Moreover, these studies have focused on the impact of climate change on some individual crops using cross sectional data in some parts of the country, the role of climate change in farm selection, adaptation, and mitigation strategies, and they are mostly narrowed to some selected districts or regions in Ghana. The nationwide impact of climate change on agricultural productivity has not been given much attention. This further implies that the studies do not address the country-wide impact of climate change on the agricultural sector, hence, there is a gap that needs to be filled.

To this end, the main objective of this study is to investigate the nation-wide short-run and long-run impacts of climate change on agricultural productivity in the Ghanaian context. In order to test for robustness of the results, we also perform the same analysis using cereal production instead of general agriculture production, this is due to the fact that cereal production is more vulnerable to climate change in Ghana as compared to general agricultural activities. We also examined how climate change affects food inflation and monetary policies in Ghana This study contributes to knowledge, literature, and the development of the national economy by informing policymakers regarding the long-and short-run impacts of climate change on agricultural productivity, food inflation and monetary policies in Ghana. This study is also important as it contributes to the achievement of some of the sustainable development goals (SDGs) such as zero hunger. The outcome of the study will help in the adoption and implementation of strategies and policies that are aimed at improving agricultural production in Ghana.

The rest of the paper is organized as follows. Section 2 focuses on literature review whereas the methodology the study adopts is outlined in section 3. Sections 4 and 5 present the results and discussion and concluding remarks respectively.

2. Review of related literature

Many empirical studies have examined the effects of climate change on agricultural activities. For instance, many studies have examined the effects of climate change on crop yield. Climate change is expected to reduce crop yield through changes in temperatures, precipitation, droughts, floodings, and other climatic events. A study by Amikuzuno & Donkoh (2012) found that climate change could reduce maize production by 28% by 2050, while soybean yields could decline by up to 17%. Similarly, a study by Aidoo et al. (2019) found that climate change could lead to a 12% decline in cocoa yields by 2050. Laux et al. (2010) also investigated the effects of climate change on agricultural productivity under rainfed conditions in Cameroon. The study concludes that precipitation and temperature changes have negative effects on crop productivity and yield.

Other studies have studied the effects of climate change on overall agricultural productivity. Amankwah (2019) investigated the impact of climate variability and change on agricultural productivity in the three northern regions of Ghana. Using annual data from 1961 to 2010 and the modified Mann-Kendal's test, the study found significant increase in temperatures with no significant change in rainfall over the period. It was also revealed that climate change has a significant negative impact on agriculture. Similarly, Bocchiola et al. (2019) found a negative effect of climate change on agricultural productivity. Bocchiola et al. (2019) also demonstrated that Nepal's food security is threatened by climatic events. Mohan et al. (2014) studied the three Northern regions of Ghana and reported that rainfall increases agricultural productivity in these regions. Their result is explained by the prolong dryness (dry season) of the Northern part of Ghana, which is a major hindrance to agricultural productivity in these parts of Ghana. Mohan et al. (2014) also found research and development to have a positive influence on agricultural productivity in the three Northern regions of Ghana. Ayinde et al. (2011) found no significant effect for temperature but rainfall has a positive effect on Nigeria's agricultural production.

Wood and Mendelsohn (2015) emphasized on the role of climate change on net farm revenue of farmers in the Fouta Djallon area of the Northern Guinea and Southern Senegal. The authors reported that higher temperatures and precipitation lowers agricultural incomes in the rainy season as compared to the dry season. This implies farmers are worst off as the most important part of farm incomes are made in the rainy seasons and hence affecting farmers livelihoods. Similarly, Makuvaro et al. (2018) also found that farmers perceived the projected climate to have a negative impact on their livelihoods through crop and livestock productivity, availability of water, as well as food and nutritional security.

In Ethiopia, Ogbuabor & Egwuchukwu (2017) examined the impact of carbon emissions on agricultural productivity and households' welfare and found that carbon emissions have negative effect on agricultural productivity and household welfare. Using a comparative static multi-household (CGE) model to investigate the direct and indirect effects of climate change in Nepal, Chalise et al. (2017) found a significant negative impact of climate change on the Nepalese economy through reduction in agricultural productivity. The study further revealed that rural households whose livelihood depends on subsistent farming will face additional climate change induced losses.

To mitigate the impacts of climate change on agriculture, empirical literature on climate agriculture has proposed various adaptation strategies. These include changes in crop varieties, irrigation, agroforestry, and soil and water conservation practices. A study by Abaidoo et al. (2020) found that using drought-tolerant maize varieties could reduce yield losses due to climate change by up to 15%. Similarly, a study by Dossou-Yovo et al. (2019) found that the use of agroforestry practices could increase crop yields by up to 80%. Etwire (2020) applied the multinomial logit to a sample of 8700 households. The study revealed that farmers' choice of a farm system depends on climate variables. Farmers switch from crop and tree plantation farms which are climate sensitive to livestock and mixed farming practices.

Smallholder farmers in Ghana are particularly vulnerable to the impacts of climate change due to their limited resources and access to information and technologies. A study by Dossou-Yovo et al. (2019) found that smallholder farmers were less likely to adopt adaptation strategies due to a lack of knowledge, access to credit, and institutional support. Similarly, a study by Aidoo et al. (2019) found that smallholder cocoa farmers were more vulnerable to climate change impacts due to their dependence on rain-fed agriculture and limited access to irrigation.

A study by Amikuzuno and Donkoh (2012) argued that government policies should focus on improving access to credit, markets, and information for smallholder farmers. Similarly, a study by Aidoo et al. (2019) suggested that policies should promote the adoption of climate-smart agricultural practices and provide support for smallholder farmers.

Moessner (2022) examined the effects of precipitation on food consumer price inflation. Using a fixed panel estimation on a sample of OECD countries, the study found that precipitation has significant nonlinear effects on food CPI inflation. Using sample of East and South African countries, Odongo et al., (2022) conducted a study on the impact of climate change on inflation, and their findings were in alignment. Using the generalized method of moments (GMM) estimation, their results indicated that climate change, represented by factors like rainfall levels, rainfall unpredictability, and temperature variations, significantly affect both food and overall inflation.

Similarly, in the research by Kunawotor et al., (2022), they explored the effects of severe weather circumstances on inflation and the resulting implications for monetary policy using a sample of 52 African countries. The results of the system GMM estimation indicated that extreme weather occurrences are required to produce a price increase in Africa. Furthermore, the study discovered that droughts have an effect on both headline and food inflation, whereas floods tend to cause an increase in food price inflation. Also, Abril-Salcedo et al., (2020) in their study used Generalized impulse response functions (GIRFs) and investigated the nonlinear association between the meteorological phenomena El-nino and Colombian food prices. The findings implied that weather shocks have a temporary and uneven effect on inflation. A large El Nino shock has a considerable impact on food inflation increases over the next five to nine months.

Form the review, it is observed that the short-and long run impacts of climate change on agricultural productivity and food inflation has not been given much attention in the Ghanaian context. Studies on Ghana have concentrated mostly on the effect of climate change on selected crops and the role of climate change in crop selection and adaptation strategies. Therefore, this study fills lacuna in literature by examining both the short-and long-run impacts of climate change on agricultural productivity in the context of Ghana.

3. Methodology

This section focuses on the methodology of the study, and it is divided into three parts. The first part looks at the empirical model specification whereas the second and the third parts present data and estimation strategy respectively.

3.1 Model specification

In order to evaluate the impact of climate change on agricultural productivity, a neoclassical production function proposed by Solow and Swan is adopted. The representation of the model is given by Equation (1).

$$Y = f(K, L, A) \tag{1}$$

where, *Y, K, L* and *A* denote agricultural productivity (output), capital, labor, and technological progress (which also captures other factors including technology and climatic factors) respectively.

Following Muller-Kuckelberg (2012) and Ogbuabor & Egwuchukwu (2017), the study adopts carbon dioxide emissions (CO_2) and forest depletion as proxies for climate change. This study further extends this argument by including total agricultural arable land, number of tractors per 100 sq of arable land, and agricultural labor force as other potential drivers of agricultural productivity.

Taking agricultural value added as a measure of agricultural productivity, the specific empirical model for estimation is specified in Equation (2).

$$AVA = K^{\beta_1} L^{\beta_2} {CO_2}^{\beta_3} FDL^{\beta_4} AL^{\beta_5} e^{\varepsilon} \tag{2}$$

where *AVA, K, L,* CO_2, *FDL*, and *AL* represent agricultural value added, capital (proxied by number of agricultural machineries per hectare), labor (proxied by agricultural labor force), carbon dioxide emissions, forest depletion and agricultural arable land. The estimable form of Equation (2) is specified in Equation (3).

$$lnAVA_t = \beta_0 + \beta_1 lnK_t + \beta_2 lnL_t + \beta_3 lnCO_{2_t} + \beta_4 lnFDL_t + \beta_5 lnAL_t + \varepsilon_t \quad (3)$$

where *ln* is natural log, β_0 represents the constant term, β_1 to β_5 represent elasticities, ε_t is the white noise, which is assumed to have zero mean, homoscedastic variance, and non-contemporaneous correlation with the independent variables.

3.2 Data

The analysis is based on annual time series data from 1970 to 2017. The period of the study is based on data availability. The dataset used in the empirical analysis include agricultural value added (measured in US$), food inflation, exchange rate, real GDP growth, output gap, broad money supply, number of tractors per hectare of agricultural arable land, agricultural labor force, carbon dioxide emissions (measured in kt), forest depletion (measured as a percentage of gross national income), and total agricultural land used for cultivation in a particular year. All the variables are sourced from the World Bank's World Development Indicators (WDI), Bank of Ghana, and World Bank's Climate Change Knowledge Portal.

Agricultural value added is the dependent variable and it is measured as total output from forestry, hunting, fishing and cultivation of crops and livestock production less intermediate inputs. Carbon emissions and forest depletion are the main climate factors in this study. Carbon emissions capture all greenhouse gas emissions from all sectors of the economy. The expectation is that carbon emissions may cause temperatures to increase, high variability in rainfall patterns and prolong droughts, which affect crop productivity, forestry and fishing negatively. Forest depletion is measured as forest loss as a percentage of gross national income. An increase in forest depletion is expected to cause environmental degradation, loss of soil fertility and depletion of watersheds, which may have negative effect on crop production, fisheries, and forestry. Following Alagidede et al. (2015), capital per hectare of agricultural arable land is expected to have a positive impact on agricultural productivity. The expectation is that an increase in agricultural machinery and tractors per hectare would increase productivity per hectare contributing to gross agricultural value added.

3.3 Estimation Strategy

The study adopts the autoregressive distributed lag (ARDL) model bounds test as proposed by Pesaran et al. (2001). The autoregressive distributed lag model is a robust model and generates efficient and consistent results when dealing with finite-sized samples (Pesaran et al., 2001). The ARDL method of estimation also allows for more options in selection of optimal lags. In order to confirm the appropriateness of the autoregressive distributed lag model, the stationarity properties of the variables are first examined using the Dickey-Fuller and Phillips-Perron unit root tests. The existence of cointegration at the level, $I(0)$, first difference, $I(1)$ or mixture and not higher order, $I(2)$ lends support to the utilization of the ARDL bounds test method.

The next is to establish whether a possible long run equilibrium relationship exists among the variables. The optimal model selection is based on the minimum value of the Akaike Information Criterion (AIC). The choice of the AIC is due to the fact that it has the property of testing for the significance of differences between functions of different specifications (Akaike, 1973; Abango et al., 2019). According to Pesaran and Shin (1997), the optimal model (appropriate lag) selection sufficiently corrects for serial correlation among the residuals and the contemporaneous problem of regressor endogeneity in the model.

The study proceeds to test the cointegration hypothesis, which involves testing the significance of the coefficients of the lagged independent variables in the following multivariate equilibrium correction framework:

$$\Delta lnY_t = \gamma_0 + \sum_{i=1}^{p} \alpha_g \Delta lnY_{t-i} + \sum_{j=1}^{q} \beta_h \Delta lnX_{t-j} + \theta_1 lnY_{t-1} + \theta_2 lnX_{t-1} + \varepsilon_t \tag{4}$$

The parameters α_g and β_h are the short-run coefficients whereas θ_1 and θ_2 are the long-run coefficients. X_t represents explanatory variables in the study, Δ is the first difference operator, γ_0 denotes the drift component, ε_t depicts the disturbance error term (assumed to be white noise), and p and q represent optimal length of lags. The null hypothesis of no cointegration is tested against the alternative hypothesis of cointegration by conducting F-test for the joint significance of the long run coefficients. The null and alternative hypotheses are stated in Equations (5) and (6) respectively.

$$H_0: \theta_1 = \theta_2 = 0 \tag{5}$$

$$H_1 = \theta_1 \neq \theta_2 \neq 0 \tag{6}$$

To establish whether there is cointegration or not the calculated Wald (F-statistic) is compared with the lower and upper bound critical values; $I(0)$ and $I(1)$ respectively. The null hypothesis of no cointegration is rejected when the F-statistic is greater than the upper bound critical value. On the other hand, the null hypothesis is not rejected when the F-statistic is less than the lower bound critical value. The cointegration relationship becomes inconclusive when the F-statistic falls within the lower and upper bound critical values. After establishing a valid long run cointegration among the variables, the long-run parameters are then estimated.

The following error correction model (ecm) is specified to estimate the short-run parameters and to obtain the error correction term which measures the speed of adjustment.

$$\Delta lnY_t = \pi_0 + \sum_{i=1}^{n} \pi_n \Delta lnY_{t-i} + \sum_{j=1}^{m} \sigma_m \Delta lnX_{t-j} + \delta ect_{t-1} + \mu_t \tag{6}$$

where the variables are as already defined, *ect* is the error correction term variable and δ is the coefficient. The error correction term is an important variable that explains the correction speed of short run deviations to the long run equilibrium. The coefficient of the error correction term (δ) is expected to negative and significant and between zero and one. Obtaining a significant negative value which is between zero and one further confirms the long-run relationship. π_0 and μ_t are the constant and error terms respectively whereas π_n and σ_m are the short-run parameters.

4. Results and Discussion

This section presents and discusses the results of the study. Specifically, it focuses on the results of the unit root test, ARDL bounds test, long- and short-run results, robustness analysis, and the residual diagnostics.

4.1 Preliminary Analysis

In this section we present descriptive statistics and unit root results for all the variables we used in the study. The purpose of this section is to aid understand the evolution of the variables and their stationarity properties. The results of the descriptive statistics and the unit root test are present in the appendix in Table A1 and A2 respectively.

From Table A1, agricultural value added which measures the value added from all agricultural activities within a year, recorded an average value of 3.7 billion US dollars, a minimum value of 0.98 billion US dollars and a maximum value of 10.4 billion US dollars. This shows some improvements in the agricultural sector, however, since agricultural value added is strongly influenced by the price and exchange, we also used cereal production measured in metric tons. Which has a mean of 1.54 million metric tons with a minimum value of 0.43 million metric tons and a maximum of 3.13 million metric tons. For the climate-related variables, for instance, rainfall in Ghana has a high variability of about 25.4mm with a mean of 194.3mm, minimum of 150.7mm and maximum of 252.3mm. Temperature has been very volatile and unpredictable recording a mean of 0.615^0C change with a minimum change of -0.328^0C and a maximum change of 1.405^0C.

The unit root test results are reported in Table 4.1. Both the Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) test results are reported accordingly. The results show that mostly all the variables are stationary after first differencing except agricultural labour force, food inflation, exchange rate, money supply, monetary policy rate, temperature changes, and rainfall are stationary in levels, however, agricultural value added, cereal production, agricultural land, machinery, and fertilizer usage are stationary after first differencing. Hence, the mixed levels of cointegration confirms the use of the ARDL in corroborating the relationship between agricultural productivity and climate related variables.

4.2 Long Run Bound Test

The bound test results are reported in Table 1. The results show that the computed F-statistic exceeds the upper bound critical value at 5 percent significance level for both models, indicating the rejection of the null hypothesis of no cointegration among the variables. This implies there is a long. This establishes the presence of a steady state long run relationship between log of agricultural productivity and the rest of the variables in the models. Thus, it is realistic to corroborate long run and short run dynamics within the ARDL framework.

Table 1: Bound test for Long Run Cointegration

Model	F-statistic	Lower bound	Upper bound
$AVA = f(CO2, RF, Tem, Fer, AL, L, K)$	6.436**	2.32	3.50
CP $= f(CO2, RF, Tem, Fer, AL, L, K)$	26.778***	2.32	3.50
$FI = f(m2, Exr, RF, CO2, Tem, RGDP, FP)$	5.218***	2.32	3.50
$FI = f(m2, Exr, RF, RFsq, CO2, Tem, RGDP, FP)$	4.009***	2.32	3.50

Note: ** represents the rejection of no cointegration at 5% significance level.
Source: Authors' estimation from Stata 16

4.3 Residual Diagnostics and Model Stability Test

The validity of the estimated model was confirmed by diagnosing standardized residuals for normality, heteroskedastic and serial correlation. The correct functional form was confirmed using the Ramsey RESET test. The Chi-square test statistics for all the tests are statistically insignificant as shown in Table 2 for both models, which indicates that the models do not suffer from Heteroskedasticity, serial correlation and specification errors. The Jacque-Berra Normality statistic also confirms the normality of the error residuals. In addition, the plots of CUSUM and CUSUMSQ of recursive residuals show movements within the boundary of critical points, confirming stability of the residual variance. Therefore, the residual and stability diagnostics suggest that the models are statistically fit for purpose. The P-values of the Chi-square test statistics are larger than the 5 per cent level, showing that the selected model passed the test against normality, serial correlation, and heteroscedasticity. The CUSUM and CUSUMSQ of recursive residuals also show parameter stability within the boundaries of critical points as shown in figure 1. Therefore, the absence of autocorrelation, heteroscedasticity and non-normality of the error terms confirms the adequacy of the models.

Table 2: Results of Residual Diagnostics and Model Stability Tests

Residual and Stability Diagnostics	Model 1	Model 2	Model 3	Model 4
Normality (Jacque-Berra)	5.79 (0.430)	3.58 (0.577)	0.0562 (0.972)	1.281 (0.527)
Autocorrelation (Durbin Watson)	2.249	2.257	2.091	1.892
Autocorrelation (Breusch-Godfrey LM)	2.912 (0.0879)	0.88 (0.3486)	2.147 (0.0901)	2.235 (0.893)
Functional form (Ramsey RESET)	0.99 (0.413)	1.47 (0.2426)	2.628 (0.117)	3.616 (0.071)
Heteroskedasticity (White General)	46.00 (0.430)	46.00 (0.430)	27.089 (0.586)	45.08 (0.447)
Autoregressive Conditional Heteroskedasticity)	0.979 (0.322)	0.841 (0.433)	0.090 (0.483)	0.961 (0.526)
CUSUM	Stable	Stable	Stable	Stable
CUSUMSQ	Stable	Stable	Stable	Stable

Source: Authors' estimation from Stata 16

4.4 ARDL Long Run Results

The long run results are shown in table 3. The results show that climate change exerts a negative significant impact on agricultural productivity in the long run as expected in both models. The coefficients are -1.289 and -0.433, indicating a percentage increase carbon emissions causes agricultural value added and cereal production to fall by 1.3% and 0.4% respectively on average in the long run. This is consistent with Chalise *et al.* (2017). Large emissions of carbons increase the among of carbon concentration on the earth surface, therefore exerting more pressure on global temperatures and rainfall patterns which lead to higher global temperatures, erratic rainfall patterns, frequent droughts and floods that imposes a severe threat to agricultural productivity as also demonstrated by (Lemi, 2019; Makuvaro et al., 2018; Amankwah, 2019).

Rainfall is another climatic variable that influences agricultural productivity across the world, especially in Africa. Our predicts that increases in precipitation levels significantly decrease cereal production in Ghana in the long run. However, precipitation has no effect on overall agricultural production. Our results show evidence of farmers switching from crop or cereal production to tree plantation which are climate sensitive and to livestock and mixed farming practices as indicated by Etwire (2020). On contrary, we found that rise in temperature is associated with an increase in agricultural production in the long run, however, it has no effect on cereal production in Ghana. This is in contrary to our apriori expectations that rise in temperatures decreases agricultural production through intensive drought and withering of crops. This finding can either be as result of the fact that farmers develop climate response or mitigation initiatives by either adopting climate friendly seedlings or through switching and mix farming practices. Or this result is strongly derived by seasonality, that is short rainy seasons with lower temperatures during which agricultural activities are carried out and a long dry season with higher temperatures.

We also found that all other agricultural inputs included in the analysis are critical to the development of agricultural production and the quest for food security in the country. For instance, fertilizer usage is found to have a significant positive effect on both agricultural production and cereal production. Fertilizer application enhances soil fertility, which is essential for plants and crops growth, and thereby enhancing crop yields. Similarly, Du et al. (2020) found that fertilizer applications increase crop yield, however, they argued that manure fertilizers increase crop yield by 7.6% compared to mineral fertilizers.

The results in Table 3 also show that the coefficient of agricultural arable land is statistically significant in both models implying that increases in the size of the cultivating land causes an increase in agricultural value added or cereal production in the long run. This indicates that the size of agricultural arable land does influence agricultural productivity in the long run. This is consistent with Amankwah (2019) who reported that individual agricultural arable land influences agricultural productivity in the three northern regions of Ghana.

The results also show that the number of agricultural machinery and tractors per hectare of cultivated land have a positive effect on agricultural production and cereal production in Ghana. This implies that capital investment in the agricultural sector is essential for the growth of the agricultural sector and the quest for food security. Bocchiola et al. (2019 and Laux et al. (2010) also emphasized the importance of machinery and tractors in promoting agricultural activities. We also found that agricultural labour force has a positive effect on agricultural production, but no effect on cereal production in the long run. Labour force is the main driver of the agricultural sector in Ghana due to less mechanization of the sector. Although there is some form of mechanization of the sector, it is mainly centered on plantations, animal farming, fisheries, and some other crops, but cereal production seems to be the least in mechanization. Mechanization complements labour forces making it more productive, thus explaining why labour increases overall agricultural productivity but does not affect cereal production in the long run.

In this section we presented the long run effects of climate change measured as carbon emissions, rainfall, and changes in temperature on agricultural and cereal production in Ghana. Our results show that climate change is a threat to food security in Ghana, our review also shows that climate change also affects livelihood, health, and other aspects of human life. We also found that labour, capital, fertilizer, and arable land are long run drivers of agricultural production in Ghana. Based on these findings we have suggested some policies or implications of the results in section five of the study.

Table 3: Long Run Results

Variable	**Model 1**	**Model 2**
Carbon Emission	-1.289263***	-0.4325177***
	(0.3351062)	(0.1223331)
Arable Land Size	1.645249**	0.79075***
	(0.7755266)	(0.1992028)
Agricultural Labour force	7.699841***	0.7199484
	(1.247881)	(0.4955528)
Fertilizer	0.2073283**	0.0102981***
	(0.084401)	(0.0030047)
Rainfall	-0.4313103	-0.379339**
	(0.2734801)	(0.1231102)
Temperature	-0.6120091***	-0.1371711*
	(0.2090191)	(0.0753705)
Agricultural machinery	0.5627943***	0.0671408**
	(0.1027131)	(0.0301162)

Note: *, **, & *** denote significance at 10%, 5%, and 1% respectively. Coefficients in parentheses are standard errors. Source: Authors' construction from Stata 16

4.5 Analysis of Short Run Results

The short run estimates together with the error correction terms are reported in Table 4 for both models. The error correction terms are negative and significant at 5% level. The negative sign of the coefficient suggests the possibility of reverse adjustment to long run equilibrium, following short run disturbances. The coefficient of the error correction terms is -0.5709 and -0.3455 for agricultural production and cereal production respectively, indicating the speed of the error correction term to be 57% and 35% for the long run estimates, taking approximately two years and three years to complete for agricultural production and cereal production respectively. The results support the ARDL bounds cointegration test in Table 1.

Among the regressors in Table 4, carbon emissions, agricultural labour, temperature changes, and agricultural machinery are the relevant short run drivers of agricultural production in Ghana. In terms of direction of impact, carbon emissions have a negative effect on agricultural production, while temperature, machinery, and labour have a positive influence on agricultural production. However, arable land, fertilizer usage, and rainfall do not have influence overall agricultural activities in the short run. The previous level of agricultural productivity also positively drives agricultural production in the current period. This finding is consistent with (Ayinde et al., 2011 and Chalise et al., 2017). The short run results are therefore consistent with the long run results. This confirms that carbon emissions, labour employed in the agricultural sector, temperature changes, and capital per hectare of agricultural arable land are the main drivers of agricultural productivity. This suggests that current percentage increase in agricultural production causes future agricultural productivity to increase by 0.7% on average.

For cereal production, we found that carbon emissions, land size, labour, rainfall, machinery, and fertilizer usage are the main driver of cereal production in the short run in Ghana. Carbon emissions and rainfall have negative effects on cereal production in Ghana while land size, labour force, machinery, and fertilizer usage have positive effects on cereal production in Ghana in the short run. These results are consistent with the long run results discussed in section 4.5.

Table 4. ARDL Short Run Results

Variable	Model 1	Model 2
Agricultural output (-1)	0.6659563***	
	(0.1387417)	
Cereal Production (-1)		0.345588***
		(0.099612)
Carbon Emissions	-0.0384205	-0.5819876***
	(0.1864724)	(0.1743484)
Carbon Emissions (-1)	-0.1685977	
	(0.2156911)	
Carbon Emissions (-2)	-0.5291182**	
	(0.1902502)	
Arable Land Size	0.0150903	1.379896***
	(0.6989366)	(0.187254)
Arable Land Size (-1)	0.9544857	0.3158777
	(0.6896059)	(0.2531594)
Agricultural labour force	7.495409	9.797444*
	(4.823838)	(5.046996)
Agricultural Labour force (-1)	11.89182**	10.76619**
	(4.936609)	(5.100204)
Fertilizer	0.0367138	0.013856***
	(0.0503338)	(0.0045953)
Fertilizer (-1)	0.0816653*	
	(0.0469025)	
Rainfall	-0.2462672	-0.1123189
	(0.1562275)	(0.1593438)
Rainfall (-1)		-0.3981055**
		(0.1643375)
Temperature	0.1897385**	0.0737091
	(0.0733212)	(0.0745336)
Temperature (-1)	0.1597035*	0.1108657
	(0.0794603)	(0.078631)
Agricultural machinery	0.158642**	0.0351017

	(0.0620732)	(0.0482786)
Agricultural machinery (-1)	-0.0255799	0.1254451**
	(0.0688637)	(0.048128)
Agricultural machinery (-2)	0.1882791***	
	(0.058097)	
Constant	-68.20305***	-23.49187**
	(17.28589)	(10.3311)
Error correction term	-0.5709745***	-0.345581***
	(0.0988617)	(0.0199692)

Note: *, ** and *** represent significance at 10%, 5% and 1% levels respectively; Standard errors are in parentheses.
Source: Authors' estimation from Stata 16

4.6 Effects of Climate Change on Food Inflation

4.6.1 Short Run Results

Table 5. Short Run Results for the effects of Climate change on Food Inflation

	Short Run		Long Run	
Variable	**Model 3**	**Model 4**	**Model 3**	**Model 4**
Food inflation (-1)	0.2275***	0.1781**		
	(0.0826)	(0.0826)		
Temperature	9.3027***	7.8002***	0.8141***	0.9145***
	(3.0191)	(2.031)	(0.2768)	(0.2768)
Precipitation	-2.9065***	-2.9065***	-4.9491**	-4.9491**
	(0.9586)	(0.9586)	(2.8087)	(2.8087)
Precipitation squared		3.2114**		6.0041**
		(1.763)		(3.0210)
Carbon emission	-1.2783	-1.2783	-2.1073	-2.1073
	(1.1195)	(1.1195)	(2.3082)	(2.3082)
Food Production Index	-8.6009	-8.6009	-1.8782**	-1.8782**
	(18.944)	(18.944)	(0.8965)	(0.8965)
GDP growth rate	-0.0015	-0.0015	-0.0408***	-0.0408***
	(0.0135)	(0.0135)	(0.0167)	(0.0167)
GDP growth rate (-1)	0.0395***	0.0395***		
	(0.0137)	(0.0137)		
Output gap	2.5028***	2.5028***	-0.2867	-0.2867
	(0.4426)	(0.4426)	(0.0167)	(0.0167)
Money supply	-0.1596	-0.1596	0.4647***	0.4647***
	(0.3744)	(0.3744)	(0.1477)	(0.1477)
Money supply (-1)	2.6110***	2.6110***		
	(0.4426)	(0.4426)		
Exchange rate	-0.54**	-0.54**	-0.4014***	-0.4501***
	(0.2132)	(0.2132)	(0.0702)	(0.0811)
ECM (-1)	-0.5407***	-0.5897***		
	(0.1359)	(0.20141)		
Constant			7.5510***	8.4731***
			(0.6167)	(1.0942)

Notes: '***', '**' and '*' are significance levels at 1%, 5% and 10% respectively. Robust standard errors are in parenthesis.

5. Concluding remarks

The main objective of the study is to investigate the long-run and short-run impacts of climate change on Ghana's agricultural performance. In doing this, the study used annual data from 1970 to 2017 with the application of the ARDL estimation strategy. Carbon emissions, temperature, and precipitation (rainfall) are used as measures of climate change in the study. The study controlled for differences in agricultural capital (measured as machinery and tractors per hectare), agricultural arable land size, fertilizer usage, and labour force in agriculture. As highlighted above, previous value of agricultural performance, agricultural labour force, fertilizer usage, and agricultural machinery have significant positive impacts on agricultural performance and cereal production in the short run. While the measures of climate change have a significant negative impact on agricultural performance in the short run. Hence, the main short run drivers of agricultural performance in Ghana are climate change variables, agricultural labour, fertilizer usage, and capital. The results also shows that only climate change (through carbon emissions, precipitation, and temperature) and agricultural labour force, land, fertilizer usage, and agricultural machinery continue to explain growth in agricultural performance in the long run. Our findings are highly consistent with previous studies.

With regards to food inflation, we found that increases in atmospheric temperature is detrimental to food inflation and headline inflation. Precipitation reduces food inflation to some extent, after which precipitation becomes detrimental to food inflation. This can be explained by the fact that agricultural productivity dependence on precipitation, however excessive precipitation leads to floods which causes losses to the agricultural sector and even losses to human life. These losses contribute to heightened food inflation.

In conclusion, the findings implies that climate change is a threat to agricultural performance and food inflation, especially cereal production in Ghana through frequent flooding, droughts, erratic rainfall patterns, high temperatures and among others. Therefore, the study has the following implications: First, the study draws to attention the urgent need to address the negative effects of climate change by developing measures for reducing weather-dependent agricultural activities through installing irrigation systems. Second, lessening the negative impacts of climate change on agricultural productivity through mitigation of carbon emissions or promoting afforestation.

References

Abango, M. A., Yusif, H., & Issifu, A. (2019). Monetary aggregates targeting, inflation targeting and inflation stabilization in Ghana. *African Development Review*, *31*(4), 448-461.

Abubakari, Z., Van der Molen, P., Bennett, R. M., & Kuusaana, E. D. (2016). Land consolidation, customary lands, and Ghana's Northern Savannah Ecological Zone: An evaluation of the possibilities and pitfalls. *Land use policy*, *54*, 386-398.

Akaike, H. (1973). Maximum likelihood identification of Gaussian autoregressive moving average models. *Biometrika*, *60*(2), 255-265.

Alagidede, P., Adu, G., & Frimpong, P. B. (2015). The effect of climate change on economic growth : evidence from Sub-Saharan Africa The effect of climate change on economic growth : *Environmental Economics and Policy Studies*, *June*. https://doi.org/10.1007/s10018-015-0116-3

Amankwah, E. (2019). *Impact of Climate variability and change on agricultural productivity in the three* *northern regions of Ghana*. *3*(1), 30–41.

Ayinde, O. E., Muchie, M., Olatunji, G. B., Street, S., Africa, S., & Management, F. (2011). *Effect of Climate Change on Agricultural Productivity in Nigeria : A Co-integration Model Approach*. *35*(3), 189–194.

Badiane, O., & Ulimwengu, J. (2017). Business pathways to the future of smallholder farming in the context of transforming value chains. *African Agriculture Status Report*.

Bocchiola, D., Brunetti, L., Soncini, A., Polinelli, F., & Gianinetto, M. (2019). Impact of climate change on agricultural productivity and food security in the Himalayas : A case study in Nepal. *Agricultural Systems*, *171*(February), 113–125. https://doi.org/10.1016/j.agsy.2019.01.008

Chalise, S., Naranpanawa, A., Bandara, J. S., & Sarker, T. (2017). A general equilibrium assessment of climate change – induced loss of agricultural productivity in Nepal. *Economic Modelling*, *62*(January), 43–50. https://doi.org/10.1016/j.econmod.2017.01.014

Etwire, P. M. (2020). The impact of climate change on farming system selection in Ghana. *Agricultural Systems*, *179*(January 2019), 102773. https://doi.org/10.1016/j.agsy.2019.102773

IPCC. (1990). *First report.pdf*.

Kariuki, J., Galie, A., Birner, R., Oyieng, E., Chagunda, M. G., Jakinda, S., ... & Ojango, J. M. (2022). Does the gender of farmers matter for improving small ruminant productivity? A Kenyan case study. *Small Ruminant Research*, *206*, 106574.

Kariuki, G. M., Njaramba, J., & Ombuki, C. (2022). Tea Production Response to Climate Change in Kenya: An Autoregressive Distributed Lag Approach. *African Journal of Economic Review*, *10*(1), 2-26.

Kormawa, P., & Jerome, A. (2014). Renewing industrialization strategies in Africa. *Beyond a middle income Africa: Transforming African economies for sustained growth with rising employment and incomes. ReSAKSS Annual Trends and Outlook Report*.

Laux, P., Jäckel, G., Tingem, R. M., & Kunstmann, H. (2010). Impact of climate change on agricultural productivity under rainfed conditions in Cameroon-A method to improve attainable crop yields by planting date adaptations. *Agricultural and Forest Meteorology*, *150*(9), 1258–1271. https://doi.org/10.1016/j.agrformet.2010.05.008

Lemi, T. (2019). Effects of Climate Change Variability on Agricultural Productivity. *International Journal of Environmental Sciences & Natural Resources*, *17*(1). https://doi.org/10.19080/ijesnr.2019.17.555953

Makuvaro, V., Walker, S., Masere, T. P., & Dimes, J. (2018). Smallholder farmer perceived effects of climate change on agricultural productivity and adaptation strategies. *Journal of Arid Environments*, *152*, 75–82. https://doi.org/10.1016/j.jaridenv.2018.01.016

Mendelsohn, R., Dinar, A., & Williams, L. (2006). The distributional impact of climate change on rich and poor countries. *Environment and development economics*, *11*(2), 159-178.Mohan, G., Matsuda, H., Donkoh, S. A., Lolig, V., & Abbeam, G. D. (2014). *Effects of Research and Development Expenditure and Climate Variability on Agricultural Productivity Growth in Ghana*. 443–451.

Müller-Kuckelberg, K. (2012). Climate change and its impact on the livelihood of farmers and agricultural workers in Ghana. *Preliminary research results. General agricultural workers' union of GTUC. friedrich ebert stiftung (Fes)*, 1-47.

Mulungu, K., & Ng, J. N. (n.d.). *We are IntechOpen , the world ' s leading publisher of Open Access books*

Built by scientists , for scientists TOP 1 % Climate Change Impacts on Sustainable Maize Production in Sub-Saharan Africa : A Review.

Naab, F. Z., Abubakari, Z., & Ahmed, A. (2019). The role of climate services in agricultural productivity in Ghana : The perspectives of farmers and institutions. *Climate Services*, *13*(November 2018), 24–32. https://doi.org/10.1016/j.cliser.2019.01.007

Nicklin, S., Cornwell, B., Witthaus, M., Rowlands, C., & Griffiths, J. (2012). Climate exchange. *Tudor Rose, Geneva*.

Ogbuabor, J. E., & Egwuchukwu, E. I. (2017). *The Impact of Climate Change on the Nigerian Economy*. *7*(2), 217–223.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289-326.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1997). Pooled estimation of long-run relationships in dynamic heterogeneous panels.

Royal, T., Society, G., & Geographers, B. (1988). *Carbon Dioxide , Climatic Change and Agriculture Author (s): R . A . Warrick Published by : The Royal Geographical Society (with the Institute of British Geographers) Stable URL : https://www.jstor.org/stable/633848 REFERENCES Linked references are av*. *154*(2), 221–233.

Sarpong, D. B., & Anyidoho, N. A. (2012). *Climate Change and Agricultural Policy Processes in Ghana*. *September*.

Tester, M., & Langridge, P. (2010). Breeding technologies to increase crop production in a changing world. *Science*, *327*(5967), 818-822.

Appendix

A1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
AVA	48	3.73e+09	2.72e+09	9.85e+08	1.04e+10
AL	48	3153458	1125904	1700000	4720000
CO2	48	6086.227	3819.914	2295.542	14620.33
RP	48	9649538	2067579	6107469	1.29e+07
K	48	7.367272	2.717524	4.5175	12.25882
RF	48	194.3167	25.39102	150.7	252.3
FER	48	37191.81	41796.53	2885	174600
TEM	48	.6152083	.409027	-.328	1.405
cerealprod~n	48	1541543	780117.9	432000	3126784
cerealperh~e	48	1206.633	357.5335	517.4	1912.3
cerealland	48	1201398	289477.1	645000	1642866

Source: Authors' estimation from stata 16

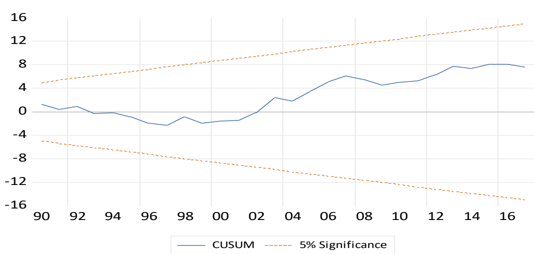
A2. Unit Root Test Results

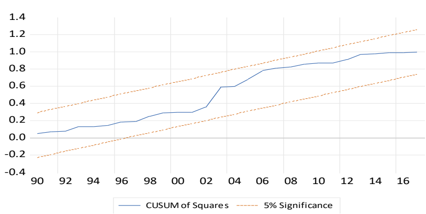
Table 1: Unit root test results

	ADF		PP	
Variable	**Intercept**	**Intercept + trend**	**Intercept**	**Intercept + trend**
lnAVA	-1.101	-2.249	-0.563	-1.737
ΔlnAVA	-5.594***	-5.532***	-5.567***	-5.503***
lnAL	-0.094	-1.876	-0.217	-2.248
ΔlnAL	-5.484***	-5.506***	-5.510***	-5.513***
lnCO2	0.809	-1.706	1.312	-1.537
$\Delta lnCO_2$	-9.964***	-9.956***	-11.329***	-11.706***
lnL	-2.963**	-0.069	-4.805***	-0.670
ΔlnL	-1.045**	-6.634***	-1.643	-2.636
RF	-7.887***	-7.834***	-7.903***	-7.862***
ΔRF	-14.012***	-13.874***	-16.802***	-16.614***
K	-1.740	-0.852	-1.859	-0.633
ΔK	-7.185***	-7.569***	-7.187***	-7.653***
FER	-0.858	-2.549	0.162	-2.296
ΔFER	-10.107***	-10.274***	-11.567***	-12.427***
TEM	-2.588	-5.916***	-2.188	-5.849***
ΔTEM	-8.896***	-8.799***	-11.305***	-11.142***

Note: *, ** and *** represent rejection of the null hypothesis at 10%, 5% and 1% respectively
Source: Authors estimation from stata 16

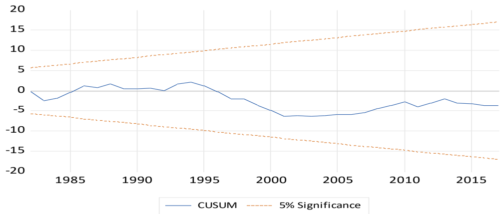
A3. CUSUM and CUSUM Square Graph for Model 1

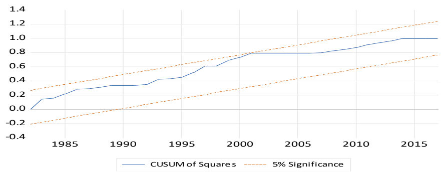




A4.

A4. CUSUM and CUSUM Squared Graph for Model 2


20
15
10
5
0
-5
-10
-15
-20
1985
1990
1995
2000
2005
2010
2015
CUSUM
5% Significance


1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
1985
1990
1995
2000
2005
2010
2015
CUSUM of Squares
5% Significance