Journal of Economic Impact 5 (2) 2023. 132-145

Available Online
Journal of Economic Impact
ISSN: 2664-9764 (Online), 2664-9756 (Print)
https://www.scienceimpactpub.com/jei

MODELING THE EFFECTS OF CLIMATE CHANGE ON FOOD PRODUCTION IN IVORY COAST: EVIDENCE FROM ARDL APPROACH

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ARTICLE INFO

Article history
Received: March 10, 2023
Revised: June 19, 2023
Accepted: June 26, 2023

Keywords
Agriculture production
ARDL
Climate change
Ivory Coast
West Africa

ABSTRACT

There is a direct link between global warming and hunger in emerging West African nations like Ivory Coast, where the population is overgrowing, and food insecurity is rising. This work aims to examine and explore climate change's effects on agriculture production in Ivory Coast from 1990 to 2019. Various stationarity tests, including the Phillips-Perron (PP) and the Augmented Dickey-Fuller (ADF), are applied to determine the variables' order of integration. The autoregressive distributed lag (ARDL) approach is employed to model the long- and short-run relationships between temperature, rainfall, carbon dioxide emissions, domestic credit, gross capital formation, and agriculture sector and subsectors. The present study uses the Johansen cointegration test to verify the long-run cointegration of the ARDL estimation. The findings reveal that all the variables are integrated into order zero or one. Cointegration tests demonstrate a valid long-term association between the variables. Agriculture and related subsectors in Ivory Coast were found to benefit from increasing temperature over the long run, except for the fishery subsector, where the impact is negligible. In the short run, temperature's effect is positive on aggregate agriculture, although it is not statistically significant. Its effect is beneficial to agriculture's subsectors, except for fishery production. In both runs, Ivory Coast's aggregate agriculture sector and fishery subsector are negatively affected by rainfall. An insignificant favorable effect of rainfall is found on crop production in both runs. The estimated results indicated that the role of CO_2 is positive on agriculture and crop production in both run estimations. However, CO_2 does not impact livestock production. It has a long-term positive influence on fishery production but no effect in the short run. Domestic credit is found to have a beneficial influence on agriculture and its subsectors in both runs, except for crop and livestock production, where the effect is negative and insignificant in the short run. Gross capital formation negatively impacts agriculture and its subsectors in Ivory Coast, except crop production, where it only has an insignificant beneficial effect in the short run. The same is true for fishery production, which only had a significant favourable impact effect in the short run. For the government and policymakers, the findings guide the formulation of suitable policies to address global warming's effects on agriculture and guarantee sustainable food production for the increasing population.

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https://doi.org/10.52223/jei5022302

INTRODUCTION

Thirty percent or more of the world's population is at risk of hunger, showing that food insecurity is rising worldwide (Sibanda and Mwamakamba, 2021). According to FAO (2021), 927.6 million people worldwide were affected by food insecurity in some form or another. Africa accounts for 37.3% of this total, with 346.6 million people suffering from food insecurity (Xie et al., 2021). Economic instability, population growth, and climate change continue to cause severe hunger in most nations, even though the coronavirus (COVID-19) pandemic has been the primary driver of food insecurity over the past year (IFPRI, 2021). Population expansion, climate change, and economic instability have all contributed to a rise in undernourishment across Africa between 2017 and 2019, as reported by Schilling et al. (2020). Food insecurity is expected to reach an alarming 25.9% (346.6 million) in Africa by 2020, against 17.7% (203.5 million) in 2014. Specifically, West Africa is the worst hit, with 28.8% of its population (115.7 million) threatened by food insecurity in 2020, against 8.6% in 2014 (FAO, IFAD, UNICEF, WFP, WHO, 2021; Otekunrin et al., 2021). The ability to adapt to climate change is often limited in countries where food is scarce (IFPRI, 2020). Over 115 million people in West Africa are severely food insecure, and climate change is a major contributor to this problem (Ntiamoah et al., 2022).

Natural resources are impacted by climate change, which in turn has repercussions for food security, human health, the labor market, and the economy (Thiault et al., 2019; Chandio et al., 2020c). The agricultural sector is one of the most at risk from climate change, and changes in weather patterns can have far-reaching effects on the amount of food that can be produced worldwide (Kirby et al., 2016). Changes in temperature, precipitation, and sunshine duration due to human-caused climate change have direct and indirect effects on agricultural productivity cycles. These shifts are a major contributor to the growing problem of food insecurity since they have altered the historical pattern of agricultural productivity. The impacts of climate change on agriculture are seen worldwide, but they are felt most acutely in low-income nations (Ali et al., 2017). Sub-Saharan Africa, home to over a billion people across fifty-four nations (World Bank, 2019), is highly susceptible to climate change impacts (Boko et al., 2016; Gan et al., 2016). Because they rely on rainfed agriculture, African nations, especially sub-Saharan African ones, are particularly sensitive to climate shocks (Mihiretu et al., 2019). Modeling climate change's effects on food security is essential to lessen the agriculture sector's susceptibility to climate change and mitigate its negative consequences (Atanga and Tankpa, 2021). Carbon dioxide emissions, temperature, precipitation, domestic credit, and gross capital formation were all evaluated to see how they would affect Ivory Coast's primary food-producing systems.

Twenty-one percent of GDP, fifty percent of all jobs, and sixty percent of all merchandise exports in Ivory Coast in 2018 came from the agricultural sector, making it a vital part of the economy (World Bank, 2023). However, in the present context of climate change, the hazards associated with rising temperatures and increased climate weigh severely on Ivorian agriculture. Food production is impacted by climate change in several ways, including direct and indirect effects on the crop and livestock subsectors (Dumortier et al., 2021; Warsame et al., 2022). Fish production is also seriously threatened by climate change (Pauly and Cheung, 2018), which reduces the fish's possibilities of maturing and reproducing, thus their chances of survival (Clarke et al., 2021). Ivory Coast's agricultural sector must be more resilient, so it is important to learn about the risks of climate change. The implications of climate change on the various agricultural sectors must be uncovered through an integrated investigation. This paper examines climate change's effects on Ivory Coast's agricultural systems. The following is a list of the specific aims: To (1) evaluate how climate change affected the country's overall agricultural system, (2) evaluate how it affected the country's crop production system, (3) evaluate how it affected the country's livestock production system, and (4) evaluate how it affected the country's fishery production system.

This research contributes to the existing body of knowledge in the following ways. First, this is a nationwide study examining how factors including carbon dioxide emissions, domestic credit, precipitation, temperature, and gross capital formation affect agricultural output in the long and short term. Second, the relationship between climate change and food production has been the subject of numerous studies. However, additional research is needed across various agricultural subsectors, including crop, livestock, and fishery. Third, assessing the impact of climate change on agricultural productivity using econometric models like the autoregressive distributed lag (ARDL) model is a new field of study, with few studies in Ivory Coast. Last but not least, the available studies did not consider other factors expected to affect agricultural performance, such as domestic financing to the private sector and gross capital formation (Misra et al., 2016). The present study fills this gap by including domestic credit and gross capital formation as control variables. According to previous research, domestic credit increases agricultural output, and capital formation provides infrastructure for the agricultural sector, contributing to increased agricultural productivity (Chandio et al., 2022c; Zakaria et al., 2019). Mwabutwa (2017) claims that public investment in agriculture is essential to the sector's expansion. Growth in agriculture may be possible only if public investments in irrigation, extension, and research complement the expansion of the credit supply to agriculture from traditional sources (Misra et al., 2016). Finally, this study provides a valuable policy for enhancing agricultural production, coping with the effects of climate change, and achieving long-term food security. Policymakers should pay close attention to the findings of this study because they highlight the importance of climate-smart agriculture in increasing agricultural productivity and the need for governments and policymakers to develop effective and efficient policies to combat climate change and increase agricultural productivity in the context of climatic change.

The remaining parts of the study contain a literature review, data and methods, results and discussion, and a conclusion and policy implications. The "Literature review" section explores the literature and explains how climate change affects agricultural outputs like crops, animals, and fishery. The econometric models developed to investigate climate change's impact on agricultural output are also included. Data (variable definitions) and methods (theoretical and economic models) are outlined in the research's "Materials and Methods" section. In "Results and Discussion," the outcomes of employing the ARDL methodologically-based data technique are displayed. In the paper's closing section, titled "Conclusion and policy implications," we present the study's key findings and potential policy alternatives for mitigating the effects of climate change on aggregate agriculture and its subsectors' production.

Uncertainty in climate projections and changes in environmental conditions pose additional threats to food security in developing countries, emphasizing the importance of finding a connection between global warming and agricultural productivity (Rosegrant et al., 2008; Khor, 2009; Dudu and Cakmak, 2018). Furthermore, the influence of climate change on agricultural production indirectly produces major changes in consumption trends through prices, such as higher animal feed costs due to drought, which leads to higher meat prices and, subsequently, lower meat consumption. As a result, policymakers need to weigh the potential effects of climate change on agriculture. Empirical models, such as econometric models (time series or panel data) and the Ricardian model, are commonly used in socioeconomics to examine climate change's effects on agricultural production (Nasrullah et al., 2021). Conversely, the econometric method is relatively recent (Chandio et al., 2021b).

Numerous studies have demonstrated the detrimental consequences of climate change on agricultural production. Akhtar and Masud (2022), using the GMM approach with 1985 to 2016 time series data, found that temperature reduces rice and vegetable production in Malaysia while CO_2 decreases coffee production. In Iran, increasing temperature and precipitation above identified threshold levels reduced barley yield in the long run during the 1999-2015 period using the DOLS approach with panel data (Azizi et al., 2022). According to the results of the ARDL approach, from 1968-2014 in Turkey, CO_2 and temperature decreased cereal yield, but rainfall improved it in both runs (Chandio et al., 2020b). In Turkey, using the ARDL technique with time series data from 1980 to 2016, CO_2 and temperature adversely affected wheat production in both runs, but precipitation improved it (Chandio et al., 2021a). Bangladesh's fishery subsector was positively influenced by rainfall, sunshine, and SST between 1961 and 2019. ARDL findings also indicated that temperature negatively impacts fish production in both runs, but CO_2 negatively affects it only in the short run (Begum et al., 2022). Based on time series data from 1965 to 2015 using ARDL, temperature and CO_2 were observed to unfavorably impact agricultural output in India, while rainfall was found to influence it favorably (Chandio et al., 2022a). Somalia's livestock subsector was unfavorably influenced by temperature but favorably impacted by rainfall in both runs between 1985 and 2016. ARDL findings also indicated that CO_2 enhances livestock production in the short run but has no significant impact in the long run (Warsame et al., 2022). A study utilizing data from 1988 to 2014 in Bangladesh discovered that rainfall improves cereal production in both runs, but CO_2 decreases it. The ARDL approach findings also show that temperature decreases cereal production in the short run (Chandio et al., 2022b). In Nigeria, rainfall has a beneficial but insignificant effect on agriculture, and all subsectors studied between the 1970 and 2012 period using the GMM approach (Olayide et al., 2016). There was no evidence of a negative impact of CO_2 on crop production in a study conducted in Somalia between 1985 and 2016 using the ARDL analysis approach. However, results further show that rainfall improves crop production in the long run but decreases it in the short run, whereas temperature decreases it in both runs.

MATERIALS AND METHODS

Data and Variables

All variables were analyzed using data from 1990 to 2019. The World Bank Development Indicators (WDI) were used to gather data on agriculture GDP (AGDP) in 2015 constant USD, gross capital formation (GCF) in 2015 constant USD, domestic credit (DC) in 2015 constant USD, and CO_2 emissions in kt. The annual mean temperature (TEMP) and annual rainfall (RF) variables of climate change were obtained from the World Bank's Climate Change Knowledge Portal (CCKP). Gross domestic product (GDP) data in 2015 constant USD and the contribution of the agricultural subsectors to agriculture data from the website of the National Institute of Statistics of Ivory Coast have been used to calculate variables on crop GDP (CGDP), livestock GDP (LGDP), and fish and forestry GDP (FGDP) in 2015 constant USD. The multicollinearity issue was resolved by transforming all variables into natural logarithms. The variables can also be read as elasticities due to their natural logarithmic forms. Aggregate agriculture, crop, livestock, and fishery outputs were accounted for in this study using AGDP, CGDP, LGDP, and FGDP, respectively, as dependent variables in each model. However, we used other factors such as CO_2 emissions, average temperature, rainfall, domestic credit, and gross capital formation as control variables. Information on the data, its origins, and some descriptive statistics are summarized in Table 1.

Methodology

The study's analytical procedures are outlined in Figure 1. The first step was identifying relevant variables explaining agricultural productivity and climate change's impact on it. The literature guided the selection of variables. The impacts of climate change on agriculture and its subsectors (1990-2019) were then determined, and a suitable data range was identified. This information was selected due to its availability. After descriptive data were assessed, first-generation unit root tests (ADF and PP) were used to conduct unit root tests. Following the long- and short-run estimates for the ARDL model, we conducted a bounds test to test for cointegration. Next, we used FMOLS, DOLS, and CCR models to test the model's durability. Serial correlation, heteroscedasticity, normalcy, and error specification were all examined usinThere was no evidence of a detrimental impact of temperature on agricultural total factor productivity (ATFP) growth in a study that involved 36 African countries between 1981 and 2010 using the FGLS panel data approach. However, findings further reveal a beneficial effect of precipitation on ATFP growth in those countries (Ogundari and Onyeaghala, 2021). A 1971-2016 analysis employing the FGLS and FMOLS in a panel data set in 11 Asian and African countries found that temperature rise decreases cereal production, but CO_2 and rainfall improve it (Kumar et al., 2021). A shortage of rainfall was found to decrease cereal crop productivity, but the temperature was observed to increase it in Tunisia using the ARDL with 1975 to 2014 panel data (Attiaoui and Boufateh, 2019). While there is a plethora of econometric research looking at the effects of climate change on agriculture, only some of these studies have specifically targeted West African countries. This research was motivated by a lack of previous efforts to quantify the impact of climate change on agriculture and its subsectors in Ivory Coast.
g diagnostic tests like the Breusch-Godfrey LM test, the Breusch-Pagan Godfrey test, the Jarque-Bera test, and the Ramsey RESET test. Finally, we used the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) tests to examine the structural reliability of our models.

Table 1. Data description and source.

Variables	Description	Source
Dependent variables		
AGDP (model 1)	Agricultural GDP (constant 2015 US$)	WDI
CGDP (model 2)	Crop GDP (constant 2015 US$)	AC
LGDP (model 3)	Livestock GDP (constant 2015 US$)	AC
FGDP (model 4)	Fishery and Forestry GDP (constant 2015 US$)	AC
Independent variables		
TEMP	Annual temperature (average in ^{0}C)	CCKP
RF	Annual rainfall (average in mm)	CCKP
CO_2	Annual carbon dioxide emissions (kt)	WDI
DC	Domestic credit (constant 2015 US$)	WDI
GCF	Gross Capital Formation (constant 2015 US$)	WDI

Note: AC: Author's calculations; CCKP: Climate change knowledge Portal of the World Bank; WDI: World development indicators.

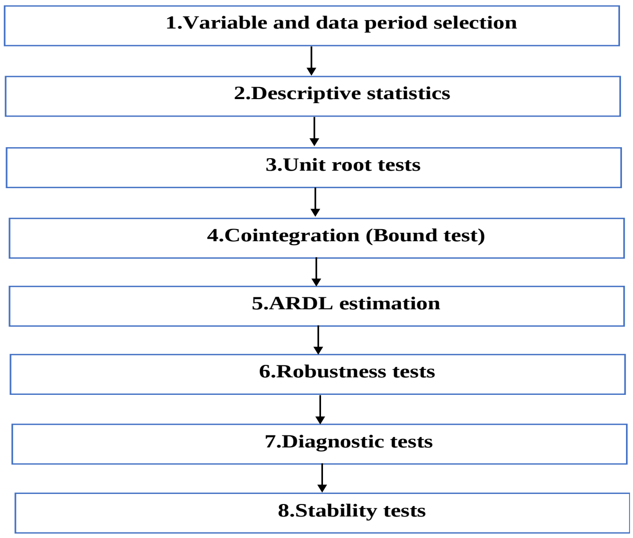

Figure 1. Study analytical techniques steps.

Econometric Modeling

This analysis employs the time series econometric program EViews 12 and the ARDL method created by Pesaran et al. (2001) to assess the impact of climate on agricultural, crop, livestock, and fishing output in Ivory Coast over the short and long term. Because of its widespread use in the academic literature for studying cointegration and short- and long-run interactions (Abbas, 2020; Asumadu-Sarkodie and Owusu, 2016; Chandio et al., 2020a, b; Warsame et al., 2021), ARDL is implemented in this empirical investigation. The cointegration approach is favored since it naturally divides the model into the short and long run (Pesaran et al., 2001). In addition, it offers some benefits that standard statistical methods lack. In the first place, when some endogenous variables act as regressors, the ARDL method nevertheless yields an unbiased long-run estimation (Adom et al., 2012). Second, the Ordinary Least Squares (OLS) method is used to cointegrate variables and short-run, and long-run coefficients are calculated simultaneously. Thirdly, ARDL can be applied even if some or all of the regressors in the model are fully I (0), I (1), or mutually cointegrated. Because it does not rely on residual correlation, the ARDL test is able to deal with cases of endogeneity (Pesaran et al., 2001). Finally, the ARDL method yields robust and consistent results for small sample sizes, whereas other cointegration procedures are sensitive to sample size (Pesaran and Shin, 1998; Pesaran et al., 2001; Adom et al., 2012). A limitation of the model is that it makes the linearity assumption between the dependent and independent variables. It has been shown that larger sample sizes are not appropriate for this method (Warsame et al., 2021; Abbas et al., 2022; Asfew and Bedemo, 2022; Begum et al., 2022; Emenekwe et al., 2022).

In order to express the connection between the dependent variables and the climatic variables in Ivory Coast, the following linear functions were utilized based on the research of Chandio et al. (2020c) and Pickson et al. (2022).

Model 1: Effect of climatic factors on agriculture production

$$AGDP_t = \beta_0 + \beta_1 TEMP_t + \beta_2 RF_t + \beta_3 CO_{2t} + \beta_4 DC_t + \beta_5 GCF_t + \varepsilon_t \quad (1)$$

Model 2: Impact of climate variables on crop production

$$CGDP_t = \beta_0 + \beta_1 TEMP_t + \beta_2 RF_t + \beta_3 CO_{2t} + \beta_4 DC_t + \beta_5 GCF_t + \varepsilon_t \quad (2)$$

Model 3: Influence of climate indicators on livestock production

$$LGDP_t = \beta_0 + \beta_1 TEMP_t + \beta_2 RF_t + \beta_3 CO_{2t} + \beta_4 DC_t + \beta_5 GCF_t + \varepsilon_t \quad (3)$$

Model 4: Impact of climate factors on fishery production

$$FGDP_t = \beta_0 + \beta_1 TEMP_t + \beta_2 RF_t + \beta_3 CO_{2t} + \beta_4 DC_t + \beta_5 GCF_t + \varepsilon_t \quad (4)$$

Where $\mathcal{E}_t$ is the disturbance term in time, AGDP represents agricultural GDP, CGDP denotes crop GDP, LGDP shows livestock GDP, FGDP stands for fish and forestry GDP, TEMP indicates temperature, RF presents rainfall, CO_2 specifies carbon dioxide emissions, DC is domestic credit, and GCF stands for gross capital formation.

The natural logarithm forms of Equations 1, 2, 3, and 4 are as follows:

Model 1: Influence of climatic factors on agriculture production

$$lnAGDP_t = \beta_0 + \beta_1 lnTEMP_t + \beta_2 lnRF_t + \beta_3 lnCO_{2t} + \beta_4 lnDC_t + \beta_5 lnGCF_t + \varepsilon_t \quad (5)$$

Model 2: Effect of climate indicators on crop production

$$lnCGDP_t = \beta_0 + \beta_1 lnTEMP_t + \beta_2 lnRF_t + \beta_3 lnCO_{2t} + \beta_4 lnDC_t + \beta_5 lnGCF_t + \varepsilon_t \quad (6)$$

Model 3: Impact of climate variables on livestock production

$$lnLGDP_t = \beta_0 + \beta_1 lnTEMP_t + \beta_2 lnRF_t + \beta_3 lnCO_{2t} + \beta_4 lnDC_t + \beta_5 lnGCF_t + \varepsilon_t \quad (7)$$

Model 4: Effect of climatic factors on fishery production

$$lnFGDP_t = \beta_0 + \beta_1 lnTEMP_t + \beta_2 lnRF_t + \beta_3 lnCO_{2t} + \beta_4 lnDC_t + \beta_5 lnGCF_t + \varepsilon_t \quad (8)$$

Where lnAGDP is the natural logarithm of agriculture GDP, lnCGDP stands for the logarithm of base e of crop GDP, lnLGDP indicates the natural logarithm of livestock GDP, lnFGDP represents the logarithm of base e of fish and forestry GDP, lnTEMP signifies the natural logarithm of temperature, lnRF specifies the logarithm for base e of rainfall, $lnCO_2$ is the natural logarithm of CO_2, lnDC presents the logarithm for base e of domestic credit, lnGCF denotes the natural logarithm of gross capital formation, while $\mathcal{E}_t$ is defined above.

There are two main phases to the ARDL model's investigation. The first thing to do is to see if there is a correlation between the variables over time. In this study, the long-term correlation between each model's dependent and independent variables was analyzed using the bound test. According to Pesaran et al. (2001), the bound test has two critical values: lower and upper bounds. Lower-bound critical values are the critical values for variables with a value of I (0). In contrast, critical values for I (1) variables are upper-bound critical values.

The following are the hypotheses for the ARDL bounds test.

H_0: absence of equilibrium relationship/variables are not cointegrated.

H_a: presence of long-run relationships/variables are cointegrated.

If the calculated F-statistic is more than the upper bounds, we reject H_0 and prove the existence of cointegration between the variables. Conversely, if the computed F-statistic is less than the lower bounds, we cannot reject H_0, implying no equilibrium link among the variables. However, if it is within limits, the cointegration test is said to be inconclusive (Attiaoui and Boufateh, 2019; Demirhan, 2020; Begum et al., 2022).

The following representations of the error correction model (ECM) are used to investigate both the short- and long-run linkages between the studied variables.

Model 1: Impact of climatic indicators on agricultural production

$$\Delta lnAGDP_t = \beta_0 + \sum_{i=1}^{p} \vartheta_{1i} \Delta lnAGDP_{t-i} + \sum_{i=0}^{q_1} \vartheta_{2i} \Delta lnTEMP_{t-i} + \sum_{i=0}^{q_2} \vartheta_{3i} \Delta lnRF_{t-i} + \sum_{i=0}^{q_3} \vartheta_{4i} \Delta lnCO_{2t-i} + \sum_{i=0}^{q_4} \vartheta_{5i} \Delta lnDC_{t-i} + \sum_{i=0}^{q_5} \vartheta_{6i} \Delta lnGCF_{t-i} + \varphi ECM_{t-1} + \varepsilon_t \quad (9)$$

Model 2: Effect of climatic factors on crop production

$$\Delta lnCGDP_t = \beta_0 + \sum_{i=1}^{p} \vartheta_{1i} \Delta lnCGDP_{t-i} + \sum_{i=0}^{q_1} \vartheta_{2i} \Delta lnTEMP_{t-i} + \sum_{i=0}^{q_2} \vartheta_{3i} \Delta lnRF_{t-i} + \sum_{i=0}^{q_3} \vartheta_{4i} \Delta lnCO_{2t-i} + \sum_{i=0}^{q_4} \vartheta_{5i} \Delta lnDC_{t-i} + \sum_{i=0}^{q_5} \vartheta_{6i} \Delta lnGCF_{t-i} + \varphi ECM_{t-1} + \varepsilon_t \quad (10)$$

Model 3: Influence of climate variables on livestock production

$$\Delta lnLGDP_t = \beta_0 + \sum_{i=1}^{p} \vartheta_{1i} \Delta lnLGDP_{t-i} + \sum_{i=0}^{q_1} \vartheta_{2i} \Delta lnTEMP_{t-i} + \sum_{i=0}^{q_2} \vartheta_{3i} \Delta lnRF_{t-i} + \sum_{i=0}^{q_3} \vartheta_{4i} \Delta lnCO_{2t-i} + \sum_{i=0}^{q_4} \vartheta_{5i} \Delta lnDC_{t-i} + \sum_{i=0}^{q_5} \vartheta_{6i} \Delta lnGCF_{t-i} + \varphi ECM_{t-1} + \varepsilon_t \quad (11)$$

Model 4: Impact of climatic factors on fishery production

$$\Delta lnFGDP_t = \beta_0 + \sum_{i=1}^{p} \vartheta_{1i} \Delta lnFGDP_{t-i} + \sum_{i=0}^{q_1} \vartheta_{2i} \Delta lnTEMP_{t-i} + \sum_{i=0}^{q_2} \vartheta_{3i} \Delta lnRF_{t-i} + \sum_{i=0}^{q_3} \vartheta_{4i} \Delta lnCO_{2t-i} + \sum_{i=0}^{q_4} \vartheta_{5i} \Delta lnDC_{t-i} + \sum_{i=0}^{q_5} \vartheta_{6i} \Delta lnGCF_{t-i} + \varphi ECM_{t-1} + \varepsilon_t \quad (12)$$

Here, ECM connotes the error correction model, and φ shows its coefficient, representing the adjustment time required to return to equilibrium after a short-term shock to the system. For a significant ECM model, φ should be negative (Janjua et al., 2014). By taking the coefficient of φ to be significantly negative, empirical research shows that any temporary shock in the short run will automatically converge to equilibrium in the long term (Omoke et al., 2020; Emenekwe et al., 2022).

RESULTS AND DISCUSSION

Descriptive Statistics

Table 2 displays the descriptive statistics for each variable. The mean values of the dependent variables AGDP, CGDP, LGDP, and FGDP are 6.37E+09, 5.54E+09, 4.40E+08, and 3.92E+08, respectively, and their standard deviations are 2.12E+09, 1.99E+09, 1.85E+08, and 3.27E+08, respectively. The mean values of explanatory variables, TEMP, RF, CO_2, DC, and GCF are 26.786, 1292.843, 6275, 5.23E+09, and 5.69E+09, respectively, and their standard deviations are 0.256187, 112.6953, 2447.612, 2.73E+09, and 3.15E+09, respectively. The standard deviations of all variables are less than their mean values, which suggests that the variables under consideration are not volatile. In addition, Figure 2 shows the trend of all study variables.

Correlation Matrices

The correlation matrices for agriculture production (model 1), crop production (model 2), livestock production (model 3), and fishery production (model 4) are shown in Table 3. The results suggest that TEMP, CO_2, DC, and GCF are positively correlated to AGDP. At the same time, RF is negatively related to it. In Model 2, all the variables positively correlate to CGDP. However, in models 3 and 4, only DC is positively related to LGDP and FGDP. All the remaining variables negatively correlate with LGDP and FGDP. The correlation coefficients among the regressors in each model are less than one, indicating that the multicollinearity problem is not mild.

Unit Root Test

The Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) tests were utilized to ensure that the underlying variables in the current work were stationary. The level and the first difference unit root tests were initially performed, with only the intercept. Second, with the constant and trend terms, and third, with neither term. ADF and PP tests have been examined, considering the SC criterion at 1%, 5%, and 10% significance levels. Table 4 exhibits the findings of the ADF and PP unit root tests, respectively., revealing that all the variables under consideration had a combined order of integration. This means that some variables were integrated into order one [I (1)], while some were stationary at level [I (0)]. Importantly, the results show no variable integrations in the second order [I (2)] or above. This allows using the ARDL bounds test, proposed by Pesaran and Shin (1998) and Pesaran et al. (2001), to examine the short- and long-term association between the considered variables.

Cointegration Test

We applied the ARDL bounds method for cointegration to assess each model's long-term association between variables. Table 5 presents the results of the four models, including the relevant critical value boundaries. According to these results, the computed value of the F-statistic is higher than the upper bounds limits in all cases, suggesting that in all models, variables have an equilibrium relationship among them.

Lag Selection

The VAR lag length selection test yielded five distinct criteria (Table 6), including the LR (sequential modified LR test statistic), FPE (final prediction error), AIC (Akaike information criterion), SC (Schwarz information criterion), and HQ (Hannan-Quinn information criterion). According to Table 6, the majority of the test statistics suggest that lag 3 is the best value for all models.

Table 2. Descriptive statistics.

Variables	Observation	Mean	Std. Dev.	Min	Max
AGDP	30	6.37E+09	2.12E+09	4.36E+09	1.24E+10
CGDP	30	5.54E+09	1.99E+09	3.87E+09	1.14E+10
LGDP	30	4.40E+08	1.85E+08	2.27E+08	9.07E+08
FGDP	30	3.92E+08	3.27E+08	1.06E+08	1.09E+09
TEMP	30	26.786	0.256187	26.33	27.32
RF	30	1292.843	112.6953	1113.93	1580.48
CO_2	30	6275	2447.612	2710	10830
DC	30	5.23E+09	2.73E+09	2.49E+09	1.18E+10
GCF	30	5.69E+09	3.15E+09	1.52E+09	1.20E+10

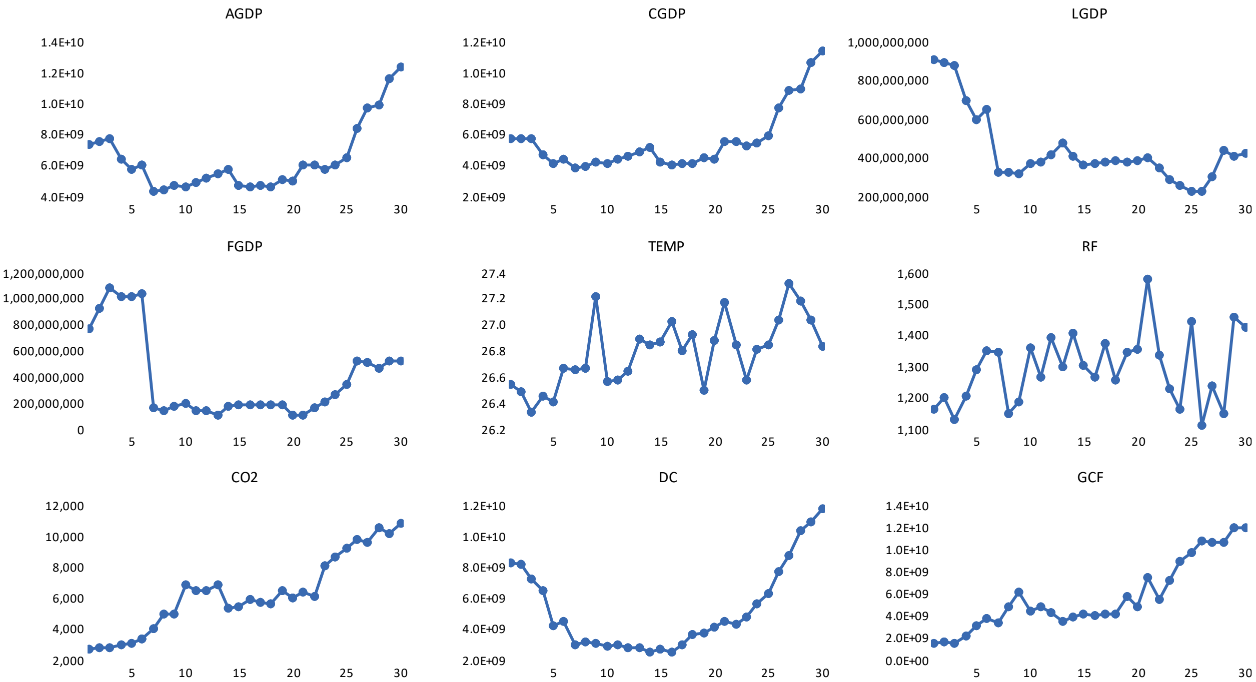

Figure 2. Trend of studied variables.

Table 3. Correlation matrices.

Model 1: Agricultural production						
Variables	lnAGDP	lnTEMP	lnRF	$lnCO_2$	lnDC	lnGCF
lnAGDP	1					
lnTEMP	0.230	1				
lnRF	-0.063	0.146	1			
$lnCO_2$	0.319*	0.636***	0.240	1		
lnDC	0.925***	0.103	-0.218	0.182	1	
lnGCF	0.370**	0.677***	0.250	0.923***	0.272	1
Model 2: Crop production						
Variables	lnCGDP	lnTEMP	lnRF	$lnCO_2$	lnDC	lnGCF
lnCGDP	1					
lnTEMP	0.396**	1				
lnRF	0.015	0.146	1			
$lnCO_2$	0.539***	0.636***	0.240	1		
lnDC	0.857***	0.103	-0.218	0.182	1	
lnGCF	0.559***	0.677***	0.250	0.923***	0.272	1
Model 3: Livestock production						
Variables	lnLGDP	lnTEMP	lnRF	$lnCO_2$	lnDC	lnGCF
lnLGDP	1					
lnTEMP	-0.539***	1				
lnRF	-0.155	0.146	1			
$lnCO_2$	-0.762***	0.636***	0.240	1		
lnDC	0.235	0.103	-0.218	0.182	1	
lnGCF	-0.770***	0.677***	0.250	0.923***	0.272	1
Model 4: Fishery production						
Variables	lnFGDP	lnTEMP	lnRF	$lnCO_2$	lnDC	lnGCF
lnFGDP	1					
lnTEMP	-0.312*	1				
lnRF	-0.359*	0.146	1			
$lnCO_2$	-0.374**	0.636***	0.240	1		
lnDC	0.709***	0.103	-0.218	0.182	1	

Note: ***, **, and * show 1%, 5%, and 10% significance levels, respectively.

Table 4. Unit root tests.

Variables	ADF			PP		
	Intercept	Intercept and trend	None	Intercept	Intercept and trend	None
At level						
lnAGDP	0.315	-0.721	0.829	-0.136	-0.638	0.68
lnCGDP	1.010	-0.777	1.234	0.761	-0.653	0.995
lnLGDP	-2.711*	-2.828	-0.690	-2.39	-1.806	-0.774
lnFGDP	-1.634	-1.304	-0.242	-1.634	-1.268	-0.238
lnTEMP	-3.021**	-4.291**	0.206	-2.981**	-4.244**	0.865
lnRF	-4.528***	-4.647***	0.500	-4.457***	-4.597***	0.951
$lnCO_2$	-1.099	-1.890	2.309	-1.106	-2.053	2.238
lnDC	-0.148	-3.521*	3.071	-0.841	-1.595	0.267
lnGCF	-1.327	-2.487	2.357	-1.384	-1.384	-1.384
At first difference						
dlnAGDP	-4.397***	-5.886***	-4.391***	-4.483***	-6.014***	-4.484***
dlnCGDP	-4.117***	-5.478***	-4.010***	-4.177***	-4.177***	-4.177***
dlnLGDP	-4.539***	-4.874***	-4.542***	-4.539***	-4.867***	-4.539***
dlnFGDP	-4.741***	-5.041***	-4.820***	-4.73***	-6.882***	-4.812***
dlnTEMP	-6.858***	-6.742***	-6.962***	-15.645***	-15.645***	-15.645***
dlnRF	-8.803***	-8.635***	-8.909***	-20.546***	-20.054***	-15.457***
$dlnCO_2$	-5.859***	-5.802***	-4.933***	-5.827***	-5.775***	-5.127***
dlnDC	-1.681	-7.911***	-1.632*	-4.714***	-7.911***	-4.766***
dlnGCF	-7.147***	-7.070***	-6.209***	-7.067***	-7.008***	-6.126***

Note: ***; ** and * denote the rejection of the null hypothesis by the presence of a unit root at 1%, 5%, and 10% levels, respectively; Automatic lag selection based on SC.

Table 5. ARDL bounds test.

Dependent variable	Model	F-statistic	Result
lnAGDP	1	23.90667	Cointegration
lnCGDP	2	5.463936	Cointegration
lnLGDP	3	5.168879	Cointegration
lnFGDP	4	17.58274	Cointegration
	Significance	Lower bounds I (0)	Upper bounds I (1)
	10%	2.26	3.35
	5%	2.62	3.79
	2.50%	2.96	4.18
	1%	3.41	4.68

Table 6. VAR lag length selection.

Lag	LogL	LR	FPE	AIC	SC	HQ
Model 1						
0	137.989	NA	2.29E-12	-9.777	-9.489	-9.691
1	235.988	145.183	2.49E-14	-14.369	-12.354	-13.770
2	287.414	53.331	1.24E-14	-15.512	-11.769	-14.399
3	391.100	61.443*	3.81e-16*	-20.526*	-15.055*	-18.899*
Model 2						
0	139.045	NA	2.11E-12	-9.855	-9.567	-9.769
1	240.441	150.215	1.79E-14	-14.699	-12.683	-14.099
2	295.204	56.791	6.98E-15	-16.089	-12.345	-14.976
3	384.219	52.749*	6.35e-16*	-20.016*	-14.545*	-18.389
Model 3						
0	125.690	NA	5.69E-12	-8.866	-8.577	-8.780
1	225.587	147.994	5.38E-14	-13.599	-11.583	-12.999
2	275.022	51.266*	3.11E-14	-14.594	-10.851	-13.481
3	356.613	48.350	4.91e-15*	-17.971*	-12.500*	-16.344*
Model 4						
0	102.429	NA	3.18E-11	-7.143	-6.855	-7.057
1	195.293	137.575	5.07E-13	-11.355	-9.339	-10.756
2	232.037	38.105	7.52E-13	-11.410	-7.666	-10.297
3	335.102	1.075*	2.42e-14*	-16.378*	-10.906*	-14.751*

Note: Included observations: 27; * Indicates the lag order selected by the criterion.

Short- and Long-run Estimations

The short- and long-run estimates of temperature, rainfall, CO_2, domestic credit, and gross capital formation effects on Ivory Coast agriculture, crop, livestock, and fishery production are reported in Tables 7, 8, 9, and 10, respectively.

Agriculture and related subsectors in Ivory Coast were found to benefit from increasing temperatures over the long run. However, when considering the fishery subsector, this impact is negligible. This signifies that when temperature increases by 1%, there are 6.71%, 14.13%, and 17.18% improvements in agriculture, crop, and livestock production, respectively. The conclusions on the favorable effect of temperature on agriculture and crop production are consistent with those of Chandio et al. (2020a), Chandio et al. (2021a, b), and Pickson et al. (2022), who concluded that temperature improves rice and maize production in both runs. Our findings on the beneficial effect of temperature on livestock contradict Warsame et al. (2022), who found a detrimental impact of temperature on livestock in Somalia. On the other hand, our results are consistent with those of Kabubo-Mariara (2009), who discovered that a unit increase in temperature would lead to about a 5% gain in net revenue from livestock. This could be because farmers associate animal breeding with crop farming as a strategy to reduce the adverse effect of global warming on crop productivity (Fadina and Barjolle, 2018). The study also observed that temperature's effect on aggregate agriculture is positive in the short run, although it is not statistically significant. In addition, the temperature had a beneficial effect on agriculture's subsectors, except for fishery production. This means that when the temperature rises by 1% in the short term, crop production increases by 5.78%, livestock production improves by 8.97%, and fish production decreases by 20.92%. Our result on the short-run detrimental effect of temperature on the fishery subsector is in line with Begum et al. (2022), who found a negative effect of temperature on fish production in Bangladesh in the short term.

This research suggests that in both runs, Ivory Coast's aggregate agriculture sector and fishery subsector are negatively affected by rainfall. This implies that a 10% rise in precipitation decreases agriculture output by 1.4% in the short run and 3.98% in the long term. Likewise, a one percent increase in rainfall leads to a 3.16% short-term and a 5.95% long-term reduction in fishery production. These results oppose those of Begum et al. (2022) and Chandio et al. (2022a, b), who both discovered a beneficial effect of rainfall on fishery and agriculture production, respectively. However, our finding on the negative effect of rainfall on agriculture is partially consistent with Chandio et al. (2020c), who discovered a long-run negative impact of precipitation on agriculture output. The adverse effect of precipitation on aggregate agriculture and fishery production in Ivory Coast can be explained by repetitive flood events in the country in the past years (CCKP 2021). According to the CCKP (2021), Ivory Coast is very prone to flooding, especially in the southern region with the highest rainfall. One of the most important climatic factors is precipitation, which is essential to the success of farming everywhere. Regarding its intensity and frequency, extreme precipitation can have devastating societal and economic consequences (Almazroui, 2020a, b). It is important to notice that precipitation has a greater negative effect on agriculture and fishery outputs in the long term than in the short term. This asserts that over time, this factor will have a more harmful impact on aggregate agriculture and fishery production in Ivory Coast and constitutes a serious threat to agriculture in the country. Our results, in line with Warsame et al. (2022), also concluded a beneficial effect of rainfall on livestock production in both runs. In other words, when rainfall rises by 10%, livestock production improves by 7.11% in the short term and 9.29% in the long run. These findings make sense, considering that rainfall is a key factor in raising livestock and producing milk and meat. Grazing animals benefit from rainfall because it encourages the growth of shrubs and grasses used as pasture by livestock. Our findings further reveal an insignificant favorable effect of rainfall on crop production in Ivory Coast in both runs. This result is similar to that of N'Zué (2018), who found a positive effect of precipitation on crop yield in Ivory Coast.

The estimated results indicated that the role of CO_2 is positive on agriculture and crop production in both run estimations. It means that a 1% rise in CO_2 will lead to a 0.63% and 0.14% increase in agriculture over the long and short run, respectively. Likewise, a 1.16% long-run and 0.94% short-term increase in crop production are related to a one percent rise in CO_2. Our conclusions are in line with those of studies by Chandio et al. (2020a, c), Rehman et al. (2020), Ntiamoah et al. (2022), and Pickson et al. (2022). The findings further demonstrate that CO_2 does not impact livestock production in Ivory Coast. This result is consistent, to some extent, with that of Warsame et al. (2022), who found that in Somalia, CO_2 had no long-term effect on livestock production but had a positive impact in the short run. According to our results, CO_2 has a positive long-term influence on fishery production but no effect in the short run. This means that over time, fish production will enhance by 3.45% for every increase in CO_2. In Bangladesh, Begum et al. (2022) discovered a short-term negative impact of CO_2 on fishery production but no impact in the long run. With a carbon emissions per capita ranking of 103 out of 221 nations, Ivory Coast is among the World's lowest polluters (Globalcarbonatlas, 2022). This could explain the short- and long-run non-association between CO_2 and livestock production and the short-run non-association between CO_2 and fishery production.

Domestic credit is found to have a beneficial influence on agriculture and its subsectors in both runs, except for crop and livestock production, where the effect is negative and insignificant in the short run. In other words, a one percent increment in domestic credit leads to 0.57% long-term and 0.12% short-term improvements in agriculture production, a 0.55% long-term improvement in crop production, a 0.39% long-term improvement in livestock production, as well as a 1.43% long-term and 1.34% short-term improvements in fishery production. The results on the favorable effect of domestic credit on agriculture and its subsectors are logical and consistent with studies by Chandio et al. (2021a) and Chandio et al. (2022a, b), who suggested that domestic credit has a positive association with agricultural output. Domestic financing ensures that agricultural inputs are purchased and distributed efficiently, increasing productivity (Awunyo-Vitor, 2017; Belete, 2020; Melkani et al., 2021).

Surprisingly, gross capital formation negatively impacts agriculture and its subsectors in Ivory Coast, except crop production, where it only has an insignificant positive effect in the short run. The same is true for fishery production, which only had a significant favorable impact in the short term. This signifies that a 1% increase in gross capital formation has a negative long-term impact of 0.27% and a short-term effect of 0.06% on agricultural output, a long-term negative influence of 0.63% on crop production, a long-term detrimental impact of 0.80% and short-term effect of 0.34% on livestock production, and a long-term negative influence of 2.75% on fishery production. Similarly, a one percent rise in gross capital formation has a short-term positive effect of 0.31% on fishery production. Chandio et al. (2022a) state that capital formation provides infrastructure for agricultural production, which helps increase agricultural productivity. However, our findings on the negative impact of gross capital formation on agriculture and its subsectors in Ivory Coast are similar to the results of N'Zué (2018), who found that Ivory Coast's gross capital formation adversely affected the value added to agricultural products. This makes sense, especially if investments are made outside the agricultural sector to enable the processing of agricultural products (N'Zué, 2018). Under such conditions, the industrial sector's contribution to GDP will rise while agricultural value added will fall.

The coefficients of determination (R^2) of 0.99 in all models revealed that the selected independent variables explain 99% of variations in the regressand. The probability values of F-statistics in all models, which are lower than 5%, proved the goodness of fit of the models.

Table 7. Long- and short-run estimates for model 1.

Dependent Variable: lnAGDP; ARDL (2, 3, 3, 3, 3, 3) selected based on SC				
Variables	Coefficient	Std. Error	t-Statistic	Probability
Long-run estimates				
lnTEMP	6.714831	2.34396	2.864737	0.0457
lnRF	-0.3977	0.114313	-3.47904	0.0254
lnCO_2	0.629844	0.153996	4.089987	0.015
lnDC	0.569775	0.021045	27.07392	0
lnGCF	-0.27452	0.128118	-2.14268	0.0988
Short-run estimates				
D (lnAGDP (-1))	0.706359	0.065422	10.79704	0.0004
D (lnTEMP)	0.682386	0.566732	1.204072	0.2949
D (lnTEMP (-1))	-2.86108	0.69714	-4.10403	0.0148
D (lnTEMP (-2))	-4.40149	0.622983	-7.06518	0.0021
D (lnRF)	-0.14055	0.056941	-2.46839	0.0691
D (lnRF (-1))	0.546995	0.051612	10.59824	0.0004
D (lnRF (-2))	0.452129	0.043145	10.47928	0.0005
D (lnCO_2)	0.144826	0.063532	2.279559	0.0848
D (lnCO_2 (-1))	-0.64787	0.07622	-8.49999	0.0011
D (lnCO_2 (-2))	-0.55707	0.052616	-10.5874	0.0005
D (lnDC)	0.124982	0.039893	3.132944	0.0351
D (lnDC (-1))	-1.35387	0.090604	-14.9426	0.0001
D (lnDC (-2))	-0.69846	0.06092	-11.4652	0.0003
D (lnGCF)	-0.06073	0.021475	-2.82777	0.0475
D (lnGCF (-1))	0.223605	0.027306	8.188978	0.0012
D (lnGCF (-2))	0.067309	0.034288	1.963074	0.1211
ECM (-1)	-1.88118	0.104714	-17.965	0.0001

R-squared	0.99908	Adjusted R-squared	0.994023
F-statistic	197.5447	Prob(F-statistic)	0.000055
Durbin-Watson statistic	1.624689		

Table 8. Long- and short-run estimates for model 2.

Dependent Variable: lnCGDP; ARDL (3, 3, 3, 3, 3, 3) selected based on SC				
Variables	Coefficient	Std. Error	t-Statistic	Probability
Long-run estimates				
lnTEMP	14.13255	3.100919	4.557537	0.0198
lnRF	0.033084	0.174433	0.189666	0.8617
lnCO_2	1.160506	0.213525	5.434986	0.0122
lnDC	0.548811	0.032459	16.90783	0.0005
lnGCF	-0.62903	0.183585	-3.42639	0.0416
Short-run estimates				
D (lnCGDP (-1))	1.025027	0.143117	7.162134	0.0056
D (lnCGDP (-2))	0.148439	0.079723	1.861938	0.1595
D (lnTEMP)	5.782941	0.992999	5.823712	0.0101
D (lnTEMP (-1))	-7.03044	1.583659	-4.43936	0.0213
D (lnTEMP (-2))	-4.39394	1.025727	-4.28373	0.0234
D (lnRF)	0.075637	0.070667	1.07032	0.3629
D (lnRF (-1))	0.348275	0.076391	4.559099	0.0198
D (lnRF (-2))	0.492951	0.060216	8.186419	0.0038
D (lnCO_2)	0.944941	0.135863	6.955098	0.0061
D (lnCO_2 (-1))	-0.25935	0.106354	-2.43851	0.0926
D (lnCO_2 (-2))	-0.25891	0.067379	-3.84258	0.0311
D (lnDC)	-0.01546	0.077733	-0.19883	0.8551
D (lnDC (-1))	-1.29684	0.167067	-7.7624	0.0044
D (lnDC (-2))	-0.74268	0.103285	-7.19057	0.0055
D (lnGCF)	0.000861	0.026532	0.032461	0.9761
D (lnGCF (-1))	0.693244	0.086355	8.027799	0.004
D (lnGCF (-2))	0.206585	0.055464	3.724661	0.0337
ECM (-1)	-1.79384	0.191854	-9.35003	0.0026
R-squared	0.998797	Prob(F-statistic)		0.001255
Adjusted R-squared	0.98957	Durbin-Watson statistic		2.726696
F-statistic	108.2551			

Table 9. Long- and short-run estimates for model 3.

Dependent Variable: lnLGDP; ARDL (2, 3, 1, 0, 2, 2) selected based on SC				
Variables	Coefficient	Std. Error	t-Statistic	Probability
Long-run estimates				
lnTEMP	17.18104	4.125391	4.164705	0.0016
lnRF	0.929405	0.234049	3.970984	0.0022
lnCO_2	0.227623	0.224504	1.013893	0.3324
lnDC	0.38718	0.041061	9.429367	0
lnGCF	-0.80201	0.158167	-5.07066	0.0004
Short-run estimates				
D (lnLGDP (-1))	1.335918	0.225627	5.920922	0.0001
D (lnTEMP)	8.973517	2.379636	3.770962	0.0031
D (lnTEMP (-1))	-18.4332	4.039379	-4.56338	0.0008
D (lnTEMP (-2))	-15.4333	3.207937	-4.81097	0.0005
D (lnRF)	0.711252	0.236161	3.011731	0.0118
D (lnDC)	-0.33749	0.221416	-1.52425	0.1557
D (lnDC (-1))	-1.92866	0.282354	-6.83065	0
D (lnGCF)	-0.33743	0.116641	-2.89292	0.0146
D (lnGCF (-1))	0.661145	0.143711	4.600523	0.0008
ECM (-1)	-1.93897	0.288692	-6.71641	0
R-squared	0.931943	Prob(F-statistic)		0.000231
Adjusted R-squared	0.839138	Durbin-Watson statistic		2.042413
F-statistic	10.04197			

Table 10. Long- and short-run estimates for model 4.

Dependent Variable: lnFGDP				
ARDL (3, 3, 3, 2, 3, 3) selected based on SC				
Variables	Coefficient	Std. Error	t-Statistic	Probability
Long-run estimates				
lnTEMP	19.62388	11.74087	1.671415	0.17
lnRF	-5.95364	0.905753	-6.57315	0.0028
lnCO_2	3.452463	0.977458	3.532082	0.0242
lnDC	1.432674	0.162748	8.80301	0.0009
lnGCF	-2.75323	0.706502	-3.89699	0.0176
Short-run estimates				
D (lnFGDP (-1))	0.249955	0.065021	3.844219	0.0184

D (lnFGDP (-2))	0.202866	0.057115	3.551873	0.0238
D (lnTEMP)	-20.9235	3.300319	-6.33983	0.0032
D (lnTEMP (-1))	-1.60106	3.494273	-0.4582	0.6706
D (lnTEMP (-2))	-9.2054	3.267822	-2.81698	0.048
D (lnRF)	-3.16397	0.32739	-9.66421	0.0006
D (lnRF (-1))	2.639046	0.370548	7.122016	0.0021
D (lnRF (-2))	2.64416	0.303267	8.718918	0.001
D ($lnCO_2$)	-0.07113	0.379814	-0.18728	0.8606
D ($lnCO_2$ (-1))	-0.90883	0.268375	-3.38642	0.0276
D (lnDC)	1.340006	0.179127	7.480746	0.0017
D (lnDC (-1))	-2.46429	0.181165	-13.6025	0.0002
D (lnDC (-2))	-2.08368	0.274928	-7.579	0.0016
D (lnGCF)	0.310128	0.10557	2.937646	0.0425
D (lnGCF (-1))	3.455629	0.255672	13.51589	0.0002
D (lnGCF (-2))	1.574555	0.255533	6.161852	0.0035
ECM (-1)	-1.07927	0.070052	-15.4067	0.0001
R-squared	0.994933	Prob(F-statistic)		0.001638
Adjusted R-squared	0.967065	Durbin-Watson statistic		2.041151
F-statistic	35.70181			

Robustness Tests

We applied the Johansen cointegration method to check the robustness of the outcomes of the ARDL bounds test. The results in Table 11 revealed at least one cointegration equation (CE) in all models. Additionally, we utilize the FMOLS, DOLS, and CCR regression models to validate the estimated coefficients of the ARDL method. Table 12 displays the estimated long-term coefficients of the three regression models, all comparable to the long-term estimates produced using the ARDL approach. The results then verified the accuracy of the predictions of the ARDL model.

Diagnostic and Stability Tests

Several diagnostic and stability tests have been applied to the estimated models to investigate the accuracy and consistency of the predictions. The probabilities of the statistics of the Ramsey RESET test for error specification, Jarque-Bera test for normality, Breusch-Godfrey LM test for serial correlation, and Breusch-Pagan Godfrey test for heteroscedasticity are all greater than 5% in all models (Table 12). This demonstrates that the residuals are normally distributed, and our models are free from serial correlation, heteroscedasticity, and error specification issues. In addition, we checked the structural stability of our models by employing the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) tests. Figures 3, 4, 5, and 6 show the graphical representations of both tests for each model. The CUSUM and CUSUMQ for models 2, 3, and 4 fall within the 5% bounds limits, indicating that models 2, 3, and 4 are all stable. In the case of model one, the graph of the CUSUM falls inside the 5% critical limits. However, the CUSUMQ plot is also within the 5% bound limits most of the time. However, it must fall within bounds limits at a 10% significance level. Considering this, we deduced that our models have no diagnostic issues.

Table 11. Results of the Johansen cointegration test.

N0 of CE(s)	Trace statistic value	Max-Eigen statistic value
Model 1		
None	158.5340***	58.80063***
At most 1	99.73337***	53.03891***
At most 2	46.69446	19.66432
At most 3	27.03014	17.43995
At most 4	9.590197	9.450717
At most 5	0.139480	0.139480
Model 2		
None	161.4787***	64.72229***
At most 1	96.75644***	48.59734***
At most 2	48.15910**	20.45232
At most 3	27.70678	17.63730
At most 4	10.06948	9.994223
At most 5	0.075253	0.075253
Model 3		
None	163.0825***	68.82194***
At most 1	94.26059***	36.02966**
At most 2	58.23094***	23.75303
At most 3	34.47791**	21.82333**
At most 4	12.65458	11.41200
At most 5	1.242576	1.242576
Model 4		
None	131.6143***	48.14200***
At most 1	83.47226***	37.26361**
At most 2	46.20865	21.75320
At most 3	24.45545	14.57301
At most 4	9.882435	7.783587
At most 5	2.098848	2.098848

Note: ** and *** indicate the rejection of no cointegration at 5% and 1% significance levels, respectively.

Table 12. Diagnostic tests.

Diagnostic and stability tests	Statistics	Probability
Model 1		
Jarque-Bera normality test	0.9662	0.6168
Breusch-Godfrey LM test for serial correlation	1.272608	0.44
Breusch-Pagan Godfrey test for heteroskedasticity	25.45515	0.2758
Ramsey RESET test	3.343764	0.1649
CUSUM	Stable	
CUSUMQ	Stable	
Model 2		
Jarque-Bera normality test	0.7016	0.7041
Breusch-Godfrey LM test for serial correlation	1.558949	0.4928
Breusch-Pagan Godfrey test for heteroskedasticity	21.2973	0.5629
Ramsey RESET test	0.005097	0.9496
CUSUM	Stable	
CUSUMQ	Stable	
Model 3		
Jarque-Bera normality test	0.7155	0.6992
Breusch-Godfrey LM test for serial correlation	0.224386	0.8033
Breusch-Pagan Godfrey test for heteroskedasticity	11.21582	0.7372
Ramsey RESET test	4.932151	0.0506
CUSUM	Stable	
CUSUMQ	Stable	
Model 4		
Jarque-Bera normality test	2.0149	0.3651
Breusch-Godfrey LM test for serial correlation	9.804171	0.0926
Breusch-Pagan Godfrey test for heteroskedasticity	19.08231	0.6402
Ramsey RESET test	2.184882	0.2359
CUSUM	Stable	
CUSUMQ	Stable	

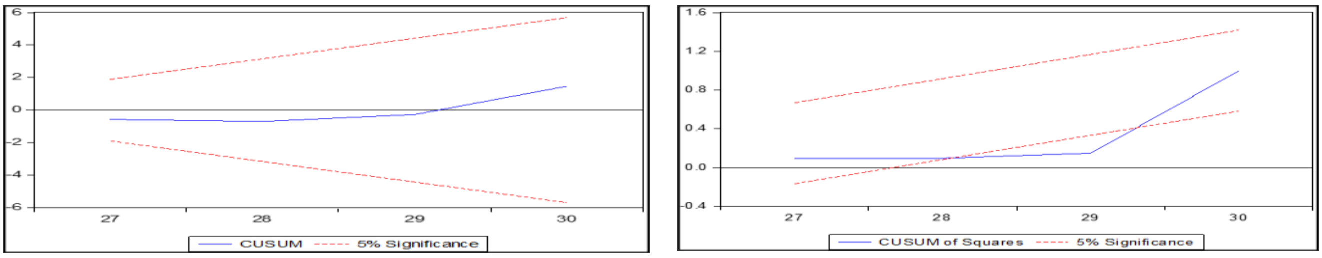

Figure 3. Graphs of CUSUM and CUSUMQ for model 1.

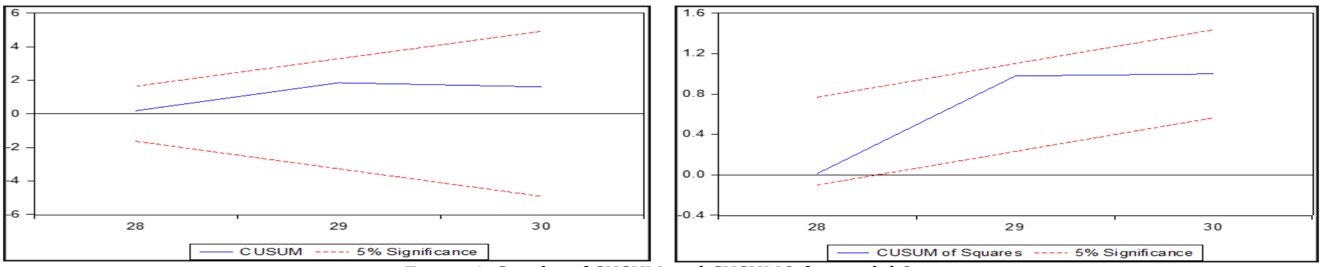

Figure 4. Graphs of CUSUM and CUSUMQ for model 2.

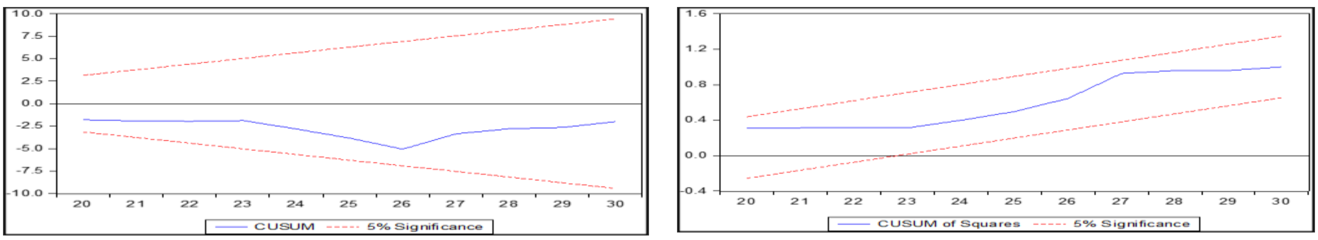

Figure 5. Graphs of CUSUM and CUSUMQ for model 3.

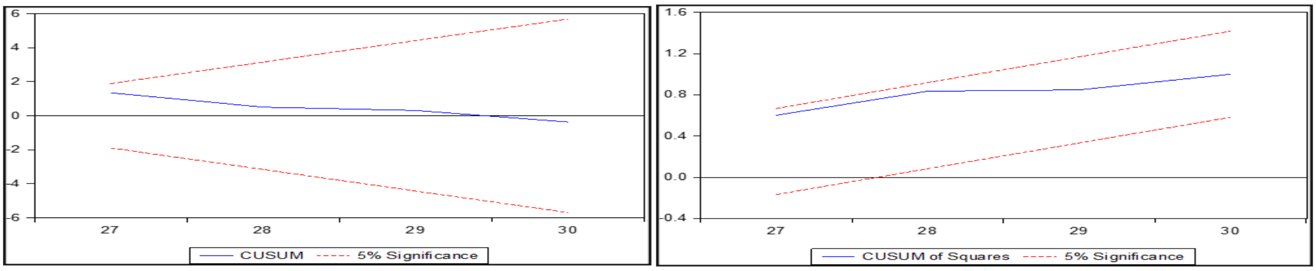

Figure 6. Graphs of CUSUM and CUSUMQ for model 4.

CONCLUSION AND POLICY IMPLICATIONS

Applying the ARDL bounds testing approach, this article examines the short- and long-term effects of temperature, rainfall, CO_2, domestic credit, and gross capital formation on agriculture production and its subsectors from 1990 to 2019 in Ivory Coast. The Johansen cointegration test is used to check the robustness of the long-term cointegration between the variables under consideration. Considering agriculture at an aggregate level, the ARDL findings indicate a positive and significant impact of temperature in Ivory Coast in the long run. Rainfall has a negative and significant impact on agriculture over the long run. Regarding CO_2, a positive and significant impact is found in the long term. Our time series analysis shows a beneficial temperature impact for crop production in both runs. The impact of CO_2 on crop production is positive in both runs. Regarding livestock, our time series analysis reveals that temperature positively impacts Ivory Coast's production in both runs. Rainfall has a positive long-term impact on Ivory Coast's livestock production. The time series long- and short-run dynamics on fishery production indicate a negative temperature impact in the short run. Rainfall is found to have a negative impact on it in both runs. CO_2 positively affects Ivory Coast's fishery production in the long run. The results confirm the dependence of the livestock subsector on rainfall. Rainfall negatively impacts the agriculture sector and the fishery subsector. Another important result is the negative effect of gross capital formation on agriculture and its subsectors. Therefore, the government should invest more in agricultural infrastructure, promote and facilitate the adoption of irrigation systems, promote the adoption of Climate-Smart Agriculture Practices (CSA), and improve grazing and water management for livestock.

Statements and declarations

Funding: This research did not receive any specific grant from public, commercial, or not-for-profit funding agencies.

Data availability: The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Ethics approval and consent to participate: Not applicable.

Consent for publication: Not applicable.

Competing interests: The authors declare no competing interests.

REFERENCES

Abbas, S., 2020. Climate change and cotton production: an empirical investigation of Pakistan. Environ. Sci. Pollut. Res. 27, 29580–29588. https://doi.org/10.1007/s11356-020-09222-0.

Abbas, S., Kousar, S., Shirazi, S.A., Yaseen, M., Latif, Y., 2022. Illuminating Empirical Evidence of Climate Change: Impacts on Rice Production in the Punjab Regions, Pakistan. Agric. Res. 11, 32–47. https://doi.org/10.1007/s40003-021-00548-w.

Adom, P.K., Bekoe, W., Akoena, S.K.K., 2012. Modelling aggregate domestic electricity demand in Ghana: An autoregressive distributed lag bounds cointegration approach. Energy Policy 42, 530–537. https://doi.org/10.1016/j.enpol.2011.12.019.

Akhtar, R., Masud, M.M., 2022. Dynamic linkages between climatic variables and agriculture production in Malaysia: a generalized method of moments approach. Environ. Sci. Pollut. Res. 29, 41557–41566. https://doi.org/10.1007/s11356-021-18210-x.

Ali, S., Liu, Y., Ishaq, M., Shah, T., Abdullah, Ilyas, A., Din, I.U., 2017. Climate change and its impact on the yield of major food crops: Evidence from Pakistan. Foods 6, 1–19. https://doi.org/10.3390/foods6060039.

Almazroui, M., 2020a. Changes in Temperature Trends and Extremes over Saudi Arabia for the Period 1978-2019. Adv. Meteorol. 2020, 1–21. https://doi.org/10.1155/2020/8828421.

Almazroui, M., 2020b. Rainfall trends and extremes in Saudi Arabia in recent decades. Atmosphere (Basel). 11, 964. https://doi.org/10.3390/atmos11090964.

Asfew, M., Bedemo, A., 2022. Impact of Climate Change on Cereal Crops Production in Ethiopia. Adv. Agric. 2022, 1–8. https://doi.org/10.1155/2022/2208694.

Asumadu-Sarkodie, S., Owusu, P.A., 2016. The relationship between carbon dioxide and agriculture in Ghana: a comparison of VECM and ARDL model. Environ. Sci. Pollut. Res. 23, 10968–10982. https://doi.org/10.1007/s11356-016-6252-x.

Atanga, R.A., Tankpa, V., 2021. Climate Change, Flood Disaster Risk and Food Security Nexus in Northern Ghana. Front. Sustain. Food Syst. 5, 706721. https://doi.org/10.3389/fsufs.2021.706721.

Attiaoui, I., Boufateh, T., 2019. Impacts of climate change on cereal farming in tunisia: A panel ARDL–PMG approach. Environ. Sci. Pollut. Res. 26, 13334–13345. https://doi.org/10.1007/s11356-019-04867-y.

Awunyo-Vitor, D., 2017. Factors Influencing Choice of Climate Change Adaptation Strategies By Maize Farmers in Upper East Region of Ghana. J. Glob. Bus. Technol. 13, 10–23.

Azizi, J., Zarei, N., Ali, S., 2022. The short- and long-term impacts of climate change on the irrigated barley yield in Iran: an application of dynamic ordinary least squares approach. Environ. Sci. Pollut. Res. 29, 40169–40177. https://doi.org/10.1007/s11356-022-19046-9.

Begum, M., Masud, M.M., Alam, L., Mokhtar, M. Bin, Amir, A.A., 2022. The impact of climate variables on marine fish production: an empirical evidence from Bangladesh based on autoregressive distributed lag (ARDL) approach. Environ. Sci. Pollut. Res. 29, 87923–87937. https://doi.org/10.1007/s11356-022-21845-z.

Belete, A.S., 2020. Analysis of technical efficiency in maize production in Guji Zone: stochastic frontier model. Agric. Food Secur. 9, 1–15. https://doi.org/10.1186/s40066-020-00270-w.

Boko, A.N.N., Cisse, G., Kone, B., Dedy, S.F., 2016. Local beliefs and strategies of adaptation to climate change in Korhogo (Ivory Coast) | Croyances locales et stratégies d'adaptation aux variations climatiques à Korhogo (Côte d'Ivoire). Tropicultura 34, 40–46.

CCKP, 2021. Climate Change Knowledge Portal (CCKP) for development practitioners and policy makers. Accessed on April 5, 2023. https://climateknowledgeportal.worldbank.org/country/cote-divoire/vulnerability.

Chandio, A.A., Gokmenoglu, K.K., Ahmad, F., 2021a. Addressing the long- and short-run effects of climate change on major food crops production in Turkey. Environ. Sci. Pollut. Res. 28, 51657–51673. https://doi.org/10.1007/s11356-021-14358-8.

Chandio, A.A., Jiang, Y., Abbas, Q., Amin, A., Mohsin, M., 2022c. Does financial development enhance agricultural production in the long-run? Evidence from China. J. Public Aff. 22, e2342. https://doi.org/10.1002/pa.2342.

Chandio, A.A., Jiang, Y., Ahmad, F., Adhikari, S., Ain, Q.U., 2021b. Assessing the impacts of climatic and technological factors on rice production: Empirical evidence from Nepal. Technol. Soc. 66, 101607. https://doi.org/10.1016/j.techsoc.2021.101607.

Chandio, A.A., Jiang, Y., Amin, A., Akram, W., Ozturk, I., Sinha, A., Ahmad, F., 2022a. Modeling the impact of climatic and non-climatic factors on cereal production: evidence from Indian agricultural sector. Environ. Sci. Pollut. Res. 29, 14634–14653. https://doi.org/10.1007/s11356-021-16751-9.

Chandio, A.A., Jiang, Y., Fatima, T., Ahmad, F., Ahmad, M., Li, J., 2022b. Assessing the impacts of climate change on cereal production in Bangladesh: evidence from ARDL modeling approach. Int. J. Clim. Chang. Strateg. Manag. 14, 125–147. https://doi.org/10.1108/IJCCSM-10-2020-0111.

Chandio, A.A., Jiang, Y., Rehman, A., Rauf, A., 2020c. Short and long-run impacts of climate change on agriculture: an empirical evidence from China. Int. J. Clim. Chang. Strateg. Manag. 12, 201–221. https://doi.org/10.1108/IJCCSM-05-2019-0026.

Chandio, A.A., Magsi, H., Ozturk, I., 2020a. Examining the effects of climate change on rice production: case study of Pakistan. Environ. Sci. Pollut. Res. 27, 7812–7822. https://doi.org/10.1007/s11356-019-07486-9.

Chandio, A.A., Ozturk, I., Akram, W., Ahmad, F., Mirani, A.A., 2020b. Empirical analysis of climate change factors affecting cereal yield: evidence from Turkey. Environ. Sci. Pollut. Res. 27, 11944–11957. https://doi.org/10.1007/s11356-020-07739-y.

Clarke, T.M., Reygondeau, G., Wabnitz, C., Robertson, R., Ixquiac-Cabrera, M., López, M., Ramírez Coghi, A.R., del Río Iglesias, J.L., Wehrtmann, I., Cheung, W.W.L., 2021. Climate change impacts on living marine resources in the Eastern Tropical Pacific. Divers. Distrib. 27, 65–81. https://doi.org/10.1111/ddi.13181.

Demirhan, H., 2020. Impact of increasing temperature anomalies and carbon dioxide emissions on wheat production. Sci. Total Environ. 741, 139616. https://doi.org/10.1016/j.scitotenv.2020.139616.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. J. Am. Stat. Assoc. 74, 427–431. https://doi.org/10.1080/01621459.1979.10482531.

Dudu, H., Çakmak, E.H., 2018. Climate change and agriculture: an integrated approach to evaluate economy-wide effects for Turkey. Clim. Dev. 10, 275–288. https://doi.org/10.1080/17565529.2017.1372259.

Dumortier, J., Carriquiry, M., Elobeid, A., 2021. Impact of climate change on global agricultural markets under different shared socioeconomic pathways. Agric. Econ. (United Kingdom) 52, 963–984. https://doi.org/10.1111/agec.12660

Emenekwe, C.C., Onyeneke, R.U., Nwajiuba, C.U., 2022. Financial development and carbon emissions in Sub-Saharan Africa. Environ. Sci. Pollut. Res. 29, 19624–19641. https://doi.org/10.1007/s11356-021-17161-7.

Fadina, A.M.R., Barjolle, D., 2018. Farmers' adaptation strategies to climate change and their implications in the Zou department of South Benin. Environ. 5, 1–17. https://doi.org/10.3390/environments5010015.

FAO, IFAD, UNICEF, WFP, WHO, 2021. The State of Food Security and Nutrition in the World 2021. Transforming food systems for food security, improved nutrition and affordable healthy diets for all. FAO, Rome.

Gan, T.Y., Ito, M., Hülsmann, S., Qin, X., Lu, X.X., Liong, S.Y., Rutschman, P., Disse, M., Koivusalo, H., 2016. Possible climate change/variability and human impacts, vulnerability of drought-prone regions, water resources and capacity building for Africa. Hydrol. Sci. J. 61, 1209–1226. https://doi.org/10.1080/02626667.2015.1057143.

Globalcarbonatlas, 2022. Carbon emissions per capita ranking. Accessed on February 28, 2023 from: http://www.globalcarbonatlas.org/en/CO2-.

IFPRI, 2020. 2020 global food policy report: building inclusive food systems. International Food Policy Research Institute (IFPRI). https://doi.org/10.2499/9780896293670.

IFPRI, 2021. 2020 Global report on food crises: Joint analysis for better decisions: September update in times of COVID-19. Food Security Information Network (FSIN) and Global Network Against Food Crises report. https://orcid.org/0000-0002-4496-080X.

Janjua, P.Z., Samad, G., Khan, N., 2014. Climate change and wheat production in Pakistan: An autoregressive distributed lag approach. NJAS - Wageningen J. Life Sci. 68, 13–19. https://doi.org/10.1016/j.njas.2013.11.002

Kabubo-Mariara, J., 2009. Global warming and livestock husbandry in Kenya: Impacts and adaptations. Ecol. Econ. 68, 1915–1924. https://doi.org/10.1016/j.ecolecon.2009.03.002.

Khor, M., 2009. Food crisis, climate change and the importance of sustainable agriculture. Environment and Development Series, 8, 1-26. Third World Network. www.twnside.org.sg.

Kirby, J.M., Mainuddin, M., Mpelasoka, F., Ahmad, M.D., Palash, W., Quadir, M.E., Shah-Newaz, S.M., Hossain, M.M., 2016. The impact of climate change on regional water balances in Bangladesh. Clim. Change 135, 481–491. https://doi.org/10.1007/s10584-016-1597-1.

Kumar, P., Sahu, N.C., Kumar, S., Ansari, M.A., 2021. Impact of climate change on cereal production: evidence from lower-middle-income countries. Environ. Sci. Pollut. Res. 28, 51597–51611. https://doi.org/10.1007/s11356-021-14373-9.

Melkani, A., Mason, N.M., Mather, D.L., Chisanga, B., 2021. Smallholder Market Participation and Choice of Marketing Channel in the Presence of Liquidity Constraints: Evidence from Zambian Maize Markets. Research in Agricultural and Applied Economics. https://doi.org/10.22004/ag.econ.315273.

Mihiretu, A., Okoyo, E.N., Lemma, T., 2019. Determinants of adaptation choices to climate change in agro-pastoral dry lands of Northeastern Amhara, Ethiopia. Cogent Environ. Sci. 5, 1636548. https://doi.org/10.1080/23311843.2019.1636548.

Misra, R., Chavan, P., Verma, R., 2016. Agricultural Credit in India in the 2000s: Growth, Distribution and Linkages with Productivity. Margin 10, 169–197. https://doi.org/10.1177/0973801015625378.

Mwabutwa, C., 2017. Localized public investment and agricultural performance in Malawi. Working paper, International Food Policy Research Institute, Washington DC.

N'Zué, F.F., 2018. Does Climate Change Have Real Negative Impact on Economic Growth in Poor Countries? Evidence from Cote d'Ivoire (Ivory Coast). Manag. Econ. Res. J. 4, 204. https://doi.org/10.18639/merj.2018.04.670069.

Nasrullah, M., Rizwanullah, M., Yu, X., Jo, H., Sohail, M.T., Liang, L., 2021. Autoregressive distributed lag (Ardl) approach to study the impact of climate change and other factors on rice production in South Korea. J. Water Clim. Chang. 12, 2256–2270. https://doi.org/10.2166/wcc.2021.030.

Ntiamoah, E.B., Li, D., Appiah-Otoo, I., Twumasi, M.A., Yeboah, E.N., 2022. Towards a sustainable food production: modelling the impacts of climate change on maize and soybean production in Ghana. Environ. Sci. Pollut. Res. 29, 72777–72796. https://doi.org/10.1007/s11356-022-20962-z.

Ogundari, K., Onyeaghala, R., 2021. The effects of climate change on African agricultural productivity growth revisited. Environ. Sci. Pollut. Res. 28, 30035–30045. https://doi.org/10.1007/s11356-021-12684-5.

Olayide, O.E., Tetteh, I.K., Popoola, L., 2016. Differential impacts of rainfall and irrigation on agricultural production in Nigeria: Any lessons for climate-smart agriculture? Agric. Water Manag. 178, 30–36. https://doi.org/10.1016/j.agwat.2016.08.034.

Omoke, P.C., Nwani, C., Effiong, E.L., Evbuomwan, O.O., Emenekwe, C.C., 2020. The impact of financial development on carbon, non-carbon, and total ecological footprint in Nigeria: new evidence from asymmetric dynamic analysis. Environ. Sci. Pollut. Res. 27, 21628–21646. https://doi.org/10.1007/s11356-020-08382-3.

Otekunrin, Olutosin A., Otekunrin, Oluwaseun A., Sawicka, B., Pszczółkowski, P., 2021. Assessing food insecurity and its drivers among smallholder farming households in rural oyo state, Nigeria: The hfias approach. Agric. 11, 1189. https://doi.org/10.3390/agriculture11121189.

Pauly, D., Cheung, W.W.L., 2018. Sound physiological knowledge and principles in modeling shrinking of fishes under climate change. Glob. Chang. Biol. 24, e15–e26. https://doi.org/10.1111/gcb.13831.

Pesaran, M.H., Shin, Y., 1998. An autoregressive distributed lag modelling approach to cointegration analysis. The Ragnar Frisch Centennial Symposium. 371 – 413. https://doi.org/10.1017/CCOL521633230.011.

Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. J. Appl. Econom. 16, 289–326. https://doi.org/10.1002/jae.616

Phillips, P.C., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika, 75, 335-346.

Pickson, R.B., Gui, P., Chen, A., Boateng, E., 2022. Empirical analysis of rice and maize production under climate change in China. Environ. Sci. Pollut. Res. 29, 70242–70261. https://doi.org/10.1007/s11356-022-20722-z.

Rehman, A., Ma, H., Irfan, M., Ahmad, M., 2020. Does carbon dioxide, methane, nitrous oxide, and GHG emissions influence the agriculture? Evidence from China. Environ. Sci. Pollut. Res. 27, 28768–28779. https://doi.org/10.1007/s11356-020-08912-z.

Rosegrant, M.W., Ewing, M., Yohe, G., Burton, I., Huq, S., Valmonte-santos, R., 2008. Climate change and agriculture threats and opportunities. Eschborn, Germany: Deutsche Gesellschaft fur Technische Zusammenarbeit (GTZ).

Schilling, J., Hertig, E., Tramblay, Y., Scheffran, J., 2020. Climate change vulnerability, water resources and social implications in North Africa. Reg. Environ. Chang. 20, 1-13. https://doi.org/10.1007/s10113-020-01597-7.

Sibanda, L.M., Mwamakamba, S.N., 2021. Policy considerations for African food systems: towards the United Nations 2021 Food Systems Summit. Sustainability, 13, 1-15. https://doi.org/10.3390/su13169018.

Thiault, L., Mora, C., Cinner, J.E., Cheung, W.W.L., Graham, N.A.J., Januchowski-Hartley, F.A., Mouillot, D., Rashid Sumaila, U., Claudet, J., 2019. Escaping the perfect storm of simultaneous climate change impacts on agriculture and marine fisheries. Sci. Adv. 5, eaaw9976. https://doi.org/10.1126/sciadv.aaw9976.

Warsame, A.A., Sheik-Ali, I.A., Ali, A.O., Sarkodie, S.A., 2021. Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. Environ. Sci. Pollut. Res. 28, 19838–19850. https://doi.org/10.1007/s11356-020-11739-3.

Warsame, A.A., Sheik-Ali, I.A., Hassan, A.A., Sarkodie, S.A., 2022. Extreme climatic effects hamper livestock production in Somalia. Environ. Sci. Pollut. Res. 29, 40755–40767. https://doi.org/10.1007/s11356-021-18114-w.

World Bank, 2019. Sub-Saharan Africa. Regional Economic Data. Abidjan (Côte d'Ivoire): The World Bank Group; (accessed 2023 Mai 6). https://data.worldbank.org/region/sub-saharan-africa.

World Bank, 2023. Agriculture, Forestry, and Fishing, Value Added (% of GDP)-Cote d'Ivoire; (accessed 2023 Mai 2). https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=CI.

Xie, H., Wen, Y., Choi, Y., Zhang, X., 2021. Global trends on food security research: A bibliometric analysis. Land 10, 1–21. https://doi.org/10.3390/land10020119.

Zakaria, M., Jun, W., Khan, M.F., 2019. Impact of financial development on agricultural productivity in South Asia. Agric. Econ. (Czech Republic) 65, 232–239. https://doi.org/10.17221/199/2018-AGRICECON.

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