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Assessing the Nexus between Weather Variables, CO_2 Emissions, Agricultural Inputs, and Food Production in Cameroon: Evidence from a NARDL Model

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ABSTRACT

This study examines the impact of weather variables, CO_2 emissions, and agricultural inputs on food production in Cameroon, using annual time series data spanning from 1961 to 2023. The independent variables representing these factors are average maximum temperature and precipitation as weather variables, alongside agricultural land, and fertilizer usage as agricultural inputs. To assess the long- and short-run asymmetrical effects of these variables on food production, we employ the Non-linear Autoregressive Distributed Lag (NARDL) model. The results confirm the existence of a long-run cointegration relationship among the variables. Long-run estimates reveal that both positive and negative shocks to maximum temperature and precipitation adversely affect food production, with effects of -7.74% and -2.94%, respectively. In contrast, carbon emissions exhibit an asymmetric but positive long-run relationship with food production. Positive and negative shocks to CO_2 emissions have a positive impact of 0.87% and 0.44%, respectively. Furthermore, agricultural inputs do not show a statistically significant long-run effect. The findings underscore the need for climate-sensitive and food-oriented agricultural policies in Cameroon, emphasizing targeted input support, planned production systems, and climate-resilient adaptation strategies to enhance long-term food security.

Keywords: Climate Change, Food Security, NARDL, Precipitation, Sub-Saharan Africa.

INTRODUCTION

The influence of climate change is felt differently across regions and communities worldwide (Pricope et al., 2013). While developed countries are responsible for more than 75% of global CO_2 emissions (Ketema and Negeso, 2020), their adverse consequences are disproportionately borne by warmer and less affluent regions, particularly rural areas in developing countries (Tume and Tanyanyiwa, 2018). Sub-Saharan Africa, already subject to intense climatic stress, is consistently identified in the literature as one of the regions facing the highest levels of exposure and vulnerability to these impacts (Dinar et al., 2012; Ofori et al., 2021). These impacts materialize through multiple and interconnected channels, including rising income

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inequality (Baarsch et al., 2020; Dasgupta et al., 2023), increasing climatic hazards (Global Center on Adaptation, 2022) and biological shocks such as locust invasions (Salih et al., 2020).

Within this broader context of climate change, understanding how weather variables affect food production remains a critical issue for agricultural economies in Sub-Saharan Africa. Given that climate change leads to increasingly unpredictable weather patterns, analyzing key weather variables can provide a clearer understanding of agricultural vulnerabilities. Despite a growing body of empirical literature on weather–agriculture linkages, evidence for individual countries such as Cameroon remains limited. Most existing studies either focus on cross-country analyses or rely on static frameworks that do not distinguish between short-run and long-run effects, and little is known about how weather variables and agricultural inputs jointly influence food production over time. To address this gap, this study provides country-specific evidence for Cameroon by employing an asymmetrical cointegration approach.

Climate-related risks have intensified in Cameroon over recent decades, with steadily rising temperatures and increasing variability in rainfall patterns. Projections suggest that these changes could reduce national GDP by between 4% and 10% by 2050, with agriculture among the most severely affected sectors (World Bank, 2022). Agriculture plays a central role in the Cameroonian economy, accounting for 17.10% of GDP, employing 43.42% of the population (World Bank, 2025), and contributing 32.50% of merchandise exports in 2023 (FAOSTAT, 2025). Nevertheless, several studies indicate that food production in many Sub-Saharan African countries, including Cameroon, has stagnated or declined over time (Epule and Bryant, 2015). According to the International Monetary Fund (2024), climate change could reduce agricultural output in the region by between 6% and 14% by 2050.

These trends have important implications for food security. Declines in agricultural production tend to increase food prices and reduce access to essential commodities, particularly for low-income households. In Cameroon, nearly one-quarter of the population currently lives under conditions of severe food insecurity, a situation that has persisted since 2015 (World Bank, 2025). Climate-related pressures are expected to further exacerbate these vulnerabilities, particularly in environmentally fragile regions such as the Sahelian zone of Cameroon (Chabejong, 2016).

Assessing the impacts of climate change on agriculture constitutes a methodologically challenging area of research, as it requires analytical approaches that are carefully tailored to data availability, research objectives, and regional contexts (Amouzay and El Ghini, 2025). Consequently, there has been a marked increase in studies investigating the impacts long-term climatic trends and short-term meteorological shocks on agricultural and food products, particularly in recent years. For instance, Ortiz-Bobea et al. (2021) found that human-induced climate change reduced global agricultural total factor productivity by approximately 21% since 1961. Linear analyses show that sustained temperature increases have been shown to reduce crop yields and overall output, as evidenced by Gul et al. (2022), and Sharma et al. (2023). Non-linear analyses, however, have found that both positive and negative temperature variations have a detrimental effect (Baig et al., 2022; Abbas et al., 2022; Benmehaia, 2023; Khan et al., 2025). On the other hand, the results for precipitation are mixed. Both positive (Çakan and Tipi, 2024; and Mahali et al., 2024) and negative (Ahmed et al., 2023; Senapati, A. K., 2022) effects of precipitation have been observed in linear and non-linear analyses. Regarding CO_2 emissions, while most studies show that increases in CO_2 levels have a positive impact on agricultural production (Anh et al. 2023; Sharma et al., 2023; Khurshid and Abid, 2024), there are also studies that have reached negative conclusions (Baig et al. (2022).

The agricultural sector is among the most vulnerable sectors to climate change (Mendelsohn et al., 1994; Ortiz-Bobea, 2021). Cameroon, an African country with a high dependence on agriculture and limited technological capacity, is therefore expected to experience the impacts of climate change more severely (Mendelsohn et al., 2020). This study examines the effects of annual weather variations, CO_2 emissions, and agricultural inputs on food production in Cameroon using the Nonlinear Autoregressive Distributed Lag (NARDL) framework, which allows for the identification of asymmetric short-run meteorological shocks and long-run climatic trends. The findings provide empirical evidence to support policy interventions aimed at mitigating climate-related risks and enhancing the resilience of the agricultural sector.

MATERIAL AND METHODS

Data

This study utilizes a dataset containing annual time series data from 1961 to 2023. We acquire data from multiple sources, including the World Bank (2025), FAOSTAT (2025), CCKP (2025), and Friedlingstein et al. (2025). We applied logarithmic transformation on the variables to enable elasticity interpretation. Table 1 provides detailed information on the dataset. Table 2 delivers information about the variables' descriptive statistics.

Table 1 Description of Variables.

Variable	Description	Source
FPI	Food production index (2014-2016=100)	FAOSTAT (2025), Original Calculations
MXTEMP	Average maximum temperature (°C)	CCKP (2025)
PRC	Aggregated accumulated precipitation (mm)	CCKP (2025)
CO_2	CO_2 emissions including fossil fuels and land-use change (ton)	Friedlingstein *et al.* (2025)
AHRV	Area Harvested (ha)	FAOSTAT (2025), Original Calculations
FRT	Fertilizer usage (ton)	FAOSTAT (2025)

Table 2. Descriptive Statistics.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.
*ln*FPI	3.556731	3.226116	4.726163	2.608409	0.675472
*ln*MXTEMP	3.400123	3.399529	3.419365	3.372798	0.009808
*ln*PRC	7.402319	7.420567	7.554534	7.212597	0.056605
lnCO_2	2.778031	2.741872	3.142676	2.423653	0.180802
*ln*AHRV	15.15940	15.04494	15.81306	14.58039	0.343082
*ln*FRT	10.37584	10.57393	11.55565	8.086410	0.804535

The food production index (FPI) used in this study is constructed by adapting the FAOSTAT food production index to better reflect the specific production structure of Cameroon. In its standard FAOSTAT definition, the FPI covers edible and nutritionally relevant food items and includes all food products except tea and coffee. However, this definition may be misleading in countries such as Cameroon, where cash crops occupy extensive production areas and where certain products classified as "food" are primarily produced for export rather than domestic consumption. To address this limitation, we constructed an alternative FPI that excludes cocoa and coffee, which constitute Cameroon's main cash crops.

Specifically, we compiled production values for all commodities classified under the FAOSTAT food category for Cameroon, excluding cocoa and coffee. These values were then aggregated and converted into an index using 2014–2016 as the base period. Fertilizer use was measured by aggregating nitrogen (N), phosphate (P_2O_5), and potash (K_2O) consumption data obtained from the FAO database. Harvested area data were sourced from FAOSTAT (2025) and calculated by summing the harvested areas of all crops classified under the primary crops category.

Model

This study aims to analyze the impact of weather factors on food production. We formulated a model for this purpose, drawing upon insights gleaned from prior studies examining food production and long-term climatic trends and short-term meteorological shocks relations (Ahmed et al., 2023; Khan et al., 2025). The structure of the model is designed to capture the multifaceted effects of weather conditions on food production. Accordingly, it incorporates key variables representing different dimensions of weather, namely precipitation, maximum temperatures. Furthermore, carbon dioxide CO_2 emissions are included to control for atmospheric variations that drive long-term climatic trends. In addition to this, the model includes selected input-related variables—fertilizer use and agricultural land—to account for the role of production inputs in shaping food output. The inclusion of a relatively limited set of explanatory variables is primarily motivated by the need to preserve the model's degrees of freedom. Moreover, data limitations precluded the inclusion of other potentially relevant inputs, such as pesticide use and agricultural energy consumption, for which consistent time-series data were unavailable. The model can be defined as follows.

$$lnFPI_t = \beta_0 + \beta_1 lnMXTEMP_t + \beta_3 lnPRC_t + \beta_4 lnCO2_t + \beta_5 lnAGLAND_t + \beta_6 lnFRT_t + \varepsilon_t$$

Where FPI is the food production index, MXTEMP, PRC, CO_2, and AGLAND represent average maximum temperature, precipitation, CO_2 emissions, agricultural land, and fertilizer usage, respectively.

Food production exhibits inherently asymmetric responses to various explanatory factors, particularly weather variables. In the long run, both positive and negative shocks to weather conditions may adversely affect agricultural production by disrupting the fragile balance of a sector highly dependent on natural conditions. On the other hand, increasing agricultural inputs are expected to positively contribute to food production in both the short and long run. Regarding carbon emissions, we anticipate asymmetric long-run effects: while emissions can signal increased production through modernization and land-use change, they can concurrently hinder yields by inducing climatic instability. Consequently, the hypotheses are summarized below:

H1: Long-run positive and negative shocks to weather variables have an adverse impact on food production.

H2: Long-run positive and negative shocks to CO2 emissions have a positive impact on food production.

H3: An increase in agricultural inputs (agricultural land and fertilizer use) improves food production in the long run.

Methodology

We employed advanced time series analysis techniques to rigorously assess the asymmetrical nexus between weather variables, CO_2 emissions, and agricultural inputs, and their collective influence on food production dynamics in Cameroon. Our approach involved conducting a cointegration analysis to discern the factors influencing food production in both the long and short run. The choice of cointegration methodology was guided by the results of the unit root tests and the conceptual structure of the model.

The study employs the Nonlinear Autoregressive Distributed Lag (NARDL) approach developed by Shin et al. (2014). The NARDL framework extends the conventional ARDL model proposed by Pesaran et al. (2001) by allowing positive and negative changes in explanatory variables to exert heterogeneous effects on the dependent variable. Similar to the standard ARDL approach, NARDL can be applied when variables are integrated of order I(0) or I(1), performs well in small samples, and accommodates both short- and long-run dynamics. Its key advantage lies in its ability to explicitly capture asymmetric relationships that may remain concealed under symmetric modeling assumptions.

The asymmetric long-run regression representation of our model is as follows:

$$\begin{aligned} lnFPI_t = \alpha_0 &+ \beta_1 lnMXTEMP_t^{+} + \beta_2 lnMXTEMP_t^{-} + \beta_3 lnPRC_t^{+} + \beta_4 lnPRC_t^{-} + \beta_5 lnCO2_t^{+} \\ &+ \beta_6 lnCO2_t^{-} + \beta_7 lnAHRV_t^{+} + \beta_8 lnAHRV_t^{-} + \beta_9 lnFRT_t^{+} + \beta_{10} lnFRT_t^{-} + u_t, \end{aligned}$$

Each explanatory variable x_t is decomposed into cumulative positive and negative changes as $x_t = x_0 + x_t^{+} + x_t^{-}$. The partial sum processes are defined as:

$$x_t^{+} = \sum_{j=1}^{t} \Delta x_j^{+} = \sum_{j=1}^{t} \max(\Delta x_j, 0)$$

$$x_t^{-} = \sum_{j=1}^{t} \Delta x_j^{-} = \sum_{j=1}^{t} \min(\Delta x_j, 0)$$

Following the ARDL approach developed by Pesaran et al. (2001), the NARDL model can be expressed in error correction form as follows:

$$\begin{aligned} \Delta lnFPI_t = \alpha_i + \delta_i lnFPI_{t-1} &+ \beta_1^{+} lnMXTEMP_{t-1}^{+} + \beta_2^{-} lnMXTEMP_{t-1}^{-} + \beta_3^{+} lnPRC_{t-1}^{+} \\ &+ \beta_4^{-} lnPRC_{t-1}^{-} + \beta_5^{+} lnCO2_{t-1}^{+} + \beta_6^{-} lnCO2_{t-1}^{-} + \beta_7^{+} lnAGLAND_{t-1}^{+} \\ &+ \beta_8^{-} lnAGLAND_{t-1}^{-} + \beta_9^{+} lnFRT_{t-1}^{+} + \beta_{10}^{-} lnFRT_{t-1}^{-} + \sum_{i=0}^{p} \varsigma_i \Delta lnFPI_{t-i} \\ &+ \sum_{i=1}^{r} (\omega_i^{+} \Delta MXTEMP_{t-i}^{+} + \omega_i^{-} \Delta MXTEMP_{t-i}^{-}) \\ &+ \sum_{i=0}^{s} (\varphi_i^{+} \Delta lnPRC_{t-i}^{+} + \varphi_i^{-} \Delta lnPRC_{t-i}^{-}) \\ &+ \sum_{i=0}^{t} (\rho_i^{+} \Delta lnCO2_{t-i}^{+} + \rho_i^{-} \Delta lnCO2_{t-i}^{-}) \\ &+ \sum_{i=0}^{v} (\phi_i^{+} \Delta lnAGLAND_{t-i}^{+} + \phi_i^{-} \Delta lnAGLAND_{t-i}^{-}) \\ &+ \sum_{i=0}^{y} (\psi_i^{+} \Delta lnFRT_{t-i}^{+} + \psi_i^{-} \Delta lnFRT_{t-i}^{-}) + \varepsilon_t \end{aligned}$$

In this specification, δ_i denotes the error correction term, β_i represents the long-run coefficients, while $\omega_i, \varphi_i, \rho_i, \phi_i, \psi_i$ represents the short-term coefficients. capture the short-run dynamic effects. The existence of a cointegration relationship among the variables is assessed using the F-bounds test. When the computed F-statistic exceeds the relevant critical values for variables integrated of order I(0) and I(1), the presence of cointegration is confirmed. Asymmetric relationships are examined using Wald tests. Long-run asymmetry is tested by evaluating the null hypothesis $H_0: \beta_i^+ = \beta_i^-$, while short-run asymmetry is assessed by testing the same restriction on the corresponding short-run coefficients.

FINDINGS

Unit Root Test Results

As noted earlier, the empirical analysis begins with unit root testing. Within the scope of the study, the order of integration of the variables is examined using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests. The results of these tests are reported in Table 3.

Table 3. Unit root test results.

Unit Root Test	Variables	Level		1st Difference	
		Intercept	Trend and Intercept	Intercept	Trend and Intercept
ADF	*ln*FPI	0.424306	-1.197668	***-6.689014	***-6.740885
	*ln*MXTEMP	***-4.168384	***-5.088845	***-9.221307	***-9.257960
	*ln*PRC	***-7.456223	***-7.877639	***-9.141789	***-9.222757
	lnCO_2	-2.652355	**-4.102669	***-11.93088	***-11.82872
	*ln*AHRV	-0.406550	-1.628914	***-9.318070	***-9.265412
	*ln*FRT	-2.634504	-3.459087	***-8.092206	***-8.233591
PP	*ln*FPI	0.379256	-1.251000	***-6.645646	***-6.742307
	*ln*MXTEMP	***-4.098064	***-5.077438	***-25.66159	***-37.77396
	*ln*PRC	***-7.685091	***-8.007181	***-34.49706	***-50.17682
	lnCO_2	-2.331417	***-4.120538	***-12.71779	***-12.60255
	*ln*AHRV	-0.318534	-1.610679	***-9.292536	***-9.256378
	*ln*FRT	-2.662998	-3.440876	***-8.095094	***-8.238757

***, ** indicate statistical significance at 1% and 5% significance levels, respectively.

The unit root test outcomes indicate heterogeneity in the integration properties of the variables. According to both the ADF and PP tests, maximum temperature and precipitation are stationary at level, whereas all remaining variables are integrated of order one. This combination of I(0) and I(1) variables confirms the suitability of the dataset for the application of the NARDL framework.

Cointegration Test Results

Cointegration analysis within the NARDL framework proceeds through three main stages: selecting the optimal lag structure, testing for the presence of cointegration, and estimating the corresponding long- and short-run effects. To determine the appropriate lag length, we jointly considered diagnostic test results and the F-test. Based on this procedure, the NARDL p(3), q(3) specification was identified as the most suitable model.

The existence of a cointegration relationship was then examined using the F-bounds test, with the results reported in Table 4. The computed F-statistic exceeds the critical value at the 1% significance level, leading to the rejection of the null hypothesis of no cointegration. These results confirm the presence of a long-run equilibrium relationship among the variables included in the model.

Table 4 F-bounds test results for NARDL model.

H_0= No Levels Relationship			
F-statistic	Significance level	I(0)	I(1)
4.99	%10	2.26	3.35
	%5	2.62	3.79
	%2.5	2.96	4.18
	%1	3.41	4.68

Long and Short-Run Estimation Results

Following the confirmation of cointegration, the long- and short-run effects of the regressors on the dependent variable are estimated. At this stage, conducting diagnostic checks is essential prior to interpreting the estimation results, as overlooking this step may lead to misinterpretation and unreliable inference. The results of the diagnostic tests are reported in Table 5. The diagnostic outcomes indicate no evidence of serial correlation or heteroskedasticity. In addition, the residuals are normally distributed, and the model passes the specification tests, suggesting that the estimated NARDL model is statistically well behaved.

Table 5. Residual Diagnostics for the NARDL Model.

Test	**Statistic**	**p-value**
Portmanteau test up to lag 28 (χ^2)	30.53	0.338
Breusch/Pagan heteroskedasticity test (χ^2)	0.001	0.970
Ramsey RESET test (F)	2.079	0.153
Jarque–Bera test on normality (χ^2)	1.388	0.500

The long- and short-run estimation results are reported in Table 5. The short-run estimates indicate that the error correction term (ECT) carries a negative and statistically significant coefficient, confirming the existence of a stable adjustment process toward the long-run equilibrium. The magnitude of the ECT implies that deviations from the long-run equilibrium are corrected in approximately one year, with the speed of adjustment calculated as 1/0.7387≈1.35 years. Once the validity and functionality of the ECT are established, the remaining short- and long-run coefficient estimates can be interpreted with confidence.

Short-run dynamics, which reflect meteorological conditions and weather-related shocks, indicate that positive shocks to maximum temperature significantly reduce food production, while positive precipitation shocks enhance output. In contrast, negative shocks to carbon emissions, harvested area, and fertilizer use generate positive, negative, and positive effects, respectively.

The long-run estimates indicate that negative shocks to maximum temperature and carbon emissions reduce food production by 7.74% and 0.44%, respectively. Conversely, positive shocks to precipitation and carbon emissions increase food production by 2.94% and 0.87%, respectively.

Table 6. Long and Short Run Estimation Results.

Variable	Coefficient	t-Statistic
Long-Run Coefficients		
$\Delta lnMXTEMP_t^+$	7.263	1.672
$\Delta lnMXTEMP_t^-$	**-7.741	4.385
$\Delta lnPRC_t^+$	***-2.941	8.162
$\Delta lnPRC_t^-$	1.069	1.465
$\Delta lnCO2_t^+$	***0.872	8.715
$\Delta lnCO2_t^-$	**0.448	5.174
$\Delta lnAGLAND_t^+$	0.589	1.907
$\Delta lnAGLAND_t^-$	0.136	0.117
$\Delta lnFRT_t^+$	-0.078	0.384
$\Delta lnFRT_t^-$	0.235	3.461
Short-Run Coefficients		
$\Delta lnMXTEMP_t^+$	-3.23989	-1.49
$\Delta lnMXTEMP_{t-1}^+$	***-9.946995	-3.25
$\Delta lnMXTEMP_{t-2}^+$	***-8.02795	-3.57
$\Delta lnMXTEMP_t^-$	2.272689	0.95
$\Delta lnMXTEMP_{t-1}^-$	1.237504	0.45
$\Delta lnMXTEMP_{t-2}^-$	4.034727	1.49
$\Delta lnPRC_t^+$	-0.3590029	-1.36
$\Delta lnPRC_{t-1}^+$	**0.800809	2.68
$\Delta lnPRC_{t-2}^+$	0.3336602	1.31
$\Delta lnPRC_t^-$	-0.2433951	-1.10
$\Delta lnPRC_{t-1}^-$	0.9387213	2.07
$\Delta lnPRC_{t-2}^-$	0.4387245	1.34
$\Delta lnCO2_t^+$	0.3490817	1.91
$\Delta lnCO2_{t-1}^+$	-0.1790627	-1.11
$\Delta lnCO2_{t-2}^+$	-0.1110609	-0.71
$\Delta lnCO2_t^-$	-0.0578312	-0.37
$\Delta lnCO2_{t-1}^-$	**0.3654982	2.39
$\Delta lnCO2_{t-2}^-$	**0.2930345	2.38
$\Delta lnAGLAND_t^+$	0.7290147	1.90
$\Delta lnAGLAND_{t-1}^+$	0.2864004	0.82
$\Delta lnAGLAND_{t-2}^+$	0.2684421	0.89
$\Delta lnAGLAND_t^-$	***-0.9421757	-2.68
$\Delta lnAGLAND_{t-1}^-$	**-0.8060919	-2.09
$\Delta lnAGLAND_{t-2}^-$	-0.5168872	-1.74
$\Delta lnFRT_t^+$	-0.1565685	-1.40
$\Delta lnFRT_{t-1}^+$	-0.0650227	-0.90
$\Delta lnFRT_{t-2}^+$	0.0605739	0.94
$\Delta lnFRT_t^-$	0.0508337	0.57
$\Delta lnFRT_{t-1}^-$	**0.2292592	2.80
$\Delta lnFRT_{t-2}^-$	-0.0506264	-0.47
C	***2.476353	4.22
ECT	***-0.7387037	-3.26

*** and ** indicate statistical significance at 1% and 5% significance levels, respectively.

Discussion

Food production holds a particularly critical role in Cameroon, as in many other African countries, compared to developed economies, owing to the widespread prevalence of food insecurity across the region. Therefore, the significance of food production extends beyond increasing producer welfare or boosting agricultural exports, reaching into the fulfillment of society's fundamental needs and even national independence.

The estimation results for weather variables reveal that increases in maximum temperature exert a negative effect under short-run meteorological conditions, whereas no statistically significant impact emerges in the long run. In contrast, decreases in maximum temperature are associated with a negative and statistically significant long-run effect on food production. Moreover, positive shocks to precipitation are found to have a statistically significant negative impact in the long run. Precipitation nevertheless is the only weather indicator that exerts a positive and statistically significant effect in the short run, reflecting transient meteorological conditions. Taken together, these findings confirm H_1 and corroborate the existing literature (Baig et al., 2022; Abbas et al., 2022; Benmehaia, 2023; Khan et al., 2025), demonstrating that deviations from long-term climatic trends exert an adverse impact on food production regardless of the direction of change. This persistent pattern highlights the sector's profound vulnerability to climatic instability, where disruptions to the fragile agro-ecological balance significantly undermine agricultural output.

The results for CO_2 emissions are particularly noteworthy. The estimations reveal a statistically significant asymmetric relationship in the long run. Specifically, a 1% increase and a 1% decrease in CO_2 emissions are associated with increases in food production of 0.87% and 0.45%, respectively. These results provide empirical support for H_2, which posited that CO_2 emissions would positively influence food production regardless of the direction of the shock. The existence of a positive relationship between CO_2 emissions and food or agricultural production has been documented in a substantial body of literature. One explanation is that rising emissions often reflect economic expansion driven by increased energy use, which, in turn, enhances pre-and post-production activities (Khurshid and Abid, 2024; Onyeneke et al., 2025). In this sense, higher emissions can serve as a proxy for improved production capacity. Additionally, several studies emphasize the direct role of atmospheric CO_2 in plant growth, particularly for C3 crops, which rely on CO_2 for photosynthesis and may benefit from higher ambient concentrations (Anh et al., 2023; Sharma et al., 2023; Mahali et al., 2024). However, as a primary driver of climate change, carbon emissions also exert adverse effects on agricultural production in the long run through increased climate variability and environmental stress. From this perspective, reductions in emissions can likewise support food production by alleviating long-term climatic pressures.

The estimation results for agricultural production factors indicate that neither harvested area nor fertilizer use exerts a statistically significant effect on food production in the long run. In the short run, however, negative shocks to harvested area are associated with a decline in production, whereas negative shocks to fertilizer use generate a positive effect. Consequently, the empirical evidence fails to support H_3, which anticipated that agricultural land growth would improve food production in the long run. The weak long-run relationship between production inputs and food production can be attributed to resource allocation patterns within Cameroonian agriculture. In the dataset covering the period 1961–2023, cocoa was excluded from the analysis, as it does not directly contribute to domestic food security. Over this period, cocoa cultivation expanded by 57%. Even more pronounced increases are observed for other industrial crops, with harvested areas for tea expanding by 188% and rubber plantations by nearly 500% (FAOSTAT, 2025). This expansion of land allocated to cash and industrial crops may limit the capacity of increases in total harvested area to support food production in the long run. Two main factors may explain the limited effectiveness of fertilizer use. First, access to fertilizer is constrained by high input costs. Evidence from Cameroon indicates that approximately 42% of farmers do not use fertilizer at all (Abia et al., 2016), while only a small share of users can afford to meet more than half of their fertilizer requirements. High access costs are identified as the one of the primary barriers (Tchouandem et al., 2024). As a result, aggregate increases in fertilizer use may fail to translate into meaningful productivity gains if the majority of producers remain excluded from effective input use. Another reason may be Africa's chronic problem with low agronomic fertilizer use efficiency. Estimates suggest that nitrogen use efficiency in Africa averages 14.2, compared with a global average of 37—more than twice as high (Sanchez, 2019). This low efficiency is driven by multiple structural constraints, including poor soil quality, climatic stress, pest and disease pressures, and limited access to high-yielding crop varieties (Vanlauwe et al., 2011; Zingore et al., 2015; Amede and Dialo, 2022).

Conclusions

This study employs the NARDL approach to examine the effects of weather factors, CO_2 emissions, and key agricultural inputs on food production. The estimation results indicate that changes in input use do not exert a statistically significant influence on food production. On the other hand, the statistically significant long-run effects of weather variables such as maximum temperature and precipitation are negative, indicating that food production is adversely affected irrespective of the direction of climatic trends. In contrast, both positive and negative shocks to CO_2 emissions are found to increase food production. While increases in emissions support food production through enhanced production capacity and productivity, reductions in emissions contribute positively by mitigating the long-term adverse effects of climatic instability on the agricultural ecosystem.

Our findings show that key production factors, such as fertilizer use and harvested area, do not exert a statistically significant influence on food production. This outcome is closely linked to the prioritization of cash crops within Cameroon's agricultural policy framework. The Cameroonian government actively supports producers' access to inputs and provides agricultural extension services through initiatives such as the Coffee and Cocoa Sub-Sector Development Fund (CCODEF) and the Cocoa and Coffee Sector Recovery and Development Plan (PRDFCC), both of which are explicitly designed to enhance coffee and cocoa production (Kenfack Essougong et al., 2024; CCODEF, 2025). In addition, rising cocoa prices—particularly in recent years—have further incentivized producers through market mechanisms. Together, input support, price incentives, and targeted extension services facilitate improved access to production factors and their more efficient use in cash crop cultivation. By contrast, food crop production benefits far less from these mechanisms. Although plans to expand CCODEF to include food products represent an important initial step (CAFI, 2025), this measure alone is unlikely to resolve the current food insecurity challenge. Given projected increases in food demand, more comprehensive policy interventions are required. In particular, improving producers' access to inputs and enhancing their technical capacity through agricultural extension necessitate a higher allocation of public resources to the agricultural sector. As of 2022, public expenditure on agriculture, forestry, and fisheries in Cameroon accounted for only 2.4% of total government spending, placing the country 25th among African economies (FAOSTAT, 2025). At this level, Cameroon's agricultural spending remains below that of relatively higher-income economies such as Morocco and Algeria, despite its greater structural dependence on agriculture. Increasing the share of central government spending devoted to agriculture is therefore essential for strengthening food production capacity and mitigating food insecurity in the long term.

Additional policy support should focus primarily on measures that enhance productivity and improve product quality. In this context, we recommend adopting a planned production framework operating at both the micro- and macroeconomic levels. At the micro level, policy interventions should address fertilizer inefficiency by encouraging producers to base input use on soil analysis. This could be achieved through targeted cash subsidies for soil testing or by establishing soil analysis laboratories under the Ministry of Agriculture to provide these services free of charge. Such measures would enable more efficient input use and help mitigate the problem of low agronomic fertilizer efficiency. At the macro level, a comprehensive assessment of Cameroon's agricultural structure is required. The country should be divided into agro-ecological basins, and the food crops best suited to each basin should be systematically identified. Farmer support schemes should then be aligned with these basin-specific production priorities, allowing public resources to be allocated more efficiently and in accordance with local ecological conditions.

In addition, given the projected adverse effects of climate change on food production, macro-level planning must explicitly incorporate climate risk considerations. According to alternative climate scenarios, maximum temperatures in Cameroon are expected to increase by approximately 3% to 15% by the end of the century (CCKP, 2025). These projections underscore the need for scenario-based risk assessments and the development of adaptive action plans tailored to different climate trajectories. In this regard, the Cameroonian government should promote climate-resilient agricultural practices, including improved water management strategies, the adoption of drought-tolerant crop varieties, and targeted financial support mechanisms to enhance farmers' adaptive capacity.

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