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Vulnerability of the agriculture of Burundi to climate change: A review and linkages between climate change, food security, and food production

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ABSTRACT: Climate change critically affects food production, availability, and stability, particularly in regions that rely on subsistence agriculture. This study examines the relationship between climate variables and food security indicators in Burundi from 1990 to 2022 using a co-integration model within an Error Correction Model framework. Results reveal that precipitation positively influences food production annually but negatively in the long run. Food consumption, producer prices, and rural populations also exhibited long-run negative effects. The findings highlight the adverse impact of climate change on agricultural yields, emphasizing the need for strategies to enhance productivity, resilience, and sustainability among smallholder farmers.

Vulnerabilidad de la agricultura de Burundi al cambio climático: Una revisión y vínculos entre cambio climático, seguridad alimentaria y producción de alimentos

RESUMEN: El cambio climático afecta críticamente la producción, disponibilidad y estabilidad de los alimentos, especialmente en regiones dependientes de la agricultura de subsistencia. Este estudio analiza la relación entre variables climáticas e indicadores de seguridad alimentaria en Burundi (1990–2022) mediante un modelo de cointegración basado en el enfoque de Corrección de Errores. Los resultados muestran que la precipitación influye positivamente en la producción anual, pero negativamente a largo plazo. El consumo de alimentos, los precios al productor y la población rural también presentan efectos negativos sostenidos. Los hallazgos evidencian el impacto adverso del cambio climático y la necesidad de fortalecer productividad, resiliencia y sostenibilidad agrícola.

KEYWORDS / PALABRAS CLAVE: Agricultural production, climate change, economic growth, food prices, food security / Producción agrícola, cambio climático, crecimiento económico, precios de los alimentos, seguridad alimentaria.

JEL classification / Clasificación JEL: A11, B23, O13, Q18.

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1. Introduction

Climate change will affect the different sectors of economic activity. When combined with other social factors (demographics, income level, technologies, lifestyle, regulatory framework, among others) can have severe consequences. According to the IPCC (2023), the estimates of the economic damage of climate change are uncertain. Estimating the global economic impacts of climate change is challenging and available estimates vary depending on the economic sectors considered and rely on a series of questionable assumptions (Hsiang *et al*., 2017; Rao, 2016; Brown & Saunders, 2020). These estimates indicate global economic losses of 0.2 and 2.0 % of income for 2 °C warming. Furthermore, low global estimates of damage mask wide disparities between countries (Dennig *et al*., 2015). These estimates agree that climate change will affect less developed countries earlier and with larger damages (Traore & Puscas, 2019). Understanding how climate variability and change affect food security is a key research area (Vermeulen *et al*., 2010).

Climate change will also alter the prices of agricultural products, the reallocation of resources in the agricultural sector, and the structure of the economies of least-developed countries (Nath, 2022). Climate change will alter the country's comparative advantage of the agricultural sector since changes in agricultural production will have effects on prices, and employment. According to the study of Li *et al.* (2022), climate change will lead to a slowdown in economic growth and poverty reduction. Hence, an unfavorable climate change scenario will make achieving development goals much costlier for the poorer countries and may have further macroeconomic effects leading to slower poverty reduction. Furthermore, climate change disrupts environmental resources essential to agricultural and food production (Yuan *et al*., 2024). By impacting harvests, climate change also contributes to increased volatility in agricultural commodity prices and, beyond that, to reduced food supply.

Yet, empirical studies assessing the linkage between climate change, food security, and food production in sub-Saharan African countries and Burundi in particular are limited. The choice of Burundi is not fortuitous, as it is the most vulnerable and least resilient country in the world to extreme climatic events. Admittedly, many empirical studies have addressed the relationship between climate change, agriculture, and, by extension, food security. But very few have focused on this country, which nevertheless deserves special attention. This study uses an ECM model with time series data to estimate the impact of climate change on food security. The main hypothesis is that long-term changes in climatic conditions affect agricultural production, which in turn influences food security in the country.

2. Previous related studies

2.1. A review of the empirical literature

The theoretical framework focuses on how climate change impacts agriculture, a key factor in defining food security. The impact of climate change on food production and therefore on food security has become a controversial issue, with empirical research producing diverse and often contradictory results. Numerous empirical studies have addressed the relationship between climate change, agriculture, and food security.

Using the pooled fixed effects model, Mahrous (2019) estimates the impact of global climate change on food security in the East African Community region. The results show that food security in the East African Community is negatively affected by temperature. However, increased rainfall and cultivation of cereals will help to ensure food security for all. Similar studies include the work of Affoh *et al*. (2022), who analyzed the relationship between climate variables and three aspects of food security: availability, accessibility, and utilization. Applying an ARDL model as well as FMOLS and DOLS methods, they found that rainfall has a positive long-term impact on all three dimensions, while temperature negatively affects long-term food availability and accessibility, with no impact on food utilization.

Along the same lines, Febriandika & Rahayu (2021) carried out a study on the economic impact of climate change on Indonesian agriculture. Based on the fixed effects model developed in the study, adapting an econometric formulation to panel data, changes in temperature, increased rainfall, and increased air quality index partially do not affect production. However, the extent of agricultural land area partially has a positive effect on production. Bai *et al*. (2022) analyze the impact of climate change on agricultural production by using a three-stage spatial Durbin model (SDM) and entropy method. The results show that climate change negatively affects agricultural production, but annual precipitation has had no significant impact on the growth of agricultural productivity. Also, in a study examining the impact of climate change on food security in China, Lee *et al*. (2024) demonstrated that climate change is significantly affecting food security, bringing more risks of uncertainty.

In Chandio *et al*. (2021b), a study of the impacts of climate change variables (temperature, rainfall, and carbon dioxide) on grain production in Bangladesh, rainfall improves grain production in both the short and long term. Conversely, CO_2 emissions have a significant negative effect on grain production in both the short and long term. Temperature also has a negative effect on grain production in the short term. Besides, Belloumi (2014), a study on the impact of climate change on agricultural production in eleven Eastern and Southern African countries, reveals that variable rainfall positively influences agricultural production, while the overall increase in mean annual temperature negatively affects agricultural production in the region.

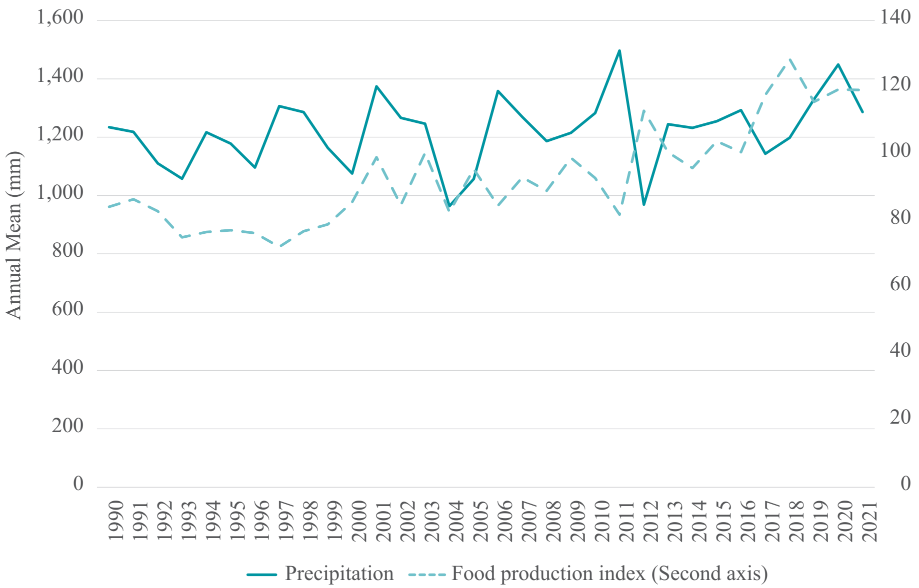
2.2. A review of Burundi's vulnerability to climate change

Burundi, a landlocked country in the heart of Central Africa, covers an area of 27,834 km². Despite its wealth in natural resources, water is a vulnerable resource, limited by various factors, including often unfavourable climatic conditions in specific regions and the uneven spatio-temporal distribution of rainfall.

Globally, Burundi was ranked the 24th most vulnerable country and the 171st most ready country in the 2022 ND-GAIN Index, which summarizes a country's vulnerability to climate change and other global challenges. The country is exposed to extreme climatic phenomena like drought, soil erosion, landslides, strong winds, and floods. In Burundi, climatic extremes, such as drought, floods, and heat waves, accounted for 91 % of forced population displacements in 2021 (IOM, 2022). Analysis of trends seems to confirm that Burundi will continue to experience shocks linked to climate change, epidemics, and population displacements while maintaining its population growth. These risks can lead to negative impacts on sustainable development if the country does not develop adaptation strategies. While rainfall promotes crop growth, localized rainfall throughout the period had a particularly positive effect on enhancing agricultural yields (Figure 1).

FIGURE 1

Average precipitation (PR) and food production (FP)



Source: Own elaboration based on World Bank indicators: Burundi (1990-2021).

Vulnerability studies by Ndayiragije & Li (2022) and Schneiderbauer *et al.* (2020) show that climate variability and change affect all vital sectors of the national economy. As shown in the World Bank/Government of Burundi Partnership Framework Document, 2017-2022, climate hazards affect different socio-economic sectors of the country, and the rural world is the first victim. In addition, Burundi has lost 4 % of its gross domestic product (GDP) due to land degradation (Dampha *et al.*, 2022).

Based on a different literature review, Table 1 summarizes the vulnerability of Burundi to climate change. The data show that agriculture is the most vulnerable sector. Indeed, the ongoing climate change has led to a significant decrease in agricultural production, but as shown in Figure 1, agricultural production still depends on precipitation. This decline affects the well-being and food security of the Burundian rural population, 58 % of whom suffer from malnutrition.

TABLE 1

Effects of climate change on different sectors in Burundi

Climate risks	Adverse effects and associated risks	Economic impact	Loss of life	Duration, days	Spatial extent, km²	Frequency	Tendency
Rainfall deficit (Droughts)	Drought, late rains, famine, loss of human life, water deficit for the different uses, fall in livestock and agriculture production, and biodiversity, degradation of plant cover, bush fire, migration of population and livestock, drying up or drop in the levels of reservoir lakes and courses water, reduction of hydroelectric energy.	3	3	3	4	2	Important
Excess rainfall: Torrential rains/ Floods, hail	Rain erosion, crop losses, loss of life humans, loss of habitats for species, destruction of infrastructure, landslides, windthrow of trees, outbreaks of parasitic diseases, waterborne diseases and deficiency diseases nutritional, silting/siltation of courtyards water and lakes, flooding of lowlands and marshes, deterioration of water quality.	3	2	1	3	2	Important

TABLE 1 (CONT.)

Effects of climate change on different sectors in Burundi

Climate risks	Adverse effects and associated risks	Economic impact	Loss of life	Duration, days	Spatial extent, km^2	Frequency	Tendency
Temperatures excessive (extremes)	Heat stress, increases in diseases respiratory and diseases caused by vectors, high water consumption, increased evapotranspiration and evaporation, and accelerated bushfires.	2	1	2	4	2	Average
Lightning, thunder and lightning	Loos of human life, loss of livestock, burning of forests and afforestation, food insufficiency, deflowering of crops, destruction of large trees and infrastructure (communication and electrical), drop in yield.	1	2	1	2	1	Average

Legend:
Economic impacts: 1 = not very detrimental; 2 = Moderately harmful; 3 = too harmful.
Loss of life: 1 = 1-9 people per event; 2 = 10-99 people per event; 3 = 100-999 people per event; 4 = more than 1000 people per event.
Duration, days: 1 = 1-9 day, 2 = 10-99 days, 3 = 100 days (1 season), 4 = more than a year.
Spatial extent (km^2): 2 = 10-99 km^2; 3 = 100-999 km^2; 4 = 1000 -9999 km^2; 5 = 10,000 km^2 and more
Frequency: 1 = 1 to 20 % probability; 2 = 20 to 40 %; 3 = 40 to 60 %; 4 = 60 to 80 %; 5 = 80 to 100 %.
Trend indicators: = Important increase; Average increase.

Source: Own elaboration based on a review of the 2019 report from the Ministry of the Environment, Agriculture and Livestock (MINEAGRI, 2019).

This study contributes to the understanding of the expected Burundian evolution of agricultural production potential in the context of climate change, food security, and food production.

3. The choice of research method

There are numerous approaches to analyze agricultural vulnerability to climate change, ranging from Ricardian approaches to process-based models.

Here to examine the linkages between climate change, food security, and food production, the study uses past time series data on food production, climate, and variables that characterize food security. Such analysis assumes that management changes are not climate-related or cause it. In other words, food production responds equally to rapid and gradual climate change. On the positive side, this approach provides a quantitative assessment of uncertainties.

Using this approach, Idumah *et al*. (2016) conclude that there is a long-run co-integration relationship between the study variables. Pickson *et al*. (2023) show a two-way causal relationship between climatic conditions and cereal production. Alhas Eroğlu *et al*. (2020) indicate that temperature change, food price index, and gross production index for foods are cointegrated and move together in the long run. The Granger causality test proves the unidirectional causality from temperature change to the food price index and gross production index for foods. Kilicarslan & Dumrul (2017) reveal that precipitation positively affects agricultural GDP, and temperature negatively affects the agricultural sector.

4. Methods and data

4.1. Approach

The analysis is based on error correction modelling, whose use in econometrics dates back to Sims (1980), who wanted an alternative or even an improvement to simultaneous equation models. This modelling allows, without resorting to an upstream economic theory, to have a relatively well-adapted framework for our study. The analysis begins by studying the stationarity of the variables. To do this, the study first carries out the unit root tests developed by Dickey & Fuller (1979) and Phillips & Perron (1988). The analysis allows to determine the retained variables' integration order. Hence, a series is integrated of order (d) if its difference is stationary. After determining the order of integration, if the variables in the scene are integrated of order 1 [I (1)], this would mean that there would be a co-integration between variables.

If two series are cointegrated (the residuals estimated in the long-term relationship are stationary), the study uses the error correction model (ECM):

$$\Delta Y_t = \gamma \Delta X_t + \delta(Y_{t-1} - \hat{c}X_{t-1} - \hat{a}) + \epsilon_t;\ \text{with}\ \delta < 0 \qquad [1]$$

t represents time, $(Y_{t-1} - \hat{c}X_{t-1} - \hat{a})$ represents the co-integration relationship and refers to the estimated residuals from the regression of the explained variable, Y, on the explanatory variable, X. $\hat{c}$ represents the co-integration coefficient, and $\hat{a}$ is the estimated constant of the co-integration relationship. We can emphasize the fact that δ must be significantly negative for the equation to induce a return of Y_t to its long-term equilibrium value $(\hat{c}X_{t-1} + \hat{a})$. If this is not the case, the regression is fallacious. The Vector Error Correction Model (VECM) therefore, makes it possible to model both the short-term dynamics (represented by the first difference variables) and the long-term dynamics (represented by the level variables).

Step 1: Determination of the number of delays p of the model according to the criteria AIC, SC.

We use the Schwarz criterion, which gives some delays lower than that of Akaike. This choice is justified because many delays in the VAR model reduce the number of observations. This is all the more felt when the series is not long. The number of delays obtained is, therefore, the one which minimizes the Schwarz function:

$$SC(p) = ln\left(\frac{SCR_P}{T}\right) + \frac{pln(T)}{T} \quad [2]$$

SCR_P: sum of squares of residuals for the h-lag model.

T = number of observations.

ln: natural logarithm.

Step 2: Estimating the matrix and Johansen test allows us to know the number of co-integration relations (the software offers a certain number of alternative specifications, such as the existence of a constant term in the co-integration relation and a deterministic tendency).

Step 3: Co-integration relationships identification, i.e., long-term relationships between variables. At this stage, we choose the long-run relationships, which will give us relatively low standard deviations and the appropriate relationships.

Step 4: Estimation by the Maximum Likelihood method of the error correction vector model and validation with the usual tests: significance of the coefficients and verification of the sign and significance of the error correction terms. At this stage, the Maximum Likelihood method estimates the long-run relationship estimated by the Ordinary least-squares and provides the short-run equations.

4.2. Data

To verify the long-run relationship between climate change, food security, and food production in Burundi, the dataset used in this study is a time series observed at regular time intervals. These are annual data ranging from 1990 to 2022. The variables retained come from various sources, such as FAO STAT and WBI. Given that climate change is a latent variable, multiple, and difficult to measure directly, the study uses annual average temperature (AT) and annual precipitation (PR) to explore climate change variables. The study explores further food consumption (FC), producer price (PP), and rural population (RP) as measurements of food security variables. A statistical description of the variables is given in Table 2.

TABLE 2

Statistical properties of variables

	AT	FC	FP	PP	PR	RP
Mean	737470.9	6.824755	90.31906	65.47677	7.102225	90.26756
Median	737471.5	3.636601	83.52000	70.69000	7.117327	90.50400
Maximum	737517.0	24.00093	135.1000	165.1300	7.311238	93.72900
Minimum	737426.0	0.304040	72.35000	10.87000	6.870873	85.94200
Jarque-Bera	0.251953	8.629265	9.621222	0.878951	0.928905	2.001672
Probability	0.881636	0.013371	0.008143	0.644374	0.628479	0.367572
Observations	32	32	32	31	32	32

Source: Own elaboration.

Data are specified in the model as follow:

$$FP = f\,(PR, AT \,\&\, PP, FC, RP) \qquad [3]$$

The equation can be presented in its econometric form as:

$$FP = \beta_0 + \beta_1 PR_t + \beta_2 AT_t + \beta_3 FC_t + \beta_4 PP_t + \beta_5 RP_t + u \qquad [4]$$

Where:

FP = Food Production (stand for agricultural food production).

PR = Annual precipitation and AT = Average Temperature (stand for climate change).

PP = Producer price, FC = Food consumption and RP = Rural Population (stand for food security).

u is the error term, β_0 is the constant term; β_1 to β_5 are coefficient of the variables.

5. Results

Before estimating the model itself, we perform the following statistical tests to ensure the validity of our analysis: statistics, stationary test, and choice criteria for selecting the optimal model lag.

TABLE 3

Stationary test

Variables	ADF		PP		Decision
	t-Stat at level	t-Stat at difference	t-Stat at level	t-Stat at Difference	I(0) & I(1)
FP	-2.5608870	-5.095475*	-2453358	-16.50607*	**I(1)**
PR	-10.08845	-18.52783*	-10.08845	-18.52783*	**I(1)**
AT	-4.010478	-7.989491*	-3.987808	-20.07671	**I(1)**
PP	-1.256946	-4.736538*	-0.956277	-10.83093*	**I(1)**
RP	2.528783	-6.305199*	15.24591	0.9437*	**I(1)**
FC	0.762317	-5.350844*	1.004461	-5.350827*	**I(1)**

(*) Indicates a significance level of 5 %.

Source: Own elaboration.

The results of the unit root test (ADF&PP) in Table 3 show that all variables are non-stationary at their level but stationary after the first differentiation. We conclude at this stage that all variables are roughly integrated of order one I(1). Since variables are I(1), we estimate using VAR. However, estimating the VAR in different cases can lead to a significant loss of information if the series are effectively cointegrated. To work on this issue, Johansen & Juselius (1990) propose a VEC model estimation involving several specifications for the long–term relationship (presence of a constant/trend or not in the co-integration space).

Estimating a vector error correction model is possible. Since we have six variables, the VECM will have six equations. Error correction models make it possible to model the adjustments that lead to long-term equilibrium. These are dynamic models that integrate both short-term and long-term changes in variables. The error correction model describes an adjustment process. It combines two types of variables: first, difference variables (stationary), which represent short-term fluctuations, and level variables, a stationary linear combination of non-stationary variables, which ensure that the long term is taken into account. It makes it possible to integrate short-term fluctuations (represented by the first difference variables) around the long-term equilibrium (given by the co-integration relationship). Consequently, all the terms involved in an error correction model are stationary.

TABLE 4

Optimal Lag selection

Lag	FPE	AIC	SC	HQ
0	101.9270	21.65134	21.93681	21.73861
1	0.000127	7.994769	9.993076*	8.605671
2	*0.000101**	*7.360232**	*11.07137*	*8.494765**
3	0.000516	7.682712	13.10669	9.340876

(*) Indicates the optimal lag chosen by the criteria

Source: Own elaboration.

The choice of the number of lags considered in the model is crucial since it influences the estimation results and the number of existing co-integration relationships. To make this choice, we used the calculation of information criteria: Schwarz Criterion (SC), Akaike Information Criterion (AIC), Final Prediction Error (FPE), and Hannan-Quinn information criterion (HQ). As a result, described in Table 4, the number of delays to retain equals 2, which minimizes most of the calculated information criteria. Co-integration makes it possible to identify the proper relationship between variables. Before estimating the model equation, we must reassure ourselves that our series are cointegrated; that is to say, the model variables converge towards a long-term equilibrium. We choose to work with a model with the constant in our study. We obtained the Johansen co-integration test results presented in Table 5.

TABLE 5

Results of the JOHANSEN co-integration test

Unrestricted Co-integration Rank Test (Trace)					
H_0	H_1	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	1	0.718324	120.4165	95.75366	0.0004
At most 1 *	2	0.666863	83.67353	69.81889	0.0026
At most 2 *	3	0.599995	51.79668	47.85613	0.0204
At most 3	4	0.392376	25.22459	29.79707	0.1536
At most 4	5	0.262147	10.77684	15.49471	0.2256
At most 5	6	0.065369	1.960513	3.841465	0.1615

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level.

* indicates rejection of the hypothesis at the level of 0.05.

** p-values from MacKinnon *et al.* (1999).

Assumptions: r the number of co-integration relations:

H_0: r = 0, there is no co-integration relationship.

H_1: r > 0, there is at least one co-integration relationship.

If the Trace statistic exceeds the critical value at 0.05 %, then we reject H_0.

Source: Own elaboration.

The maximum Eigenvalue and the trace statistics presented in Table 5 show that the null hypothesis of no co-integration can be rejected at 5 % significance level. Otherwise, the results according to the trace test indicate the presence of three co-integration relationships among series.

Co-integration equation:

$$D(FP) = -207.44 - 0.951231\text{ECT1}$$

The retain short-run model is presented:

$$\begin{gathered} D(FP) = -0.95123 * D(FP(-1)) - 0.086935 * D(FP(-2)) - 3.547884 * D(AT(-1)) \\ - 3.725711 * D(AT(-2)) - 26.33824 * D(PR(-1)) - 14.34819 * D(PR(-2)) - 1.941290 \\ * D(FC(-1)) + 0.385785 * D(FC(-2)) - 0.221847 * D(PP(-1)) + 0.123701 \\ * D(PP(-2)) - 1570.644 * D(RP(-1)) + 753.5827 * D(RP(-2)) - 207.4926 \end{gathered}$$

The parameter which measures the speed of adjustment towards the long-term equilibrium level is statistically significant and has the correct sign (Table 6). This implies that an error correction mechanism exists such that a deviation from the long-term equilibrium significantly impacts food production. This corroborates our choice of an error correction framework for the analysis. Indeed, output adjusts at a speed of 95 % each year, or approximately 12 years needed to restore equilibrium when there is a shock to the steady state relationship.

TABLE 6

ECM estimation: long-run equation

Variables Dependent variable: *FP*	CointEq
ECM_{t-1}	-0.959568 (*0.30014*) [-3.19704]
PR_{t-1}	5.369075 (*16.0391*) [0.33475]
At_{t-1}	-0.182022 (*0.04802*) [-3.79028]
FC_{t-1}	-0.615633 (*0.27157*) [-2.26693]
PP_{t-1}	-0.203152 (*0.12639*) [-1.60738]
RP_{t-1}	-22.30498 (*7.03325*) [-3.17136]
C	136135.1
R-squared Adj. R-squared Sum sq. resids	0.838807 0.689128 410.4138

Standard errors in ( ) & t-statistics in [ ].

Source: Own elaboration.

6. Discussion

For there to be a return to equilibrium (characteristic of error correction models), the restoring force term must be negative and significant. This condition is respected (recall force = 0.959568), which shows that food production is caused in the long run by the variables estimated in this model. The estimation of the long-term block is consistent with theory in that the adjustment speeds are assigned signs compatible with an error correction mechanism. For our model, the co-integration relationship is significant and effectively plays an error-correcting role in the long-term dynamics of food production. The explanatory variables considered are significant and affected by the adjustment mechanisms.

The expected signs of variables considered are compatible with economic reality. The signs are consistent with theory expectations, which attests to this model's satisfactory level of robustness. Furthermore, a positive long-run relationship between precipitation and food production is supported in the study. The coefficient of annual precipitation itself shows a long-run positive relationship with food production. It appears that the delay in the start of the rains, the early end of the rainy season, frequent dry sequences, and excess and deficit of rain can negatively affect the production and yields of different crops, and therefore, disrupt agricultural systems (Kumar *et al*., 2021). For their part, annual temperatures present a negative long-run relationship to food production. Qi *et al*. (2022) justified that persistent high temperatures increase the risk of drought, which can severely impact food production.

These results show climate change negatively impacts food production in the long run; however, temperature is more significant in the long run than precipitation. The positive effect of precipitation on food production is justified by the dominance of rain-fed agriculture, which depends heavily on precipitation for an excellent agricultural companion.

These results confirm those obtained in studies carried out in other countries (Chandio *et al*., 2021a; Doğan & Kan, 2019). They proved that precipitation positively affects food production, temperature negatively affects food security, and there is a long-run co-integration relationship between precipitation, temperature, and food production.

Besides, variables that characterize food security substantiate a negative relation. The coefficient of the Rural Population variable presents a negative long-run relationship with food production. In the long term, population growth has a proven influence on food availability (Fukase & Martin, 2020). In addition, natural resources will be depleted, leading to more constraints on food production; the same results of Putri *et al*. (2019) confirm that the increasing population impacts food production in Indonesia.

Hence, the result proves a negative relationship between food consumption and production. Food consumption increases negatively affect food production. This result coincides with Rask & Rask (2011), who found that consumption growth outpaces production response in countries with limited land. Increasing agricultural productivity allows certain countries with sufficient resources to close the production-consumption gap at this stage and become relatively self-sufficient in food production. The results prove a negative relationship between producer price and food production. Moreover, producer prices make it possible to identify sources of inflation in the economy, to follow economic trends, and to distinguish a pure price variation from a price variation attributable to a difference in quality or volume.

TABLE 7

Granger causality tests

Dependent variable: *D*(*FP*)			P-value*
Excluded variables	Chi-sq	Df	
D(*FC*)	6.272345	2	0.0434*
D(*AT*)	0.492553	2	0.7817
D(*PP*)	7.742630	2	0.0208*
D(*RP*)	17.18736	2	0.0002*
D(*PR*)	9.210924	2	0.0100*
All	56.83156	10	0.0000*

Note: (*) Indicates a significance level of 5 %.

Source: Own elaboration.

The results of the Granger causality test presented in Table 7 show that all variables jointly Granger cause the dependent variable. Besides, the probability of annual average temperature is above 5 %. Hence, the null hypothesis H_0, delays in Y do not explain current X, is rejected at each usual level of significance, and we accept H_1: delays in Y can explain current X. The Granger causality tests, therefore, conclude a causal relationship between climate change variables (annual average temperature, annual precipitation), food security variables (food consumption, producer price, and rural population), and food production.

TABLE 8

Residual diagnostic test

Diagnostic	Statistics	Comment
VEC Residual Serial Correlation LM Tests	Df = (36, 15.9) Prob. = 0.7284	No serial correlation
LM Tests Jacque- Bera	JB = 13.65470 Df = 12 Prob. = 0.3233	Residuals are normally distributed
VEC Residual Heteroscedasticity Tests (Levels and Squares)	Df = 546 Prob = 0.3093	No Heteroscedasticity

Source: Own elaboration.

The outcome of the diagnostic tests as shown in Table 8 proves that the model is well specified, and hence the results are credible.

7. Conclusions

The estimation results confirm the existence of a long-run relationship between the variables indicating climate change, food security, and food production. Hence, annual precipitation is positively linked to food production and annual average temperature and, conversely, negatively related to food production in the long term. These results show climate change negatively impacts food production in the long run; however, temperature is more significant in the long run than precipitation. This indicates that food production is more influenced by increasing temperature in the long run. Improving food production requires a reduction in temperature levels in the long run. A long-run negative relationship between food consumption, producer price, rural population, and food production is also validated in the model. Besides, the Granger causality results conclude a two-way causality between exogenous variables and endogenous. Food consumption evolves depending on factors linked to the environment, supply (production, availability and distribution, product costs), or socio-demographic characteristics (household composition and income, location and mode of housing, etc.). To minimize the effects of climate change on food production and food security in Burundi, future policies should focus on actions that simultaneously mitigate climate change and sustainably increase the resilience of food systems and societies. Future policies should prioritize actions that both address climate change and strengthen the sustainability and resilience of food systems and societies. For example, this could involve promoting agricultural practices that boost productivity, enhance resilience to climate impacts, mitigate climate-related risks, and support the achievement of national food security and development objectives.

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