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Analysis of the Effects of Climate Change on Maize Production in Mali

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The objective of this paper is to analyze the effects of climate change on maize production in Mali during the period 1990-2020. The unit root test (augmented Dickey-Fuller) was used to check the order of integration between the variables in the study. The ARDL (autoregressive distributed lag) approach to cointegration limits is applied to assess the association between the study variables with evidence of a long-term relationship. The unit root test estimates confirm that all variables are stationary at the combination of I(0) and I(1). The results show that precipitation and temperature in June and July have a negative and highly significant effect on maize production in both the short and long term analyses. Among other determinants, the area of land devoted to maize crops and GDP per capita have a positive effect on production. The estimated coefficient on the error correction term is also highly also highly significant As Mali's population grows, in the coming decades the country will face food security challenges. Possible initiatives are needed to configure the Malian government to address the negative effects of climate change on agriculture and ensure adequate food for the growing population.

Keywords: Maize; production; climate change; ARDL; Mali.

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1. INTRODUCTION

Climate change is one of the greatest challenges of this century, affecting almost every country in the world with disastrous consequences on livelihoods [1]. It is mainly caused by human activities, especially industrial activities that lead to a high rate of greenhouse gas emissions into the atmosphere [2]. This causes global warming and subsequently leads to extreme climates such as drought and flooding. One of the significant events of the last decade was the twenty-first conference of the parties of the United Nations Framework Convention on Climate Change held in Paris. At the end of this conference, the signatory countries of the climate agreement adopted the goal of limiting global warming to "well below 2°C above pre-industrial levels″ and to continue efforts to limit the temperature increase to 1.5°C. This historic event has helped reignite the international community's interest in climate change issues. Topics such as climate change impact, mitigation and adaptation are at the forefront of the media. Indeed, like many scientific contributions, the report of the Intergovernmental Panel on Climate Change [3] indicates that on a global scale, climate change is harmful to the entire planet and particularly harsh for vulnerable regions such as sub-Saharan Africa.

Agriculture is highly sensitive to climate change [4]. A 2°C increase in average temperatures would destabilize today's agricultural systems. Climate change may transform food production, including the patterns of operation and productivity of crops, livestock, forestry, aquaculture and fisheries [5]. Populations in developed countries are the most sensitive to the negative effects of climate change that would affect human productivity and health [6]. [7] have shown that rainfall and temperature have negative effects on agricultural production in Ethiopia. The high temperatures caused by this warming decrease the yields of useful crops. The high temperatures caused by this warming decrease the yields of useful crops. The change in rainfall patterns will increase the likelihood of crop failure in the short term and lower production levels in the long term.

Per capita cereal production in developed countries increases from 690 kg/capita in 1980 to 984 kg/capita in 2060. In developing countries, cereal production increases from 179 kg to 282 kg/capita. Aggregate world cereal production per capita increases from 327 kg/capita in 1980 to 319 kg/capita in 2060 [8]. Production conditions are made increasingly difficult by climate hazards [9,10]. Currently, climate change is the focus of both scientific actors and policy makers at the global level [11,12], as it is one of the obstacles to human development [13,14]. Although Africa contributes only marginally to global pollution (10%), it is the most affected by climate change [3]. The Intergovernmental Panel on Climate Change predicts a 21-9% decline in agricultural productivity in sub-Saharan Africa by 2080 [15]. The effects of climate change are particularly severe in Sahelian countries.

[16] indicate that the Sudano-Sahelian countries (located in northern West Africa) could experience a greater loss of agricultural yield (18%) than countries located in southwest Africa (11%). The work of [17,18] argues that Burkina Faso and Niger could experience a loss of agricultural production of 19, 9% and 30.5% respectively by 2050. Moreover, the agricultural system that prevails in most African countries remains rainfed, and therefore highly dependent on climatic conditions [19]. This explains the relatively high sensitivity of the agricultural sector to climate change [20]. The vulnerability of this sector is related to the increase in temperature and decrease in rainfall.

Mali is an agricultural country in the WAEMU zone. The population represents more than 80% of the agricultural sector [21]. In this area in general and in Mali in particular, agriculture is rainfed, very extensive and not very mechanized. Climate scenarios for Mali by 2025 predict a decrease in rainfall with loss rates of 2 to 6% compared to normal and an increase in temperature of 1°C compared to normal [22]. Several policies have been put in place to improve maize productivity; from 1990 to 2010, Mali produced a surplus of 1,159,464 tons with an average growth rate of 2%. Despite these incentives, from 2011 to 2020, we note a decrease in the growth rate of 1% each year in maize production. The objective of this study is to analyze the effects of climate change on maize production in Mali. In order to measure the evolution of this agricultural production, we will use the volume of maize production, the climate change variables (rainfall and temperature), the area and the share of fertilizer consumption.

2. METHODOLOGY AND DATA SOURCES

This section will allow us to define the theoretical and conceptual framework.

2.1 Theoretical Framework

Since the 1990s, the issue of climate change has been of concern to everyone especially scientists [23]. This has led for years to several meetings of international organizations on climate to provide answers to this problem that affects the living conditions of populations through international negotiations. Two approaches with economic considerations have often been used in the literature to measure the impacts of climate change on agriculture: the agroeconomic approach and the Ricardian approach [24].

The production function approach fits with our objectives, as it is an experimental approach that measures the direct effects of production factors on the level of production. It is based on the existence of a production function for any crop, which relates the production (or yield) of the crop to its biophysical environment. This approach estimates the change in yield directly from the crop response patterns. It estimates the impact of climate change on yield by varying the levels of climate stimuli.

Therefore, we opted for the production function approach because it will allow us to assess the impact of climatic variables on the productivity of cereal crops. These results offer an idealistic presentation of crop production phases, which tends to give results different from real-world conditions [25]. This study aims to determine the variation in maize production as a result of variations in climatic variables (temperature and rainfall).

2.1.1 Model specification

We adopted the Cobb Douglas functional form for the estimation of the variation of cereal production as a function of time trend and climatic variables, according to some authors [26,7,27] this form is the most adapted for this type of analysis.

Usually in Mali, the sowing date of this crop is between June and July. The harvest date is between August and September. Maize, like other crops, requires water throughout its development cycle. However, certain periods are considered more critical (for cereal production from June to September). Indeed, a lack of water during these periods acts considerably on the yield by decreasing it [25]. The maize crop is also sensitive to low temperatures during June-July and high temperatures during August-September. The climatic variables (rainfall and temperature), considered in the empirical analysis, are those related to the critical periods for the growth of the maize crop in Mali.

Thus, the economic model is presented as follows:

$$Prod = (\mathrm{rainf}_{JJ}, \mathrm{rainf}_{AS}, Temp_{JJ}, Temp_{AS}, Surf, GDP\_c)$$

The econometric model is as follows :

$$\begin{aligned} Prod_t = \ & \alpha_0 + \alpha_1 \mathrm{rainf}_{jj}(t) + \ \alpha_2 \mathrm{rainf}_{as}(t) \\ & + \alpha_3 Temp_{JJ}(t) + \alpha_4 Temp_{JJ}(t) \\ & + \alpha_5 surf(t) + \alpha_6 GDP\_c(t) + \varepsilon(t) \end{aligned}$$

Where :

Prod_t: the production of corn in year t
$\mathrm{rainf}_{jj}(t)$: average June – July precipitation of year t
$\mathrm{rainf}_{as}(t)$ average precipitation in August – September of year t
$\mathrm{Temp}_{JJ}(t)$ average temperature of June – July of the year t
$\mathrm{Temp}_{as}(t)$ average temperature in August – September of the year t
Surf(t) : the annual area used
GDP_c (t) : Gross domestic product per capita
$\varepsilon\ (t)$: terms of errors

2.1.2 Description of variables

- ✓ **Dependent variable**

In this study, we choose corn production as the dependent variable or endogenous variable. It is expressed in tons and collected over a period from 1990 to 2020. This crop was chosen because it is the most consumed food crop in Mali [28].

- ✓ **Explanatory variables**

The explanatory variables or exogenous variables selected were identified on the basis of the literature. However, not all variables were taken into account due to data availability. The variables selected are fertilizer consumption, area, temperature and rainfall during the cropping season in Mali from June to September. These climate variables have been by several authors such as [25,29]. The temperature variable is the average temperature for the month of June to September, the precipitation variable is the average precipitation for the month of June to September, the temperature is expressed in degrees Celsius and the area variable is the area used for crops and finally the fertilizer consumption is the kilogram per hectare. Changes in temperature and precipitation are both major determinants in recent trends observed in agricultural production in Africa [30,24].

In Mali given the current climate situation, increasing temperatures, decreasing water availability and shortening of the rainy season, it is assumed that a reduction in crop production in Africa, particularly Mali, may affect food security on the continent.

2.1.3 Empirical strategy

Our empirical strategy consists, first, in determining the stationarity of the variables. Indeed, all the variables must be stationary to proceed to the next step of the cointegration analysis. The unit root test on which we rely is the Augmented Dickey-Fuller test (ADF). Then, we will determine the number of lags of each variable in our model by referring to the Akaike criterion (AIC). In the third step, we will use the Johansen test to examine the cointegration between the variables involved in our model[31]. If a cointegrating relationship is observed, the causality tests will be based on vector error correction models (VECM). Otherwise, they will be based on traditional Vector Auto Regressive (VAR) models. In the last step, we will use diagnostic and stability tests to verify the robustness and credibility of our model and empirical results.

The specification of the ARDL model (P, q1, q2, ...qk) is given as follows. The writing of this equation according to the ARDL model is in the following form:

$$\begin{aligned}\Delta \mathrm{Prod}_t = {} & c + \alpha_1 \mathrm{rainf}_{jj}(t) + \alpha_2 \mathrm{rainf}_{as}(t) \\ & + \alpha_3 \mathrm{Temp}_{jj}(t) + \alpha_4 \mathrm{Sup}(t) + \alpha_5 \\ & + \alpha_6 \mathrm{GDP\_c}(t) + \sum_{i=1}^{p} \beta_{1i} \Delta \mathrm{rainf}_{jj}(t) \\ & + \sum_{i=0}^{q1} \beta_{2i} \mathrm{rainf}_{as}(t) \\ & + \sum_{i=0}^{q2} \beta_{3i} \mathrm{Temp}_{jj}(t) \\ & + \sum_{i=0}^{q3} \beta_{4i} \mathrm{Temp}_{jj}(t) + \sum_{i=0}^{q4} \beta_5 \mathrm{Surf}(t) \\ & + \sum_{i=0}^{q5} \beta_6 \mathrm{GDP\_c}(t) + \varepsilon_t\end{aligned}$$

Avec : $c =$ The constant ; Δ $=$ the premiere difference ; ε_t $=$ the random term

$p, q1, q2, q3, q4, q5$ $=$ the maximum number of lags for each variable in the study

$\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ $=$ The parameters of the long term relationship

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ $=$ The parameters of the short term reaction (error correction)

2.2 Data Sources

Table 1. Data sources

Variables	Sources	Unit
Agricultural production	FOASTAT	Hectare
Rainfall June-July	FOASTAT	Millimeter
Rainfall August-September	FOASTAT	Millimeter
Temperature June-July	FOASTAT	Degree Celsius
Temperature August-September	FOASTAT	Degree Celsius
Surface	FOASTAT	Kilogram per hectare
Gross domestic product per capita	FOASTAT	dollars

Source : FAOSTAT (2020)

3. RESULTS AND DISCUSION

This chapter will be dedicated to analyze the short and long term result.

3.1 Descriptive Analysis of Variables

Before carrying out the various tests, it is interesting to carry out the descriptive analysis of the variables in order to obtain the preliminary results on the variables studied.

According to this table, maize production varies between 192,530 tons and 3,766,780 tons with an average production of 1,129,622 tons. We note that the average production is closer to the minimum; this is explained by a decrease in the volume of production during these few years. We also note that the average annual temperatures observed during the June-July period over the last thirty-one years are higher than those observed during the August-September period with 33.16°C and 30.90°C respectively. Precipitation observed during the August-September period is higher than that observed during the June-July period during the study period with an average of 81.34 mm for the August-September period versus 58.77 mm for the June-July period.

3.2 The Result of the Different Estimations

The objective of this section is to validate the climatic variables (rainfall and temperature) affecting maize production in Mali. In the estimation procedure, we integrated the climate variables and the area. The model parameters were estimated by the production function. The overall evaluation of the regressions is done with the stationarity test, determination of lags, cointegration test (Bounds test), CUSUM and SQUARE test, normality test.

3.2.1 Stationarity test

Before estimating the model, it is necessary to ensure that the variables used in the equation are stationary. Some variables are subject to strong variability over time, which is why it is necessary to determine their order of integration. Also, the determination of the order of integration makes it possible to choose the best estimation method.

For this purpose, there are several tests. There are among others the Dickey-Fuller (DF) test, the Augmented Dickey Fuller (ADF) test and the Phillips-Perron (PP) test. [4] shows that the results of the ADF and PP tests are almost identical. As a result, the Dickey-Fuller (DF) test will be used to determine the stationarity of the variables used. The null hypothesis is the existence of a unit root. For the series to be considered stationary, the reported statistic must be below the critical value.

Table 2. Descriptive statistics of the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Agricultural production	31	1129622	1085886	192530	3766780
Temperature June-July	31	33.16645	.4010198	32.34	33.71
Temperature August-September	31	30.90097	.4342069	29.69	31.63
Rainfall June-July	31	58.77281	6.441508	48.85	72.84
Rainfall August-September	31	81.35012	12.48796	53.57	110.59
Surface	31	495909.1	316188.3	169958	1120456
Gross domestic product per capita	31	6.788871	0.187589	6.501290	7.156956

Source: Based on estimates

Table 3. Results of the stationarity tests

Variables	A level	In first difference	Order of integration
Agricultural production	2.222	-4.991***	I(1)
Temperature June-July	-4,711***		I(0)
Temperature August-September	-6,075***		I(0)
Rainfall June-July	-6,355***		I(0)
Rainfall August-September	-5,128***		I(0)
Surface	-0.408	-7.588***	I(1)
Gdp per capita	0.72182	-8.059744***	I(1)

*NB: conventional threshold; 1% = ***, 5% = **, 10% = **

Determining the stationarity of the variables is important because if two or more variables in a regression model are not stationary at the level, then the standard errors produced by the regression estimate will be biased, resulting in an unreliable relationship between the variables in the model [31]. The properties of the variables in the equation are examined by the Augmented Dickey-Fuller unit root test and become stationary after first difference as shown in the table above. As a result of which it is found that seven variables, two have a stationary unit root i.e. production and area while, the rest of the variables are all I(0) which justifies therefore the use of ARDL method of [32].

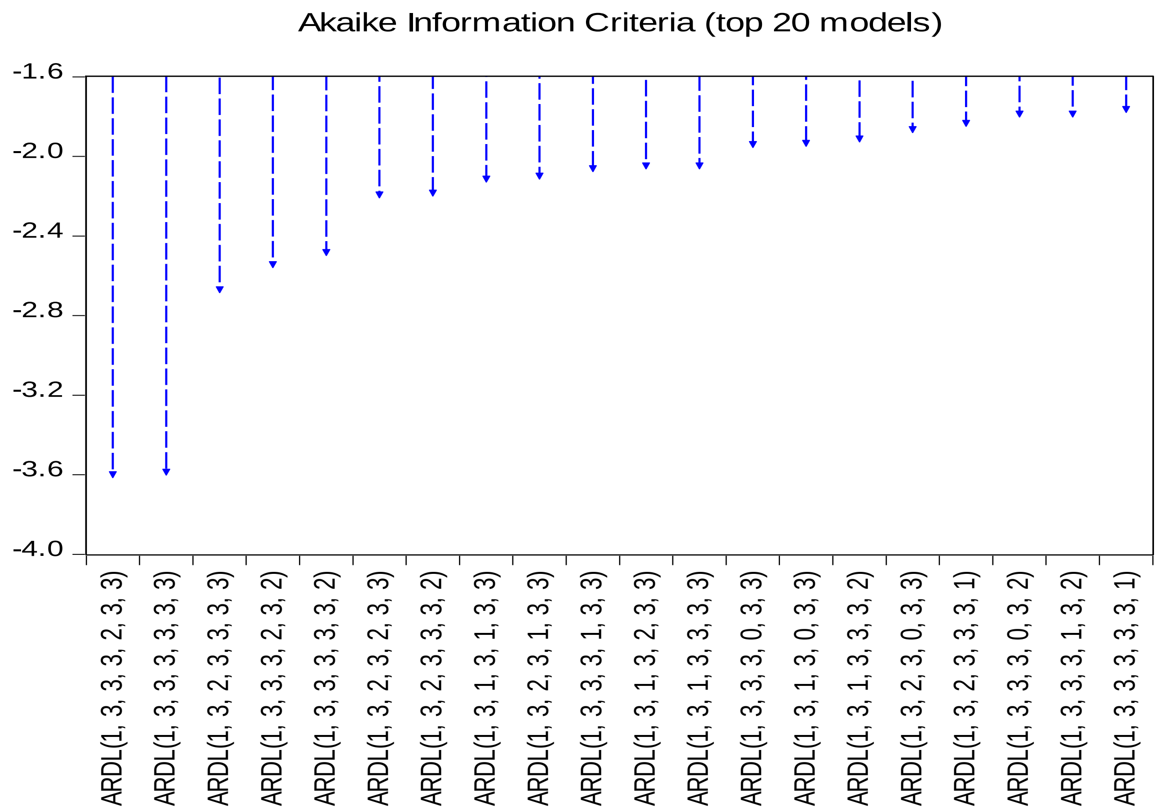
3.2.2 Determining the optimal lag

Based on the above unit root test, we apply the cointegration bounds test to determine whether there is a linear combination of the model variables that is cointegrated. Before implementing this cointegration test, it is necessary to specify the optimal lag.

The Akaike Information Criterion (AIC) is used here to determine the lag length of each variable in the level and first difference model. The results obtained in the determination of the optimal lag are 2 periods. This lag was determined by taking the climate change aggregates as variables to be explained. From the graph below (according to the Schwarz information criterion), the ARDL model (1, 3, 3, 3, 2, 3, 3) is the best model because the SIC value is the minimum. After determining the number of lags for each variable, we should proceed to the cointegration test and the short and long term analyses using the ARDL estimator.

3.2.3 Bounds test

To avoid the existence of a cointegration risk and to study the existence of a long term relationship between the variables of the effect of climate change on maize production. This leads us to move to the cointegration test using the new ARDL boundary testing procedure. The ARDL approach is used because this procedure is considered by many economists as one of the new and relatively simple concepts [32].



Graphic 1. Determination of lags

Source: Author made on Eviews 10

Table 4. ARDL test results (Bounds)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
F-statistic	20.56145	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

Source: Author performed on Eviews 10

Table 5. Short-term result Short term estimation of the ARDL model (1, 3, 3, 3, 2, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(Rainfal August-September)	0.025164***	0.001108	22.71054	0.0002
D(Rainfal August-September (-1))	0.020508***	0.001303	15.73420	0.0006
D(Rainfal August-September (-2))	0.024866***	0.001584	15.69616	0.0006
D(Rainfall June-July)	-0.019292***	0.001802	-10.70539	0.0017
D(Rainfall June-July (-1))	0.046811***	0.002972	15.74840	0.0006
D(Rainfall June-July (-2))	0.013556***	0.001230	11.02145	0.0016
D(Temperature August-September)	0.791319***	0.034087	23.21501	0.0002
D(Temperature August-September (-1))	0.425581***	0.036099	11.78911	0.0013
D(Temperature August-September (-2))	0.588139***	0.035528	16.55426	0.0005
D(Temperature June-July)	-0.390737***	0.028781	-13.57611	0.0009
D(Temperature June-July (-1))	0.612873***	0.038007	16.12523	0.0005
D(Gdp per capita)	1.323516***	0.185752	7.125195	0.0057
D(Gdp per capita (-1))	-3.440510***	0.217700	-15.80388	0.0006
D(Gdp per capita (-2))	-3.337812	0.194401	-17.16969	0.0004
D(Surface)	0.090140	0.036132	2.494728	0.0881
D(Surface (-1))	-0.472118	0.029700	-15.89597	0.0005
D(Surface (-2))	-0.218649	0.034177	-6.397490	0.0077
CointEq(-1)*	-1.575148	0.067268	-23.41592	0.0002

Source : realized on eviews 10

The Fisher statistic (F= 20.56145) is higher than the upper limit for the different significance levels 1%, 2.5%, 5%, and 10%. We therefore reject the H0 hypothesis of the absence of a long term relationship and we conclude that there is a long term relationship between the different variables, there is therefore a co-integration relationship between the variables.

3.2.4 Estimation of the short-term relationship

In the context of the application of the ARDL methodology, it is necessary to estimate an ARDL (p,q) model which will serve as a basis for conducting the bounds test, which in turn will confirm or deny the presence of a short-term or long-term relationship.

D is the first difference of the variables considered. Furthermore, the term CointEq (-1) corresponds to the one-period lagged residual of the long-run equilibrium equation. Its estimated coefficient is negative and largely significant, confirming the existence of an error correction mechanism. This coefficient, which expresses the degree of recall of the output variable towards the long-run target, is estimated at -1.575148 for our ARDL model, which reflects a more or less rapid adjustment to the long-run target (the model takes its equilibrium for two years). This means that the model finds its long-run equilibrium after two years.

The negative sign of the error correction term confirms the expected convergence process in the long-run dynamics. In fact, 157% of last year's imbalances are corrected in the current year, which suggests a good adjustment speed in the relationship process following a last year shock. Furthermore, the results indicate that precipitation and temperature in June-July have a negative and very significant influence in the short term. This is explained by a decrease in production. This result is confirmed by the work of several authors [7,25]. Unlike area and GDP per capita, we find a positive and significant influence on maize production.

3.2.5 Estimation of the long-run relationship

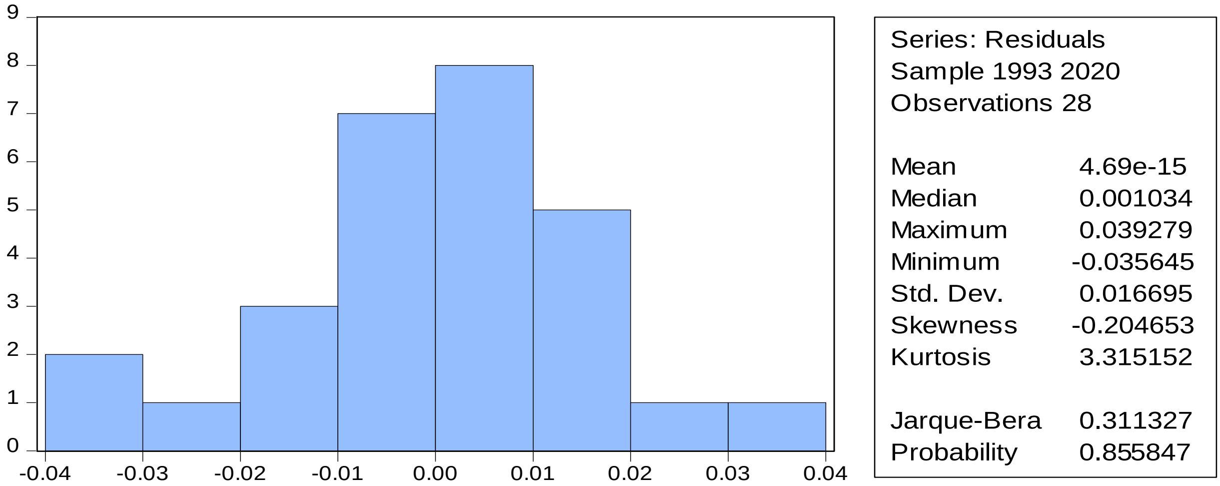
The empirical results of the long-term relationship are presented in the Table 6. Precipitation and temperature in June-July have negative and significant effects on maize production. This means that the success of maize production depends on the quality of rainfall and temperature in June and July. These results are highly anticipated and especially essential, given the role that climate change plays in reducing grain production. These results are confirmed by the work of [33] showing the negative influence of rainfall on production in Nigeria. GDP per capita and area contribute to the increase in corn production, hence their importance.

3.2.6 Normality test

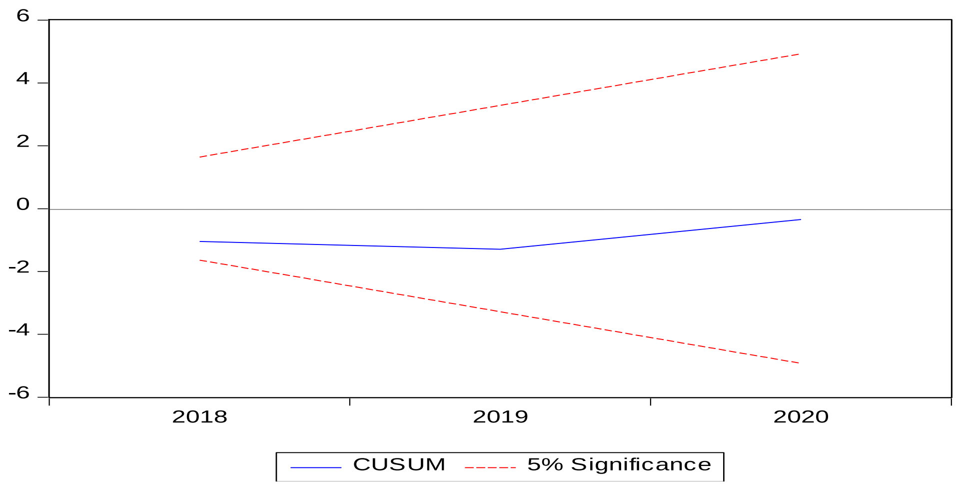
The probability associated with the Jarque-Bera statistic 0.85 is greater than 0.05. The hypothesis of normality of the residuals is therefore verified. We can therefore conclude that the residuals of the estimation of the long term model are stationary. The normality of their distribution is confirmed.

3.2.7 Cusum and Cusum Square test

In order to study the stability of our model, we also studied the CUSUM and CUSUM square tests represented respectively by the graphs:



Graphic 2. Normality test
Source: realized on Eviews 10



Graphic 3. CUSUM test
Source : realized on Eviews 10

Table 6. Long term result of the ARDL model (1, 3, 3, 3, 2, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Rainfall June-July	-0.059512***	0.009542	-6.236537	0.0083
Rainfall August-September	0.019088**	0.003815	5.003527	0.0154
Temperature June-July	-0.774087**	0.163870	-4.723792	0.0180
Temperature August-September	0.722614**	0.146699	4.925843	0.0160
Gdp per capita	3.644969***	0.415934	8.763331	0.0031
Surface	0.733501***	0.079844	9.186712	0.0027
C	-15.32290**	3.541733	-4.326384	0.0228

Source: Author performed on Eviews 10

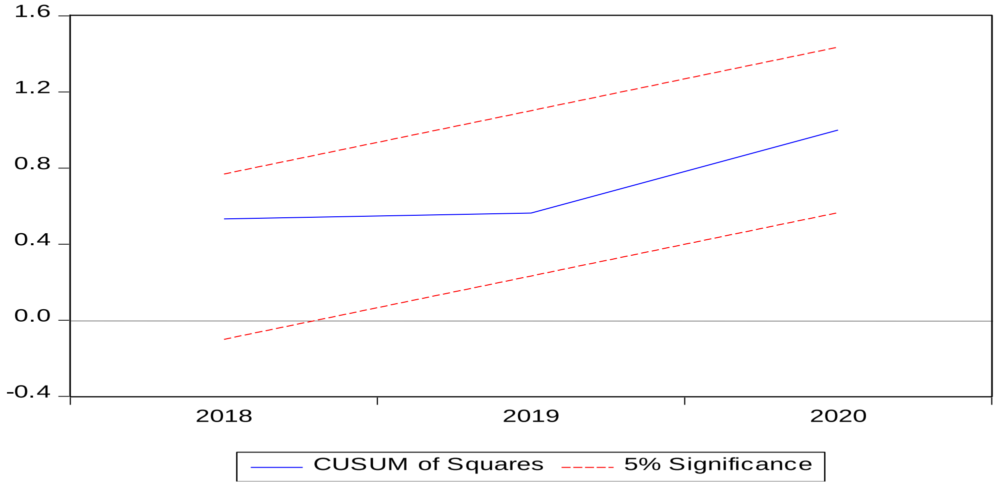


Fig. 3. Test of CUSUM CARRE
Source: realized on Eviews 10

These graphs show that the model is globally stable on the structural form. Therefore, we can conclude that the regression coefficients are stable.

4. CONCLUSION

Mali is an agricultural country, and although land suitable for agriculture represents only 14% of the total area, agriculture remains the main activity, both in terms of employment and contribution to the Malian economy. However, maize remains the most consumed food. Indeed, about 75% of Mali's population lives in rural areas and agriculture represent about 50% of the gross national product. The Malian economy is therefore highly dependent on the performance of the agricultural sector, which is particularly sensitive to climatic variations, periods of prolonged drought and the continuous southward shift of the desert over the past several decades. Agricultural production is therefore dependent on climate change factors, which weakens the country's economy.

We used the ARDL model to see the effect of climate change on maize production. From this model, we estimate the short and long term effects of climate change on maize production during the period 1990-2020. In particular, the results confirm the existence of a long-term cointegrating relationship. Overall, the short and long term results show that June and July precipitation and temperature negatively influence maize production. This result corroborates with the theory of decreased agricultural production due to climate change effects [34,35,36].

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Ali A, Erenstein O. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in

Pakistan. Climate Risk Managemen. 2017;16:183-194.
2. Gregory AS, Dungait JA, Shield IF, et al. Species and genotype effects of bioenergy crops on root production, carbon and nitrogen in temperate agricultural soil. BioEnergy Research. 2018;11(2):382-397.
3. IPCC. L'atténuation du changement climatique : Résumé à l'intention des Décideurs; 2014.
4. Maïga A, Bamba A,S, B. KGH, Mouleye IS, Diallo M. Analysis of the Effects of Public Expenditure on Agricultural Growth in Mali. Asian Journal of Agricultural Extension, Economics & Sociology. 2021;39(7):42-50.
5. Cline WR. Global warming and agriculture. Finance & Development. 2008;45(1).
6. Akram N, Hamid A. Climate change: A threat to the economic growth of Pakistan. Progress in Development Studies. 2015;15(1):73-86.
7. Ketema AM, Negeso KD. Effect of climate change on agricultural output in Ethiopia. Jurnal Perspektif Pembiayaan Dan Pembangunan Daerah. 2020;8(3):195-208.
8. Parry ML, Porter JH, Carter TR. Climatic change and its implications for agriculture. Outlook on Agriculture. 1990;19(1):9-15.
9. Caquet T, Guehl JM, Breda N. Adaptation au Changement Climatique de l'Agriculture et de la Forêt (ACCAF) de l'INRA. Le métaprogramme. Pour la science. 2015;46-50.
10. Chanzy A, Davy H, Geniaux G, et al. Regional impacts of climate change and adaptation through crop systems spatial distribution: the VIGIE-MED project. In Climate Smart Agriculture 2015; 2015.
11. Ali-Olubandwa AM, Odero-Wanga D, Kathuri NJ, Shivoga WA. Adoption of improved maize production practices among small scale farmers in the agricultural reform era: The case of Western Province of Kenya. International Agricultural and Extension Education. 2010;17(1):21-30.
12. Niang I. Le changement climatique et ses impacts: les prévisions au niveau mondial. Liaison énergie francophonie, (OCT). 2009;13-20.
13. Boko M. Climats et communautés rurales du Bénin: rythmes climatiques et rythmes de développement. Doctoral dissertation, Dijon; 1988.
14. Brown O, Crawford A. Assessing the security implications of climate change for West Africa: Country case studies of Ghana and Burkina Faso; 2008.
15. IPCC. Bilan 2007 des changements climatiques: Conséquences, adaptation et vulnérabilité; 2007.
16. Roudier P, Sultan B, Quirion P, Berg A. L'impact du changement climatique futur sur les rendements des cultures en Afrique de l'Ouest : que dit la littérature récente ? Changement Environnemental Global. 2011;21(3):1073-1083.
17. Mendelsohn R, Dinar A, Dalfelt A. Climate change impacts on African agriculture. District of Columbia; 25 2000.
18. Maddison D. The perception of and adaptation to climate change in Africa. Vol 4308: World Bank Publications; 2007.
19. Sultan B, Roudier P, Quirion P, et al. Assessing climate change impacts on sorghum and millet yields in the Sudanian and Sahelian savannas of West Africa. Environmental Research Letter. 2013;8(1).
20. Guan K, Sultan B, Biasutti M, Baron C, Lobell DB. Assessing climate adaptation options and uncertainties for cereal systems in West Africa. Agricultural and Forest Meteorology. 2017;232:291-305.
21. FAO. L'état De La Sécurite Alimentaire Et De La Nutrition Dans Le Monde. Rome; 2020.
22. UNFCCC. L'Accord de Paris: United States climate change; 2015.
23. Sonwa DJ, Dieye A, El Mzouri EH, et al. Drivers of climate risk in African agriculture. Climate and Development. 2017;9(5):383-398.
24. Mouleye IS, Diaw A, Daouda YH. Impact of climate change on poverty and inequality in Sub-Saharan Africa. Revue deconomie du developpement. 2019;27(3):5-32.
25. Chebil A, Mtimet N, Tizaoui H. Impact du changement climatique sur la productivité des cultures céréalières dans la région de Béja (Tunisie). African Journal of Agricultural and Resource Economics, 6(311-2016-5583). African Journal of Agricultural and Resource Economics. 2011;6(311).
26. Zargar M, Rebouh N, Pakina E, Gadzhikurbanov A, Lyashko M, Ortskhanov B. Impact of climate change on cereal production in the highlands of eastern Algeria. Research on Crops. 2017;18(4):575-582.
27. Iglesias A, Quiroga S. Measuring the risk of climate variability to cereal production at

five sites in Spain. Climate Research. 2007;34(1):47-57.
28. FAO. La Situation Mondiale De L'alimentation Et De L'agriculture. Rome; 2019.
29. Ouedraogo M. Impact des changements climatiques sur les revenus agricoles au Burkina Faso. Journal of Agriculture and Environment for International Development (JAEID). 2012;106(1):3-21.
30. Barrios S, Ouattara B, Strobl E. The impact of climatic change on agricultural production: Is it different for Africa? Food policy. 2008;33(4):287-298.
31. Johansen S, Juselius K. Maximum likelihood estimation and inference on cointegration-with appucations to the demand for money. Oxford Bulletin of Economics and statistics. 1990;52(2):169-210.
32. Pesaran MH, Shin Y, Smith RJ. Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics. 2001;16(3):289-326.
33. Ayinde OE, Muchie M, Olatunji GB. Effect of climate change on agricultural productivity in Nigeria: a co-integration model approach. Journal of Human Ecology. 2011;35(3):189-194.
34. Chandio AA, Jiang Y, Rehman A, Rauf A. Short and long-run impacts of climate change on agriculture: an empirical evidence from China. International Journal of Climate Change Strategies and Management. 2020.
35. Solomon R, Simane B, Zaitchik BF. The Impact of Climate Change on Agriculture Production in Ethiopia: Application of a Dynamic Computable General Equilibrium Model. American Journal of Climate Change. 2021;10(1):32-50.
36. Mahadeva L, Robinson P. Unit root testing to help model building. London: Centre for Central Banking Studies, Bank of England; 2004.

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