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RESEARCH ARTICLE

AUTOREGRESSIVE DISTRIBUTED LAG MODELING OF IMPACT OF CLIMATIC AND NON-CLIMATIC FACTORS INFLUENCING SORGHUM PRODUCTION IN ETHIOPIA

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ABSTRACT

This study examined factors influencing sorghum output in Ethiopia using ARDL model over the period 1981 to 2020. The elasticity coefficient of crop growing period mean temperature showed negatively significant impact on sorghum production in the long-run, aligning with theory. Conversely, main-season rainfall had positively significant impact on sorghum output, contrasting with the theory. Among non-climatic variables, sorghum price and area under sorghum had affirmatively considerable contribution to sorghum production as expected in theory. In the short-run, mean temperature revealed negatively significant impact on sorghum production, supporting the theory. Conversely, the main season rainfall and area under sorghum production demonstrated positively significant impact on sorghum production. Furthermore, sorghum output is positively *responsive to own price during the second lag differences, implying that any price incentive strategy should be released before the last year*. Equally, sorghum output is positively responsive to fertilizers applied in the first lag, which implies that fertilizers applied on sorghum cultivation during first lag difference have positive contribution to sorghum output supply. *In view of the results of the current study, it is strongly recommended that the government should come up with strategies and policies that help sorghum farmers to mitigate and adapt to climate change.*

KEYWORDS

Rainfall, Temperature, Elasticities, Tropical Cereal Crop

1. INTRODUCTION

Globally, shreds of evidence show that sorghum (*Sorghum bicolor* (L.) Moench) is the fourth most important tropical cereal crop next to wheat, rice and maize (Alemu and Haji, 2016). Globally, sorghum production supply is approximately 70 million tons of grains from 50 million hectares of land (Mojapelo, 2019). Sorghum is the major staple food for about 500 million family members who live in the hot semi-arid tropics of the continents of Africa and Asia, which covers nearly 80% of the world's land area. Surprisingly, over 100 million people use sorghum as the main and staple food (Alemu and Haji, 2016). Practically, sorghum was produced and used by resource-poor small-scale producers, who predominantly grow the crop under conditions of low-rainfall and arid to semiarid environments.

In Ethiopia, sorghum is primarily grown and used as major food crop and ranks third in terms of land area it covers next to teff and maize crops. It is grown on 1.828 million hectares with a total production of 5.265 million tons comprising about 15.7% of the total production next to maize, teff and wheat (CSA, 2020). The grain of sorghum is consumed as human food, whereas the residue part is utilized as livestock feed. In terms of altitude, the crop is extensively cultivated in the tropics amid elevation of 1400 to 2100 meters above sea level (m.a.s.l). Sorghum crop is considered to have high adaptive capacity to adverse environmental conditions which made it a popular crop worldwide.

However, sorghum cultivation in Ethiopia is adversely affected by climate and non-climate variables. These days, climate change is becoming a global and regional concern that is seriously affecting developing and least developed countries, which predominantly depend on rain-fed agricultural production (FAO, 2015). The adverse impacts of variability as well as change climate factors, in developing and least developed countries like Ethiopia, are recently growing over time and exerts pressure on crop production systems which changes the balance among key determinants of sorghum crop output and yield enhancement efforts. Shreds of evidence show that agriculture in Ethiopia is highly vulnerable to climatic extremes and variability, primarily caused by its high dependence on rain-fed systems (MOA, 2011). According to Aragie, many researchers found that climate change caused disparities have contributed to occurrence of frequent droughts, flooding as well as mounting mean surface temperatures, which in return critically affected production of crops over huge areas of Ethiopia (Aragie, 2013).

With an increasing inconsistency and extremes of climate variables in Ethiopia, it becomes very important to investigate potential impacts of the likely changes taking place in climatic factors (extreme, sub-seasonal rainfall deficit, and continuous warming of temperature) on sorghum crop production. The main aim of this study was, therefore, to investigate the potential impacts of factors influencing the supply of sorghum crop in Ethiopia. Such a study is important to enhance the knowledge and understanding of readers, policy makers, and scholars on the consequences of climate change and global warming and helps them to design strategies that mitigate and adapt to the likely impacts of climate change.

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2. Materials and Methods

2.1 Description of Study Area

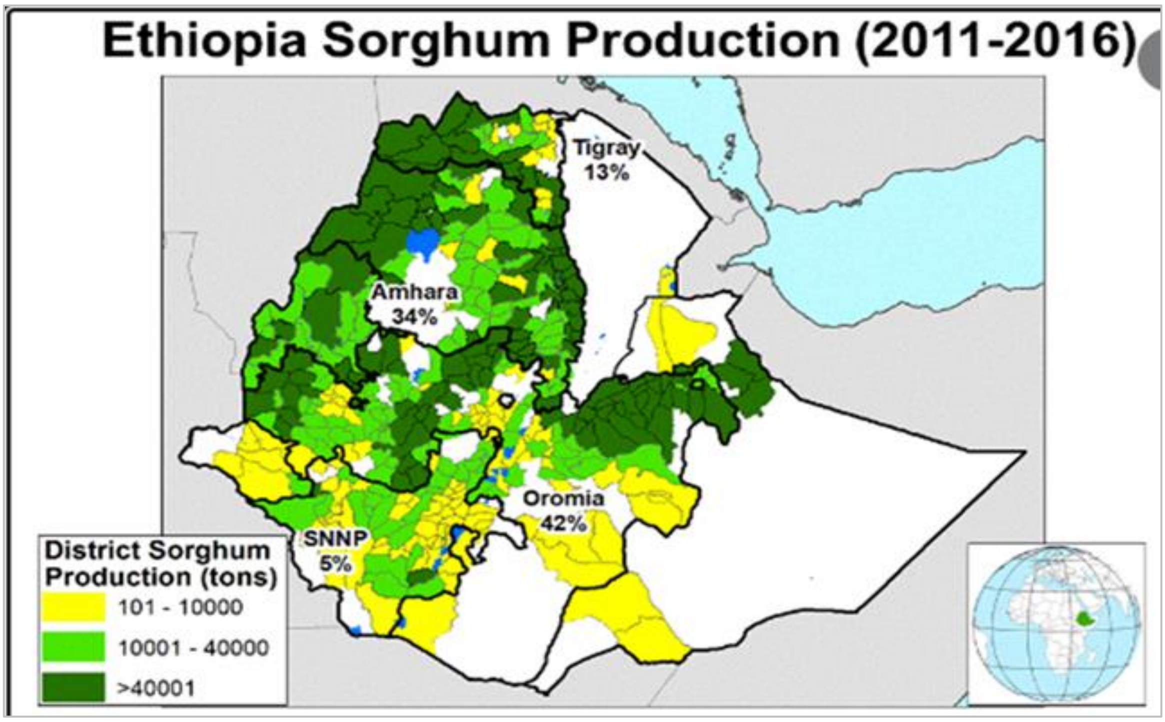

Figure 1: Major Sorghum Growing Belts of Ethiopia

2.2 Data Type and Source

In this study, secondary time series data were used for all the variables covering the period from 1981 to 2020. The study used one independent variable, viz. sorghum output expressed in a million tons; and explanatory variables, viz. crop growing period rainfall expressed in millimeters (mm), crop growing period mean temperature expressed in (ºC), price of sorghum output expressed in ETB, land area cultivated under sorghum expressed in a million hectares, and fertilizer quantity used on sorghum cultivation). Data on sorghum output as well as area allocated for sorghum cultivation have been taken from the Ethiopia Agricultural Sample Survey Reports of CSA, which covered the period from 1981 to 2020. Secondary data on weather variables (minimum and maximum temperatures and crop growing season rainfalls, i.e. short-season/*belg* and long-season/*meher* rainfalls) were obtained and compiled from the National Meteorological Agency (NMA) of Ethiopia. Representative weather stations from sorghum crop growing belts were selected (12 stations) and crop growing period precipitation and atmospheric temperature data were taken as recorded in NMA database. Then, nationally aggregated average data of crop growing period climate data were pooled by taking average of the weather stations selected for the study. Historical producer prices of sorghum crop over the observation period of 1981 to 2020 were also compiled from FAOSTAT database, CSA, and EGTE.

2.3 Empirical Model Specification

The investigator adopted an autoregressive distributed lag (ARDL) model developed by some researchers to establish the relationship existing among the variables selected for the study (Pesaran et al., 1996; Pesaran, 1997; Pesaran et al., 2001). An ARDL is a least squares regression containing lags of the dependent and explanatory variables. According to Duasa, the model is appropriate for estimating short- and long-run elasticity coefficients of small sample size using ordinary least square (OLS) for cointegration between variables incorporated in the study (Duasa, 2007). The model allows using appropriate and optimal lags, which otherwise is not possible with the use of standard cointegration test. Above all, ARDL can be used in cases the sample data or observations are small (30 – 80 observations) and where the set of critical values were originally developed by Narayan using GAUSS technique (Narayan, 2005). ARDL approach gives flexibility in order of variables under consideration are co-integrating and is appropriate for a mixture of variables of order I(0), I(1), or mutually cointegrated variables (Frimpong and Oteng, 2006). However, the model fails in case any of the variables co-integrated with order I (2).

The common form of ARDL model that establishes the association between dependent and explanatory variables can be expressed as:

$$SPro_t = \alpha_0 + \beta_1 SPri_t + \beta_2 SAr_t + \beta_3 SFert_t + \beta_4 LSRF_t + \beta_5 MeanTemp_t + \varepsilon_t \quad (1)$$

Where: SPro represents sorghum production, SPri represents price of sorghum output, SAr represents land area cultivated under sorghum crop, SFert indicates fertilizer input used in sorghum cultivation, LSRF represents long/ main season rainfall, and MeanTemp shows crop growing period mean temperature. Furthermore, α_0 represents the constant, β_1, β_2, β_3, β_4, β_5 are coefficients to be estimated and ε_t represents the error term.

Further, equation (1) should be transformed into logarithm form to achieve a suitably proficient estimated parameter from the crop supply response model, which gives Equation 2 below:

$$lnSPro_t = \alpha_0 + \beta_1 lnSPri_t + \beta_2 lnSAr_t + \beta_3 lnSFert_t + \beta_4 lnLSRF_t + \beta_5 lnMeanTemp_t + \varepsilon_t \quad (2)$$

An ARDL approach is the best tool to test the association existing among the variables incorporated in the study in the long run. The conditional ARDL model in equation (2) should then be expressed in ARDL model form as follows:

$$\Delta lnSPro_t = \alpha_0 + \sum_{k=1}^{n} \beta_1 \Delta lnSPro_{t-k} + \sum_{k=1}^{n} \beta_2 \Delta lnSPri_{t-k} + \sum_{k=1}^{n} \beta_3 \Delta lnSAr_{t-k} + \sum_{k=1}^{n} \beta_4 \Delta lnSFert_{t-k} + \sum_{k=1}^{n} \beta_5 \Delta lnLSRF_{t-k} + \sum_{k=1}^{n} \beta_6 \Delta lnMeanTemp_{t-k} + \lambda_1 lnSPRo_{t-1} + \lambda_2 lnSPRi_{t-1} + \lambda_3 lnSAr_{t-1} + \lambda_4 lnSFert_{t-1} + \lambda_5 lnLSRF_{t-1} + \lambda_6 lnMeanTemp_{t-1} + \varepsilon_t \quad (3)$$

Where: α_0 represents a drift, Δ shows first order difference, ε_t shows the error term. To choose an optimum lag length, the study used the Akaike information criterion (AIC). Subsequent to the establishment of existing long-run relationship among the variables, specification of the error correction models (ECM) has been carried out for the short-run dynamics of the variables incorporated in the study. The general form of the ECM from Equation (3) can be specified in Equation (4) as:

$$\Delta lnSPro_t = \alpha_0 + \sum_{k=1}^{n} \beta_1 \Delta lnSPro_{t-k} + \sum_{k=1}^{n} \beta_2 \Delta lnSPri_{t-k} + \sum_{k=1}^{n} \beta_3 \Delta lnSAr_{t-k} + \sum_{k=1}^{n} \beta_4 \Delta lnSFert_{t-k} + \sum_{k=1}^{n} \beta_5 \Delta lnLSRF_{t-k} + \sum_{k=1}^{n} \beta_6 \Delta lnMeanTemp_{t-k} + \emptyset ECM_{t-1} + \varepsilon_t \quad (4)$$

Where: Δ indicates first order difference operator, ECM_{t-1} is the error correction model while $\emptyset$ reflects the speed at which deviations from long-run equilibrium are corrected for the short-run.

After estimation of the ARDL model, various tests have been carried out to determine the trend of causality among the independent and explanatory variables incorporated in the model. Towards this end, Wald test was conducted to verify the long-run association existing among the variables. Furthermore, normality test (Jaque-Bera test); Heteroscedasticity test (Breusch and Godfray LM test); multicollinearity Test and Serial correlation test (Brush & Godfray LM test), Functional form test (Ramseys RESET); and Unit Root test have been carried out.

3. Results

This section presents the results of the various diagnostic tests and the supply response of sorghum crop models used in the current study.

3.1 Results of the Unit Root Tests

The investigator has conducted unit root tests of all the time series and multicollinearity tests between the variables included in the model. Augmented Dickey Fuller (ADF) and Phillips Perron (PP) tests were used to test the presence of unit root in the data series. In the ADF and PP tests for stationarity of the time series, the null hypothesis for presence of unit root is rejected when the test statistic is greater than the critical value at desired significance level, otherwise the null hypothesis is not rejected (Dickey and Fuller, 1979). Table 1 presents the results of the unit root tests. The estimated product of both tests reflected that all the study variables (lnSPro, lnSPri, lnSAr, lnSFert, lnLSRF, and lnMeanTemp) are statistically significant and are stationary at levels or order I (0). The estimated results suggest that an ARDL model could be employed for examining both the long- and short-run interrelationships existing among the variables selected for the study.

3.2 Diagnostic, Robustness and Stability Tests

In this study, an ARDL bound cointegration test technique was employed to detect the existence of long-run cointegration between the variables included in the model. Table 2 presents the outcomes of the bound's co-integration tests. As can be seen from the table, there exists long-run cointegration among the dependent and explanatory variables incorporated in the model, since the F-Statistics 3.6985 exceeds the critical upper bound 3.534 at 10% level of significance. This indicates the existence of *long-run relationships* among the dependent and explanatory variables incorporated in the estimated model.

The error term from the sorghum output response model was also subjected to certain residual tests to detect non-normality, serial correlation, and heteroscedasticity. As can be seen from Table 3 below, the distribution follows normal distribution on the basis of statistical insignificance of the Jarque–Bera statistic. Therefore, *t* and *F* tests can be correctly used for hypothesis testing in respect of the series. In addition, the results show nonexistence of autocorrelation as revealed by Breush–Godfrey Lagrange Multiplier (LM) test statistics. Nevertheless, there is presence of heteroscedasticity as shown by Lagrange Multiplier (LM) test for no autoregressive conditional heteroscedasticity (ARCH).

Table 1: Results of the Unit Root Test

Variable	ADF		PP		Results
	Level	First Difference	Level	First Difference	
LNSPRO	-3.6895**	-7.25513	-3.31685***	-9.21889	I(0)
LNSPRI	-2.3912***	-5.56108	-1.7495***	-8.78981	I(0)
lNSAR	-3.1324***	-6.28477	-2.77889***	-6.37645	I(0)
LNSFERT	-3.9043***	-6.70024	-4.01282***	-8.96121	I(0)
LNLSRF	-3.2833***	-15.64517	-6.98374	-43.5617	I(0)
LNMeanTemp	-3.9043***	-7.15842	-3.91892***	-7.29074	I(0)

*, ** and *** denotes significance level at 10%, 5% & 1%, respectively.

Table 2: Estimation of Cointegration Equations

Dependent variable	Type of test	Test statistics	Critical values	Conclusion
Sorghum output supply response	Wald test	3.6985*	3.534	Long-run cointegration exists

Note: * indicates significance level at 10%.

Table 3: Residual Properties of Barley Output Response Equation

Type of test	Test statistic	Test statistic value	Probability
Normality test - Histogram	Jarque-Bera	3.5362	0.17066
LM	Obs*R-squared	2.2644	0.3750
Heteroscedasticity (ARCH)	Obs*R-squared	16.93030	0.0498

Table 4: Results of the Ramsey RESET Test

Dependent Variable	F – statistic	Probability	Conclusion
Log sorghum output	9.763851	0.0053	No indication of misspecification

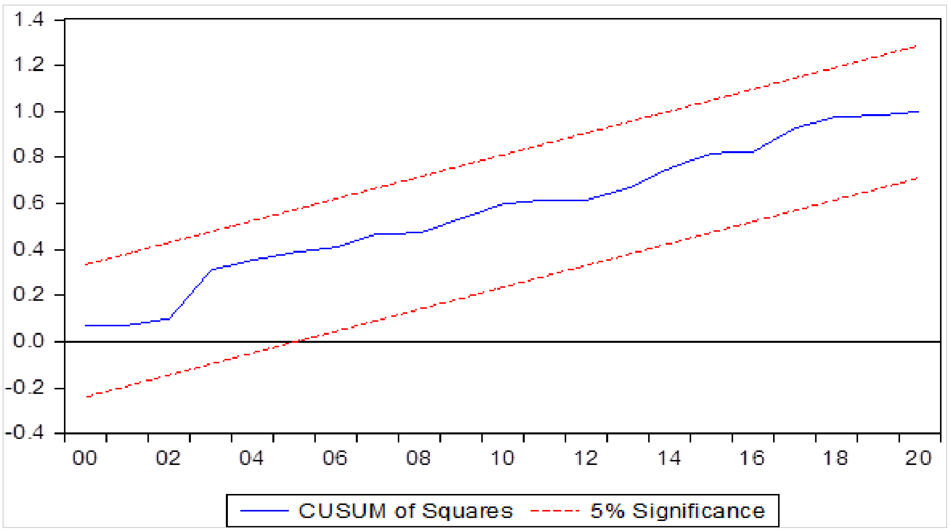

Figure 2: Plot of CUSUM of Squares of recursive Residuals

Furthermore, a test for Ramsey RESET has been carried out to detect the presence of any misspecification. Table 4 presents the results of the Ramsey RESET tests. It can be seen from the table that the model does not suffer from any form of misspecification. Equally, the robustness of the estimated parameters has been evaluated from the response equation employing the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) techniques of recursive residuals test. The results, as can be seen from Figure 2, reveal non-significant divergence of the plots from the zero line, which suggests the stability of parameters incorporated in the estimated equation.

3.3 Modeling Factors Influencing the Supply Response of Sorghum Output

The study examined how sorghum production/ output supply responds to climatic and non-climatic variables. To achieve the intended objective, the crop output supply model was estimated with both climatic (rainfall and mean temperature) and non-climatic (lagged sorghum output, producer price of sorghum, land area cultivated under sorghum crop, chemical fertilizers used under sorghum cultivation) variables. Irrigated area under sorghum crop and improved sorghum seed were initially included into the model but were dropped since the test results exhibited presence of serial correlation and multicollinearity with other variables.

The adjusted R^2 and F-statistic estimated for the ARDL regression model exhibited good fitness of the model for the sorghum output supply data series, with a value of adjusted R^2 (0.6905). The adjusted R^2 value of 0.6905 in sorghum output model implies that 69% of the disparity in sorghum output production has been explained by the explanatory variables included in the model (see Table 6). The F-statistics (9.2555) show that the model is well fitted to the data series. The Durban-Watson test further showed no existence of serial autocorrelation. The model becomes viable and fit at lag length 1 and first-order difference only; lag length 2 and second-order difference were tried but revealed high serial autocorrelation.

Since the previous test for cointegration revealed the presence of long-run cointegration, long-run elasticity coefficients have been estimated for the sorghum output supply model. Based on F-statistics, adjusted-R^2, and the AIC, an ARDL of **(**1, 0, 1, 0, 1, 0, 0**)** was selected as the best model. Table 5 presents the *long-run* elasticity coefficients estimated for sorghum output supply associated to climate and non-climate variables. After dropping serially correlated variables of irrigated area and improved seeds used, the climatic and non-climatic variables selected for the analysis were: log mean temperature recorded during crop-growing period, log long/main-season rainfall over crop growing period, log sorghum producer price, log area cultivated under sorghum crop, and log chemical fertilizers used on sorghum production.

The estimated elasticity coefficients show that mean temperature over crop growing period had negative and significant (10% level) relationship with sorghum output supply in the long run. This indicates that a 1% increase or alter in crop growing period mean temperature would decrease sorghum output by 5.5%. Conversely, the estimated elasticity coefficient of main/long-season rainfall showed affirmative and significant (10% level) impact on the supply of sorghum crop output. The result indicates that a 1% increase/change in main-season rainfall would increase sorghum output by 0.66%. Conversely, all the non-climatic explanatory variables incorporated in sorghum output model showed positive impact on sorghum output supply in the long run. However, only the coefficients estimated for log sorghum price and log area cultivated under sorghum are statistically significant. The results designate that a 1% boost in log price of sorghum and log area under sorghum cultivation over the long run would increase sorghum output supply by 0.11% and 1.51% respectively.

Table 5: Long-Run Elasticity Estimates of Variables Considered in Sorghum Output Model

Variable	Coefficient	Std. Error	t-Statistics	Prob.
Cons	11.18472	7.676728	1.456964	0.1549
LNSPri	0.114021**	0.055378	2.058974	0.0477
LNSAr	1.5132***	0.215898	7.008846	0.0000
LNFert	0.019875	0.066032	0.300995	0.7654
LNLSRF	0.664308*	0.394939	1.682053	0.1023
LNMeanTemp	-5.481787*	2.931363	-1.870047	0.0706

*, ** and *** indicate statistical significance level at 10%, 5% and 1%, respectively

Table 6: Short-Run Coefficient Estimaes of Variables Included in Sorghum Output Model

Dependent Variable: D(LNSPRO)				
Maximum dependent lags: 2 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (1 lag, automatic): ECT (-1) D(LNSPRI) D(LNSAR) D(LNSFERT) D(LNLSRF) D(LNMEANTEMP)				
Fixed regressors: C @TREND				
Selected Model: ARDL (1, 0, 1, 0, 1, 0, 0)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.22144**	1.24111	2.59560	0.0151
D (LNSPRO (-1))	-0.10398	0.110095	-0.94450	0.3533
ECT (-1)	-0.29913**	0.114885	-2.603699	0.0148
D(LNSPRI)	-0.18932*	0.096796	-1.95585	0.0609
D (LNSPRI (-1))	0.10222	0.09743	1.04923	0.3034
D(LNSAR)	1.0184***	0.15604	6.52649	0.0000
D(LNSFERT)	0.04896	0.03621	1.35222	0.1875
D (LNSFERT (-1))	-0.04884	0.03805	-1.28365	0.2102
D(LNLSRF)	0.017363	0.22675	0.07657	0.9395
D(LNMEANTEMP)	-1. 98619*	1.11224	-1.78576	0.2993
@TREND	0.00109	0.00226	0.482599	0.6333
R-squared	0.774162	Mean dependent var		0.038775
Adjusted R-squared	0.690519	S.D. dependent var		0.259452
S.E. of regression	0.144336	Akaike info criterion		-0.796149
Sum squared resid	0.562487	Schwarz criterion		-0.322111
Log likelihood	26.12683	Hannan-Quinn criter.		-0.627490
F-statistic	9.255496	Durbin-Watson stat		2.159750
Prob(F-statistic)	0.000002			

*, ** and *** indicate significance level at 10%, 5% and 1%, respectively

To depict the dynamic adjustment of all the variables considered in the model, short-run coefficients were estimated with an ECM following the ARDL bounds test approach. Table 6 shows the short-run elasticity coefficients of the variables estimated using the selected ARDL model (1, 0, 1, 0, 1, 0, 0) with optimum lag length. The selection of the model with optimum lag length was done by employing AIC procedures. It can be seen from the table that the estimated lagged ECM (-1), is negative (-0.29913) as expected and highly significant (at 5% level), with probability value less than 5% (0.0148). These results support the short-run relationship or co-integration between the regressors represented by equation (1). The pace of adjustment (-0.29913) suggests that approximately 41.93% of the short-run disequilibrium due to the previous year's shocks experienced in equation (4) can be appropriately corrected in the long-run.

In the short run, the coefficient estimates for crop growing period mean temperature had negative and significant (10% level) effect on sorghum crop output supply, which aligns with the theory. The result indicates that a 1% mount in crop growing period mean temperature would decrease sorghum output by 1.99%. Conversely, the main-season rainfall exerts affirmative effect on sorghum output supply in the short-run, although statistically insignificant. Equally, elasticity coefficient for the non-climatic factors, which include own price of sorghum, land area cultivated under sorghum, chemical fertilizers applied on sorghum production have been estimated for the short run. Among these variables, areas cultivated under sorghum crop showed affirmative and significant (1% level) impact on sorghum output supply over the short-run.

The result indicates that an expansion of land area allocated under sorghum cultivation by 1% would lead to an enlargement of sorghum crop output by 1.02%. Conversely, sorghum output supply is depressingly and considerably responsive to own price in the first lag difference and positively responsive to own price in second lag difference. This implies that a 1% increase/change in sorghum crop own price will diminish sorghum crop output by 0.19% in first lag difference (last year) and boosting sorghum crop output by 0.102% during second lag difference (before last year). Furthermore, sorghum output is positively responsive to chemical fertilizers applied during the first lag difference (last year) and negatively responsive to chemical fertilizers applied on sorghum production before last year (2nd lag difference), although the outcomes are statistically insignificant.

4. Discussion

The elasticity coefficients estimated for temperature showed that mean temperature over crop growing period had negative and significant relationship with sorghum output supply in the long run. The result was as expected and aligns with the theory proposition. Conversely, the estimated elasticity coefficient for long-season rainfall showed a positive and significant impact on the supply of sorghum crop output, which contrasts with the theory. This may be because, in Ethiopia, agriculture is primarily rain-fed-based with insufficient irrigation works. Furthermore, as temperature at earth's surface rises, more evaporation occurs, which, in turn, increases overall precipitation. Therefore, a warming climate is expected to increase precipitation in many areas, which would have a positive impact on sorghum production. This phenomenon has been confirmed by the IPCC's Fifth Assessment Report (IPCC, 2013).

This finding is consistent with empirical research findings of Ali, who in their modeling of the influence of climatic and non-climatic factors on cereal crop production in India reported that average temperature had negative and significant impact on cereal production (Ali et al., 2021). The outcome implied that a 1ºC increase in average temperature will decrease cereal production by 2.31%. Further, they reported that the estimated elasticity coefficient of average rainfall in the long-run showed positive effects on cereal production. A similar study by Asfew and Bedemo [16] also supports the result of this study. In their study of the impact of climate change on cereal crops production in Ethiopia, they found that rainfall has a positive and significant effect on cereal crops production both in the long- and short-runs, while temperature change has a significant negative effect (Asfew and Bedemo, 2022). The study on the impact of precipitation on bean farming in China also supports the current study, which exhibited a positive and significant result (Li et al., 2021).

Among the non-climatic explanatory variables, the coefficients estimated for log sorghum price and log area cultivated under sorghum crop are found to have positive and significant relationship impact on sorghum crop output in the long run. The results are as expected in theory; i.e. economic theory states that a positive association exists among own price of a commodity and the output in question. The finding in land area under sorghum farming implies that sorghum crop output is highly responsive to changes in the area allocated under sorghum cultivation, which is also in line with the theory. The outcomes of this study are similar to the findings of (Alemu et al., 2003; Muchapondwa, 2009).

A group researcher who examined supply response grain output in Ethiopia, reported that own price of sorghum depicted affirmative and momentous impact on sorghum output supply over the long-run (Alemu et al., 2003). The result indicates that a 1% raise in sorghum own price would lead to a boost of sorghum output supply by 0.43%. Equally, Muchapondwa studied the supply response of Zimbabwean agriculture and reported that land area under aggregate agricultural supply and fertilizer quantity used on aggregate agricultural production have positive impact on supply of agricultural output over the long run (Muchapondwa, 2009). In the short run, the coefficient estimates for crop growing period mean temperature had negative and significant effect on sorghum crop output supply, which aligns with the theory.

Conversely, the main-season rainfall exerts affirmative effect on sorghum output supply in the short-run, although statistically insignificant. The findings of the study are analogous with the study findings of who modeled climatic and non-climatic factors influencing agricultural crop production in India and reported that coefficient estimates of average temperature during short run had depressing and momentous (1% level) impact on cereal output while the coefficient estimates of average rainfall had affirmative effect on cereal crops output (Chandio, 2021). The study outcomes depict that a 1% mount in mean temperature would lead to decrease of cereal crops output by 2.25% while 1% enlargement in average rainfall increases cereal crop output by 0.05%. Conversely, the outcomes of the current investigation contrasts with the findings of who studied factors (climate and non-climate) impacting rice crop cultivation in South Korea (Nasrullah, 2021).

They reported that coefficient estimates of mean temperature had positive and momentous influence on the output of rice crop during the short run while estimates for mean rainfall had positive and momentous shock on the production of rice crop. Among the non-climatic variables, area cultivated under sorghum crop showed positive and significant (1% level) impact on sorghum output supply over the short run. Conversely, sorghum output supply is depressingly and considerably responsive to own price in first lag difference and positively responsive to own price in second lag difference. The results can be justified with the expression that sorghum output is negatively responsive to any own price incentive put in place during first lag difference (last year) and positively and moderately responsive to own price incentive strategies released before last year.

In other words, any own price of sorghum incentive policy and strategy should be released during the second lag difference (before last year) to yield positive increment of sorghum crop output supply. Furthermore, sorghum output is positively responsive to chemical fertilizers applied during the first lag difference (last year) and negatively responsive to chemical fertilizers applied on sorghum production before last year (2nd lag difference). These study outcomes resonate to the study outcomes (Chandio, 2021; Nasrullah, 2021; Munchapondwa, 2009). Chandio in their modeling of the influence of climatic and non-climatic factors on cereal production in India reported that cereal cropped area negatively and drastically influenced agricultural value-added during second lag difference and positively affected agricultural value added during the first lag difference (last year) (Chandio, 2021).

The outcomes point out that any increase/ change in area allocated under production of cereal crops during second lag difference (before last year) by 1% has decreased agriculture output supply by 0.59% and a 1% increase/change in area allocated under production of cereal crop during first lag difference increases agriculture output supply by 0.33%. Nasrullah, in their study of variables influencing the supply of rice crop output in South Korea reported that area cultivated under rice during first lag difference (last year) showed positive and considerable impact on supply of rice output whereas chemical fertilizer applied on rice crop farming during the first lag difference (short-run) showed harmful shock on supply of rice crop output (Nasrullah, 2021). The results implied that any enlargement in area cultivated under rice crop during the first lag difference (last year) by 1% would increase rice output by 0.69%; similarly, any increase in quantity of chemical fertilizer application by 1% would lead to a decrease of rice output supply by 0.08%.

Furthermore, Muchapondwa in his study on supply response of agriculture in Zimbabwe reported that the short-run elasticity with respect to the lagged price variable is affirmative and momentous at 5% level (Muchapondwa, 2009). Conversely, the elasticity estimates of both the short- and long-run with respect to the current prices are depressing and considerably influenced aggregate agricultural output supply. He further reported that chemical fertilizer application and land area allocated under cereal crops cultivation had affirmative effect on supply of aggregate agricultural output in the short run (current year), although not significant. The result exhibits that any boost in chemical fertilizer application and area cultivated under cereal crops by 1% would increase aggregate agricultural production by 0.39% and 0.388% respectively.

5. Conclusion

The ultimate purpose of this study was to examine the factors influencing the supply of sorghum crop output in the country. An ARDL model originally developed have been employed to set up the relationship prevailing among the variables incorporated in the crop output supply model. The study used time series secondary data of the selected variables covering the period from 1981 to 2020. The estimated elasticity coefficients for crop growing period average surface temperature had negative and considerable (10% level) impact on sorghum crop output supply during both the long- and short-run. Conversely, the estimated elasticity coefficient for main/long-season rainfall showed positive and significant (10% level) effect on sorghum crop output supply in both the long- and short-run.

The regression coefficient estimates for crop growing period average atmospheric temperature is found to be consistent with the theory proposition whereas that of main season rainfall contrasts with the theory. Among the non-climatic variables, all the regressors incorporated in the crop output supply model showed positive effect on the supply of sorghum crop output in the long-run, as expected in theory proposition. However, only the elasticity estimates of log sorghum own price and log area cultivated under sorghum are statistically significant. The finding may proof the claim towards increase in supply of sorghum crop output in the country was partly due to expansion of area cultivated under sorghum production rather than other inputs.

In the short-run, land area cultivated under sorghum crop showed affirmative and momentous (1% level) impact on the production of sorghum crop. Conversely, sorghum output supply is depressingly and considerably responsive to its own price during the last year (1st lag difference) and positively responsive to own price during the second lag difference (year before last year). The study outcomes imply that sorghum output is negatively responsive to any sorghum price incentive put in place last year (1st lag difference) and positively and moderately responsive to own price incentive strategies released during the second lag differences (before last year).

In other words, any own price of sorghum incentive policy and strategy should be released during the second lag difference (before last year) to bring any positive increment in sorghum output supply. Furthermore, sorghum output supply is positively responsive to fertilizer applied in the first lag difference (last year) and negatively responsive to fertilizer used before last year (during 2nd lag difference), although the outcomes are statistically insignificant. This result implies that application of chemical fertilizer on sorghum crop output supply during first lag difference (last year) will have positive input towards the expansion in volume of sorghum output.

The study indicated that climate variables, particularly temperature had negative impact on sorghum crop production. It is also expected that future production of sorghum crop would be adversely affected by the consequences of climate change if technical and tactical measures are not taken. Therefore, it is strongly recommended that the government should come up with strategies and policies that help sorghum farmers to adapt to the impacts exerted by climate change. Some of the strategies may include changes in planting date, practicing irrigation work, use of short duration crop variety, and fertilizer application. It is also recommended that further investigation should be undertaken to clearly assess the negative impacts of climate change on future food production and explore alternative measures that enhance and sustain sorghum crop production. The output of the study is important to enhance the knowledge and understanding of readers, policy makers, and scholars on the consequences of climate change and global warming and helps them to design strategies that mitigate and adapt to the likely impacts of climate change.

References

Alemu, G., and Haji, J., 2016. Economic Efficiency of Sorghum Production for Smallholder Farmers in Eastern Ethiopia: The Case of Habro District. Journal of Economics and Sustainable Development, 7 (15), Pp. 44 – 51.

Alemu, Z.G., Oosterhuizen, K., and van Schalkwyk, H., 2003. Grain-Supply Response in Ethiopia: An Error -Correction Approach, Agrekon, 42, Pp. 389–404.

Ali, C.A., Jiang, Y., Amin, A., Akram, W., Ozturk, I., Sinha, A., 2021. Modeling the impact of climatic and non-climatic factors on cereal production: evidence from Indian agricultural sector, MPRA Paper No. 110065, posted 08 Oct 2021, 18:29 UTC.

Aragie, A.E., 2013. Climate change, growth and poverty in Ethiopia. Volume-3.

Asfew, M., and Bedemo, A., 2022. Impact of Climate Change on Cereal Crops Production in Ethiopia; Advances in Agriculture, Pp. 1 – 8. https://doi.org/10.1155/2022/2208694.

Chandio, A.A., 2021. Modeling the impact of climatic and non-climatic factors on cereal production: evidence from Indian agricultural sector, MPRA Paper No. 110065, https://mpra.ub.uni-muenchen.de/110065/.

CSA, 2020. Report on area and production of major crops, Agricultural Sample Survey 2019-20, Addis Ababa, Ethiopia.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74 (366a), Pp. 427-431.

Duasa, J., 2007. Determinants of Malaysian trade balance: an ARDL bound testing approach. Global Economic Review, 36 (1), Pp. 89–102.

FAO (Food and Agriculture Organization), 2015. Adaptation to climate risk and food security: Evidence from smallholder farmers in Ethiopia. Food and Agriculture Organization, Rome, Italy.

Frimpong, M.J., and Oteng, E.F., 2006. Bound Testing Approach: An Examination of Foreign Direct Investment, Trade and Growth Relationships. MPRA Paper No. 352, Pp. 1–19.

IPCC, 2013. Climate change 2013: The physical science basis, Working Group I contribution to the IPCC Fifth Assessment Report, Cambridge, UK. Cambridge University Press.

Li, S., You, S., Song, Z., Zhang, L., and Liu, Y., 2021. Impacts of climate and environmental change on bean cultivation in China. Atmosphere, 12, Pp. 1591.

MoA (Ministry of Agriculture), 2011. Agriculture Sector Programme of Plan on Adaptation to Climate Change. Ministry of Agriculture, Addis Ababa, Ethiopia.

Mojapelo, M.C., 2019. Estimation of sorghum supply elasticity in South Africa. Journal of Agribusiness and Rural Development, 2 (52), Pp. 131 – 138.

Muchapondwa, E., 2009. Supply response of Zimbabwean agriculture: 1970–1999. Afjare, 3 (1), Pp. 28 – 42.

Narayan, P.K., 2005. The Saving and Investment Nexus for China: Evidence from Cointegration Tests. Applied Economics, 37, Pp. 1979–1990.

Nasrullah, M., 2021. Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. Journal of Water and Climate Change, 12 (6), Pp. 2256 – 2270.

Pesaran, H.M., 1997. The role of economic theory in modelling the long run. Economic Journal, 107 (440), Pp. 178 - 191.

Pesaran, H.M., Shin, Y., and Smith, R.J., 1996. Testing the Existence of a Long-run Relationship, DAE Working Paper Series No. 9622, Cambridge, Department of Applied Economics, University of Cambridge.

Pesaran, H.M., Shin, Y., and Smith, R.J., 2001. Bounds testing approaches the analysis of level relationships. Journal of Applied Econometrics, 16, Pp. 289 – 326.