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AUTOREGRESSIVE DISTRIBUTED LAG MODELING OF CLIMATIC FACTORS INFLUENCING SUPPLY RESPONSE OF WHEAT IN ETHIOPIA

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ABSTRACT

Climate change is among the major constraints to cereal crop productivity in Ethiopia. This study analysed the wheat supply response to climate and non-climatic variables in Ethiopia. The study employed Autoregressive Distributed Lag (ARDL) model using annual data from 1981 to 2018. The results revealed that all climatic variables have positive impact on wheat output in both the long-run and short-run. However, only the elasticity coefficients of CO_2 are statistically significant in both long- and short-terms. The estimated elasticity for CO_2 in zero order difference (current year) has positive and significant effect on wheat production. The estimated elasticity coefficients of all the non-climatic variables such as price of wheat, area under wheat, and fertilizer consumed are all positive and have significant impact on wheat output supply in the long-run. The result implies that wheat output is highly responsive to its own price, area under wheat, and fertilizer quantity used on wheat production in the long-run. On the other hand, the study result indicated that the elasticities of log wheat area in zero order, log price of wheat in first lag order, and log fertilizer quantity used in zero order have positive and highly significant effect on wheat production. This implies that wheat output is highly responsive to previous year's price, land currently under wheat production and fertilizer consumed in current year.

Keywords: Climate Change, Output Supply Response, Wheat Crop, ARDL Model, Ethiopia.

1. INTRODUCTION

Wheat is reckoned among the most important food crops in the world today. It should also be emphasized that wheat is a crop of significant nutritional and economic importance in Africa. Available statistics show that in 2017, 750 million metric tons were harvested from 220 million hectares. In sub-Sahara Africa (SSA), FAO (2017) submitted that a total of 7.5 million metric tons of wheat was produced on 2.9 million hectares of cultivated land areas in 2016. Moreover, based on the quantity of outputs, Ethiopia is among the major producers of wheat in Africa and the crop is considered as the fourth most important cereal crop in terms of both land areas cultivated and volume of production after teff, maize and sorghum (CSA, 2018).

Available data show that wheat production in Ethiopia has grown significantly over the past two decades. This growth can be attributed to government extension programs and the different initiatives implemented to promote agricultural growth through positive enhancement in the food supply channels. Production increased from around 10.72 million quintals in 2002/03 to 46.43 million quintals in 2017/18: an average annual growth of 22.2 percent. Yield of wheat also followed the same trend, its yield consistently increased from the level of 10.75 quintals/hectare in 2002/03 to 27.36 quintal /hectare during 2017/18. However, the increase in area cultivated under wheat crop during the same period is minimal, just 3.6 percent only (CSA, 2018).

In Ethiopia, climate change is one of the major problems confronting agricultural productivity and millions of farmers have historically suffered production losses resulting from periodic droughts (Benti and Abera, 2019; Beweket, 2009). These have often culminated into spatial food insecurity and famine that often requires some international interventions (Makombe, *et al,* 2007; Bekele, *et al*, 2017). Climate change affects agricultural productivity through a number of ways. These include unexpected changes in the pattern of rainfall, changes in the planting and harvesting periods, increase in annual temperature, changes in ground water levels and availability and evapo-transpiration (Pearce *et al.* 1996).

It should therefore be emphasized that wheat productivity is significantly influenced by changes in some climatic parameters. Generally, due to their anatomical and morphological compositions, changes in rainfall and other climatic variables affect cereal crop outputs. Specifically, productivity of wheat can be adversely affected by environmental stressors such as extremely high temperature, low soil water content and low intensity of sunlight, among others (Modarresi *et al*, 2010; Kajla *et al*., 2015).

In Sub-Saharan Africa, climate change brings about some socioeconomic constraints in the form of high input cost, severe droughts and infestation by pest and crop diseases. These are stressors of significant agronomic importance and they will lead to reduction in wheat production in absence of adequate coping mechanisms (Tadesse *et al*, 2018). It should also be noted that variability in environmental variables across African countries is defined in terms of changes in moisture availability, cropping systems and temperature regimes (Gebrechorkos, *et al.* 2018). Estimated climate models show that the median temperature in Africa will increase between 3 and 4°C by the end of the 21st century. This is roughly 1.5 times higher than the global mean. Therefore, some African countries such as Ethiopia are vulnerable to the adverse impacts of climate change due to limitations in access to adaptive resources (Elias, 2016; Tesso, et al, 2012).

There is paucity of empirical studies with national scope on the impact of climate change on wheat production in Ethiopia. In some previous studies, Bekele, *et al* (2017) analysed the effect of rainfall on wheat yield in Sinana Woreda area of Ethiopia. Yibrah *et al* (2018) analysed the effect of rainfall and temperature variability on wheat and barley production in Tigray region of Ethiopia. Since existing studies have mainly focused on regions and local areas within Ethiopia, this study seeks to fill an important research gap. This was motivated by potential adverse impacts that climate change could have on wheat production.

2. MATERIALS AND METHODS

2.1 Data Type and Method of collection

The study used time series data on wheat outputs, climatic variables and other agronomic input variables. Weather data for temperatures and precipitations were obtained for 1981-2018 period. These data were summarized from twelve Ethiopia's weather stations that are based in major wheat growing belts. In addition, wheat output data were compiled from several publications including database of the Food and Agriculture Organization (FAO).

2.2 Empirical Model Specification

In this study, we used the Autoregressive Distributed Lag (ARDL) model which was proposed by Pesaran *et al* (2001). This model is efficient in testing and estimating *long-run* relationships that are based on time series data (Hassler and Wolters, 2006). It also provides some flexibility in analyzing economic variables of different orders of integration. The general form of the model given a lag length *p* variable Q and *q* lag for variable X is stated as follows:

$$Q_t = \alpha_0 + \sum_{i=1}^{p} \beta_i Q_{t-i} + \sum_{i=0}^{q} \beta_i X_{t-i} + U_t \qquad (1)$$

Q_t denotes the quantity of crop supplied in year *t*, Q_{t-i} is the quantity of supplied crop output in year *t-i*, explanatory variables in year *t-i* are denoted as X_{t-i} and β_0, β_i, … are the *long-run* coefficients of used inputs, while U_t is the stochastic error term. The estimated model specified as:

$$lnQ_t = \beta_0 + \beta_1 ln PrW_t + \beta_2 ln La_t + \beta_3 ln IrrigA_t + \beta_4 ln Fert_t + \beta_5 ln ImS_t + \beta_6 ln SSR_t + \beta_7 ln LSR_t + \beta_8 ln MinTemp_t + \beta_9 ln MaxTemp_t + \beta_{10} ln CO_{2t} + \varepsilon_t \qquad (2)$$

where *ln denotes* natural logarithm, Q_t denotes wheat outputs measured in tons; PrW_t is price of wheat per ton output in Ethiopian Birr (ETB),, La_t is wheat land area, $IrrigA_t$ is irrigated wheat land area, $Fert_t$ is quantity of fertilizer consumed on wheat, ImS_t is improved wheat seed, RF_t is seasonal rainfalls (short- and long-season) measured in millimeters, $Temp_t$ is crop growing period mean temperatures (MinTemp and MaxTemp) measured in degrees Celsius, and CO_{2t} is CO_2 emission in time t measured in teragram. ε_t is the stochastic error. The estimated ARDL model is specified as:

$$lnQt = \alpha_0 + \sum \alpha_1 lnQt\text{-}i + \sum \alpha_2 lnLa_{t-i} + \sum \alpha_3 lnPrW_{t-i} + \sum \alpha_4 lnIrrigA_{t-i} + \sum \alpha_5 lnFert_{t-i} + \sum \alpha_6 lnImS_{t-i} + \sum \alpha_7 lnSSR_{t-i} + \sum \alpha_8 lnLSR_{t-i} + \sum \alpha_9 lnMinTemp_{t-i} + \sum \alpha_{10} lnMaxTemp_{t-i} + \sum \alpha_{11} lnCO_{2t-i} + \varepsilon_{t-I} \ (3)$$

If the variables are cointegrated, then there exists an error correction representation. The *short-run* coefficients were estimated by the following dynamics of ARDL error correction model (ECM):

$$Q_t = \beta_0 + \sum \beta_1 \Delta lnQ_{t-i} + \sum \beta_2 \Delta lnLa_{t-i} + \sum \beta_3 \Delta lnPrW_{t-i} + \sum \beta_4 \Delta lnIrrigA_{t-i} + \sum \beta_5 \Delta lnFert_{t-i} + \sum \beta_6 \Delta lnImS_{t-i} + \sum \beta_7 \Delta lnSSR_{t-i} + \sum \beta_8 \Delta lnLSR_{t-i} + \sum \beta_9 \Delta lnMinTemp_{t-i} + \sum \beta_{10} \Delta lnMaxTemp_{t-i} + \sum \beta_{11} \Delta lnCO_{2t-i} + \psi i ECT_{1-i} + ui \qquad (4)$$

where ψ_i represents the speed of adjustment (ECM term) which measures the deviation of Q_t from the long-run equilibrium level. The number of lags is always determined by the use of Akaike Information criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQ). The ARDL model that was specified as equation 4 was estimated with Eviews 9 software.

We tested the series for stationarity or unit root and cointegration. Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and Phillips-Perron (PP) test (Phillips and Perron, 1988) were used to test for presence of unit roots. The presence of cointegration was confirmed before estimating the model. Cointegration implies presence of long run relationship. Detection of cointegration with at least two I(1) series implies that some I(0) variables could also be added in the ARDL model without altering the characteristics of the error term (Hill *et al.,* 2012).

3. RESULTS AND DISCUSSION

3.1 Unit Root Test

Table 1 shows the results of stationarity tests on the time series data using ADF and PP approaches. The results imply that log fertilizer, log mean temperature, log belg and meher rainfall, log wheat output, log improved seed, mean rain in wheat growing areas and mean minimum and maximum temperature were stationary at levels – I(0). However, log wheat output; log price of wheat; log area under wheat; log fertilizer used in wheat production; log wheat yield; log area under wheat; log improved wheat seed; log fertilizer used in wheat production; log irrigated area under wheat; crop season mean minimum and maximum temperature in wheat growing areas were stationary at first difference – I(1). This shows that a mixture of I(0) and I(1) variables were used (Ssekuma, 2011).

In situations where time series data exhibit mixture of I(0) and I(1), some researchers recommend ARDL or Cobb-Douglas modeling as best approach (Sharma and Singh, 2019 and Dushko *et al*, 2011). In order to use the ARDL approach, bounds test of integration, model stability test and variance error correction model (VECM) should be conducted to test presence of long-term cointegration (Sharma and Singh, 2019).

Table 1: Time Series Unit Root Test Results for Wheat Output and Related Independent Variables

Variables	Type of Test	Form of Test	P-Value	Conclusion
LNWO	ADF	Intercept	0.9922	Non Stationary
		Trend & intercept	0.4064	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.8896	Non stationary
LNARW	ADF	Intercept	0.8421	Non Stationary
		Trend & intercept	0.0836	Non Stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.9337	Non stationary
LNIMS	ADF	Intercept	0.9829	Non Stationary
		Trend & intercept	0.0005	Stationary (I(0))
		First difference	0.0002	Stationary (I(1))
	PP	Intercept	0.3142	Stationary (I(0))
LNFERTW	ADF	Intercept	0.8719	Non Stationary
		Trend & intercept	0.0444	Stationary (I(0))
		First difference	0.0002	Stationary (I(1))
	PP	Intercept	0.9824	Non Stationary
LNIRRGAW	ADF	Intercept	0.6757	Non Stationary
		Trend & intercept	0.1225	Non Stationary
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.3013	Non Stationary
MEANRAIN	ADF	Intercept	0.0000	Stationary (I(0))
		Trend & intercept	0.0000	Stationary (I(0))
	PP	Intercept	0.0000	Stationary (I(0))
MINTEMP	ADF	Intercept	0.0847	Non Stationary
		Trend & intercept	0.0040	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0847	Non Stationary
MAXTEMP	ADF	Intercept	0.6878	Non Stationary
		Trend & intercept	0.0358	Stationary (I(0))
		First difference	0.0000	Stationary (I(1))
	PP	Intercept	0.0840	Non Stationary

3.2 Bound Testing Approach to Cointegration

We used the Bound test in order to detect existence of long-run relationship (cointegration) among the variables. This test begins with estimation of a regression equation with log of wheat output as dependent variable. Thereafter the predicted error terms for the model is to be tested for stationarity. The results, which are presented in Table 2, show that there is presence of cointegration and the null hypothesis of unit root was rejected (p<0.05). There is therefore presence of long-run relationship among the variables.

Table 2: Result of Cointegrating Test for wheat output data series

Type of Test	Test Statistic	Critical Values	Conclusion
Wald Test	-5.3689**	4.130	Long-run Cointegration exists

** Significant at 5 % level

3.3 Diagnostic and Stability Tests

We also tested the residual component of the ARDL model for normality, serial correlation and heteroscedasticity. The results in Table 3 show that the Jarque Bera statistic confirms that the series is normally distributed. Also, there was no evidence of autocorrelation based on Breush-Godfrey Lagrange Multiplier (LM) test. There was no heteroscedasticity based on conclusion from LM test for no autoregressive conditional heteroscedasticity (ARCH).

Table 3: Residual Properties of Wheat Output Response Equation

Type of test	Test statistic	Test statistic value	Probability
Normality test-histogram	Jarque Berra	0.23650	0.8885
Breusch-Godfrey Serial Correlation LM Test	Obs*R-squared	0.55634	0.7572
Heteroskedasticity Test: ARCH	Obs*R-squared	2.62662	0.1051

The Ramsey RESET test was also used to detect presence of model misspecification. The results in Table 4 show that there is no specification error in the model. Robustness of estimated parameters was tested with recursive coefficient tests, CUSUM tests, CUSUM residual squares test, one step forecast test and N steep forecast tests were performed. The results in Figure 1 show non-significant divergence of the lines from zero line and the residual line is within the width of the standard error. This suggests robustness of the estimated parameters.

Table 4: Ramsey Reset Tests Results

Dependant variable	F statistic	Probability	Conclusion
Log of wheat output	0.425344	0.6582	No indication of misspecification error

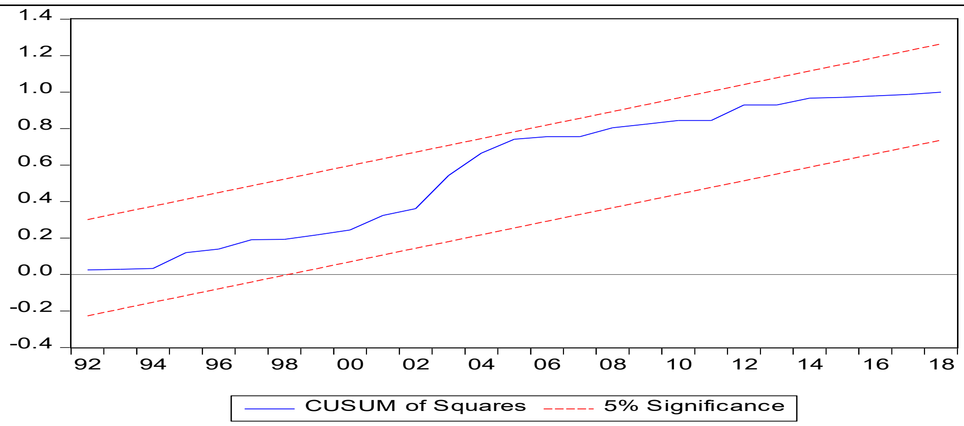

Figure 1: Recursive Residuals from the Wheat Output Response Equation

3.4 Impact of Climate and Non-Climatic Variables on Wheat Output Supply Response

To determine the response of wheat output supply to climatic (rainfall, temperature, CO_2) and non-climatic (area under wheat, fertilizer and improved seed quantity used, and price of wheat output) variables, an ARDL model was estimated and tested for fitness. Following existence of *long-run* cointegration, an ARDL approach with lag length of (1, 1, 0, 0, 0, 0.0.0) model was used to estimate *long-run* elasticities of wheat output supply with respect to climatic and non-climatic variables. The estimated ARDL regression model for supply response of wheat output yielded the best fit to the data series with high values for adjusted R squared (0.977). This implies that 97.7 percent of the variations in wheat output are explained by climatic and non-climatic variables that were included in the model. The Durban-Watson on the other hand showed no evidence of serial autocorrelation.

The estimated long-run elasticities of wheat with respect to climatic and socioeconomic variables is presented in Table 5. The estimated elasticity coefficients show that all climatic variables showed positive relationship with wheat output in the long-run. However, only log CO_2 is statistically significant. The result implies that a 1% rise in the concentration of CO_2 results in an increase of wheat output by 0.58% in the long-run. This study is contrary to the findings of Janjua *et al* (2014), who found that the estimated elasticity coefficient for CO_2 is positive, but statistically insignificant in the long-run.

Similarly, the estimated elasticity coefficients of all the non-climatic variables are positive and have significant impact on wheat output supply in the long-run. The result indicates that a 1% increase in producer price of wheat, area covered under wheat crop, and fertilizer used in wheat production system would increase wheat output by 0.17%, 0.52% and 0.19% respectively. This implies that wheat output is highly responsive to its own price, area under wheat, and fertilizer quantity used on wheat production in the long-run. Fertilizers have dual effect in this case. First they enhance the land fertility and second they increase the growth of plants. Fertilizers, in the long-run would increase land fertility, leading to increased agricultural production. Wheat farmers use natural as well as chemical fertilizers to increase the fertility of their land. Hence, for wheat crop, fertilizers play an important role in increasing production. The results are consistent with those of Chandio *et al* (2019) who found that all non-climatic explanatory variables positively and significantly affected wheat production in the long-run.

In the long run, the impact of area under cultivation on wheat production is positive and highly significant. A one percent increase in area under wheat cultivation would boost wheat production by 0.78 percent. Likewise, the support price is positively and significantly associated with wheat production. It was found that a 1 percent increase in support price would cause 0.12 percent increase in wheat production. Similarly, wheat production would enhance by 0.19 percent due to a 1 percent increase in fertilizer consumption in the long-run.

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Table 5: Estimated *long-run* elasticities of wheat output with respect to climatic and non climatic variables

Variable	Elasticity	Std. Error	T-Ratio	P-value
Constant	-9.55289*	5.50035	-1.73678	0.0938
lnPriWh	0.17070**	0.07593	2.24807	0.0329
lnArWh	0.52473***	0.16153	3.24847	0.0031
lnFertWh	0.18901**	0.07968	2.37200	0.0251
lnTemp	1.98947	1.26591	1.57157	0.1277
lnRainbel	0.01749	0.09387	0.18628	0.8536
lnRainmeh	0.09343	0.23313	0.40074	0.6918
lnCO_2	0.58011**	0.27751	2.09043	0.0461
R-squared	0.982848	Mean dependent variable	2.68240	
Adjusted R-squared	0.977130	S.D. dependent variable	0.66353	
S.E. of regression	0.100344	Akaike info criterion	-1.53497	
Sum squared resid	0.271858	Schwarz criterion	-1.09959	
Log likelihood	38.39702	Hannan-Quinn criteria	-1.38148	
F-statistic	171.9039	Durbin-Watson stat	2.18081	

*, ** and *** implies 10%, 5% and 1% significance level respectively.
Source: Authors Computation using Eviews 9.

The *short-run* elasticities were also estimated using the ARDL Approach Dynamic Error Correction Term model and presented in Table 6. The short-run estimated coefficients indicate that the elasticities of log area under wheat cultivation in zero order, log price of wheat in first lag order, and log fertilizer quantity used in zero order have positive and highly significant effect on wheat production. The results indicate that a 1 percent increase in area under cultivation, lagged price of wheat, and fertilizer quantity used raises wheat production by 0.45%, 0.18% and 0.16% respectively. This study result is analogous with the study findings of Chandio and Jiang (2019), who in their study on nexus between wheat support price and wheat production in Pakistan found that wheat incentive price, area under cultivation and fertilizer consumed have positive and highly significant effect on wheat production in the short-run. The empirical findings indicate that a 1 percent increase in area under cultivation raises wheat production by 0.87 percent. Similarly, a 1 percent increase in support price of wheat boosts wheat production by 0.13 percent while a 1 percent increase in fertilizer consumption enhances wheat production by 0.21 percent.

Further, the elasticities for all climatic variables showed positive relationship with wheat production in the short-run. However, the elasticities are statistically insignificant, except CO_2. The estimated elasticity for CO_2 in zero order difference has positive and significant effect on wheat production. The result indicates that a 1% rise in CO_2 concentration increases wheat output by 0.5 percent in the short-run. This finding is consistent with the study result of Onour (2019) who found that using Sudan data, a change in CO_2 has a positive and significant impact on cereal yield in Sudan in the short-terms. The result indicates that a 1% increase in carbon dioxide increases cereal yield by 3% in the short-term.

Table 6: *Short-Run* Elasticities for Wheat Dynamic ECT Model

Variables	Elasticities	Std. Error	t-Statistic	Prob.
C	-8.23183*	4.76654	-1.72700	0.0956
ECT_{t-1}	-0.86171***	0.16050	-5.36891	0.0000
D(LNWHO(-1))	0.13829	0.16050	0.86161	0.3965
D(LNPRIWH)	-0.03318	0.09214	-0.36008	0.7216
D(LNPRIWH(-1))	0.18027**	0.08515	2.117212	0.0436
D(LNARWH)	0.45216***	0.13643	3.314142	0.0026
D(LNFERTWH)	0.16287**	0.08022	2.030173	0.0523
D(LNTEMP)	1.714348	1.07260	1.598311	0.1216
D(LNRAINBEL)	0.015068	0.08104	0.185939	0.8539
D(LNRAINMEH)	0.080506	0.20140	0.399730	0.6925
D(LNCO2)	0.499884*	0.28105	1.778625	0.0866

*, **, and *** implies significant at 10%, 5%, and 1% level.
Source: Authors' Computation using Eviews 9

4. CONCLUSION

The objective of this study was to examine nationally aggregated supply response of wheat output to climate change in Ethiopia. Autoregressive Distributed Lag (ARDL) model was used in this study in order to check the impact of climate change on wheat production in Ethiopia. The study used time series data of the last 38 years. The results of estimated elasticity coefficients revealed that all climatic variables have positive impact on wheat output in the long-run, but only log CO_2 is statistically significant. In the short-run, the elasticities for all climatic variables showed positive relationship with wheat production. However, the elasticities are statistically significant only for CO_2. The estimated elasticity for CO_2 in zero order difference (current year) has positive and significant effect on wheat production.

The estimated elasticity coefficients of all the non climatic variables such as price of wheat, area under wheat, and fertilizer consumed are all positive and have significant impact on wheat output supply in the long-run. The result implies that wheat output is highly responsive to its own price, area under wheat, and fertilizer quantity used on wheat production in the long-run. The short-run estimated coefficients indicate that the elasticities of log area under wheat in zero order, log price of wheat in first lag order, and log fertilizer quantity used in zero order have positive and highly significant effect on wheat production. The study implies that wheat output is highly responsive to previous year's price, land currently put under wheat production, and fertilizer consumed in current year.

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Statement of Data Availability

The data used for this study can be made available upon request provided there is going to be compliance with the owners' policy concerning sharing.

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