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An Augmented Cobb-Douglas Production Function Modeling of the Impact of Climate Change on Maize Yields in Ethiopia

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ABSTRACT

Climate change remains a major problem confronting agricultural productivity in Ethiopia. Maize and some other cereal crops are susceptible to climatic parameters. This study analyzed the impacts of some climatic variables on the yields of maize crops in Ethiopia using the 1981-2018 dataset. Maize production in Ethiopia is adversely affected by climate change. The augmented Cobb-Douglas Production function was used for data analyses. The results showed that the parameters of long-season rainfall, short-season rainfall, and mean maximum temperature show a negative sign and are statistically significant ($p<0.05$). In contrast, the minimum temperature shows a positive sign. In addition, the parameters of the quantity of fertilizer and improved seed used in maize production have a positive and significant impact on the yields of maize ($p<0.10$). However, the land area's elasticity coefficient shows a negative and statistically significant sign. It was concluded that changes in climatic parameters, such as an increase in short-season and long-season rainfall and an increase in maximum temperature, would reduce maize productivity. Therefore, utilizing effective climate change adaptation measures promises to enhance maize productivity in Ethiopia.

INTRODUCTION

Globally, climate change portends significant challenges to agricultural productivity since the past few decades. There are now incidences of catastrophic and extreme climatic problems in many regions of the world (Sorecha et al., 2017; Jesse, et al., 2018). Many of these events occur as covariate shocks with indescribable productivity losses among farming households.

Although African smallholder farmers are particularly vulnerable to several production shocks, climate change portends a deepening negative influence on the sustainability of the agroecosystems of several African

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specifically, the high variability of seasonal rainfalls in some East African countries has made production decision-making by farming households a challenging task, given their low adaptation and mitigation capability (Belay et al., 2017; Nicholson, 2014).

Belay et al., (2017) and Nicholson (2014) indicated that increasing temperature and decreasing rainfall would significantly reduce agricultural outputs, affecting food supply and households' food security. There have been reliable projections on the expected negative impacts of climate change in many developing countries. Such consequences are expected to reflect in land degradation culminating in arable land availability constraints, declining crop yields, and exposure to other environment-related hazards and idiosyncratic shocks (Bell et al., 2018). The refluxes of the environmental impacts of climate change on several ecosystems and ecological indicators also manifest as health challenges among many households (Gardi et al., 2022). Different places experience the impacts of climate change differently and growth and yield responses also vary from crop to crop (Destaw and Fenta, 2021).

Although the major concerns of climate change are largely expressed from global warming, the responses of crops to variability in temperature can differ from one agro-ecological zone to another (Gohari et al. 2013; Msowoya et al., 2016).

However, there is a consensus among policy makers on the long-term consequences of climate change from the perspectives of poverty (Rao et al., 2017), food and nutritional insecurity (Bilali et al., 2018) and environmental degradation and biodiversity losses (Kapuka and Hlásny, 2021). The spectrum of climate change associated problems can be particularly high for ecologically fragile countries (McElwee, 2021).

Cereal crops are generally sensitive to changes in some climatic parameters. Maize cultivation is affected by extreme climate changes in most of Sub-Saharan Africa (SSA). It has threatened agricultural production potentials, there by affecting food security as most maize production in SSA is rain-fed (Bjornlund et al., 2020). Ethiopia ranks third as one of the largest producers of maize in Eastern and Southern Africa (Central Statistics Agency [CSA], 2018). The crop is grown mainly in the long-season rainfall (June-September) rainfalls, while it can also grow during the minor rainy season (January-May) with supplementary irrigation. Fluctuations in rainfall affect maize production in Ethiopia because the crop requires a comparatively high amount of rainfall that ranges between 500 – 800 mm and a relatively longer growing period of 125-180 days (Edao et al., 2021).It should be noted that although Ethiopia’s sub-humid regions account for the bulk of maize outputs, dry regions also record some outputs (Alemu, et al., 2014).

Maize cultivation and

productivity in Ethiopia have been significantly affected by climate change, which manifests as seasonal droughts due to inadequate rainfalls and an increase in average temperature (Abera, et al., 2018; Keno, et al, 2018). This condition is essentially pathetic given that although average global yield of maize was 5.8 tons/ha in 2017-2019 (Erenstein et al., 2022), Ethiopia recorded 3.6 tons/ha. Therefore, the fact that maize yields in Ethiopia are far lower than the expectations cannot be overemphasized (Ngoune, Tandzi & Mutengwa, 2019). More importantly, farmers are only getting about 30% of their expected yields, given a projection of 12.5 t/ha yield potential for maize in Ethiopia by the Global Yield Gap Atlas (GYGA, 2019; van Dijk et al., 2020). Therefore, there is a need to study the effects of climate change on maize yields in Ethiopia, which is the objective of this paper.

METHODS

Methods of data collection

The time series data spanning the 1981-2018 production periods were used for this study. The data were on weather parameters, yields of maize, maize land areas, other relevant input variables, and price. The climate data for average annual temperatures and precipitations were collected from Ethiopia's National Meteorological Agency (NMA) database and archives. The data were average of monthly rainfall data for the short-season (February to May) and long-season cropping season (June to September) obtained from the NMA database. Also, minimum and maximum temperature data for crop growing season (February to September) were obtained from the NMA database. The weather data were collected from thirteen weather stations and summarized by finding their annual averages (Central Statistical Agency [CSA, 2019). The selected weather stations were in the major maize producing regions in the country. Specifically, these districts were found in the two major maize producing regions that account for nearly 78.3 percent of maize land areas and account for 80.4 percent of total maize production in Ethiopia. In addition, nationally aggregated data on land area cultivated to maize, maize yield per hectare, fertilizer and improved seed applied in maize cultivation, and area irrigated land areas under maize crop were mainly compiled from several publications of the CSA. The non-climatic variables such as land areas, fertilizer, and improved seed data were aggregations of inputs used during crop growing season which match with pooled and aggregate climatic factors occurred during crop growing periods. Observed data gaps in some of these variables were provided by the Food and Agriculture Organization (FAOSTAT) database (FAO, 2021). Furthermore, other relevant data such as output prices were collected from Ethiopia Grain Trade Enterprise, National Bank of Ethiopia, and FAOSTAT databases (FAO, 2021).

Ethiopia Grain Trade Enterprise, National Bank of Ethiopia, and FAOSTAT databases (FAO, 2021).

Empirical Model Specification

In this study, the effect of climate variables (rainfall, temperature, and emission of CO2) and other variables on the yields of the maize crop was analyzed using the augmented Cobb-Douglas Production Function. This data analysis method is essential because it can estimate the parameters of multiple aggregated inputs in aggregated yield data. It also permits the statistical testing or validation of the parameter estimates and allows forecasting of future climate and yields factors (Kotulič and Pavelková, 2014; Onofri et al., 2019). Maize yield refers to the number of maize outputs per hectare. The relationship between maize yields and climatic variables is non-linearly modeled in line with production theory. The model assumes that agricultural production is a function of many variables like cultivated land area, irrigated land area, fertilizers, etc. The production function can be expressed as:

$$lnY_t = \alpha_0 + \beta_1 lnLa_t + \beta_2 lnFert_t + \beta_3 lnIS_t + \beta_4 lnCGSRain + \beta_5 lnIrrga_t + \beta_6 lnSSRain_t + \beta_7 lnLSRain_t + \beta_8 lnMinTemp_t + \beta_9 lnMaxTemp_t + \beta_{10} CO_{2t} + \varepsilon_t \quad .1$$

In equation, lnY_t is the natural log of yield of maize crop (kg per hectare), $lnLa_t$ is natural log of cropped land area under maize crop, $lnFert_t$ is natural log of fertilizer used under maize crop, $lnIS_t$ is natural log of improved seed used under maize crop, $Irrga_t$ is the natural log of irrigated area under maize crop, $lnSSRain_t$ is the natural log of *short-season* rainfall, $lnLSRain_t$ is the natural log of *long-season* rainfall, $lnTempMin_t$ is the natural log of annual minimum temperature and $lnTempmax_t$ is the natural log of the annual maximum temperature recorded during crop growing period, $lnCO_{2t}$ is the natural log of CO_2, t = time period from 1981 – 2018, α_0, β_1 to β_9 are the parameters to be estimated, and ε_t is the stochastic error term. Since this study used time series data, it was necessary to examine the series for stationarity and co-integration using some appropriate econometric methods. Towards this end, the testing techniques proposed by Nkoro and Ukohe (2016) as modified from Augmented Dickey-Fuller (ADF) and Philip-Perron (PP) testing techniques were used. The first testing technique equation can be specified as:

$$\Delta Y_t = \mu + \beta_t + \gamma Y_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta Y_{t-1} + \varepsilon_t \quad .2$$

In equation 2, μ stands for the intercept, time trend is t, number of lags is i (ΔY_{t-i}), p is the maximum number of lags which is to be determined using Akaike Information Criterion (AIC) and Schwartz Criterion (SC) and ε_t is the stochastic random error term. The tested null hypothesis is H_0: $\gamma = 0$ (unit root) while the alternative hypothesis is H_A: $\gamma < 0$ (no unit root).

Conclusions with ADF will be made to either accept or reject the null hypothesis. Precisely, the null hypothesis with the accepted (rejected) if the computed statistics is higher (lower) than the critical table value. A series that is stationary at level is denoted as I(0) while the series showing stationarity at first difference is denoted I(1) (Nkoro and Ukohe, 2016). Alternatively, the second test can also beused to conclude on the presence of unit root in the date series. The test is of the form:

$$\Delta Y_t = \theta_0 + \sum_{i=1}^{m} \delta_i \Delta Y_{t-i} + \varepsilon t \quad .3$$

In equation 3, ΔY_t denotes the first difference of the series; I denotes the number of truncation lags, where *i×7, 2,…, m*; θ and δ are coefficients and ε_t denotes the stochastic error term.

RESULTS AND DISCUSSION

Time Series Unit Root Tests

Unit root, cointegration and related diagnostic tests were performed before estimation of the Cobb-Douglas Production equation.

Table 1. Time Series Unit Root Test Results for Maize Yield and Related Independent Variables

Variables	Type of Test	Form of Test	P-Value	Conclusion
LNMZY	ADF	Intercept	0.7798	NS
		Trend & intercept	0.6891	NS
		First difference	0.0001	S (I(1))
	PP	Intercept	0.5408	NS
LNARMZ	ADF	Intercept	0.7695	NS
		Trend & intercept	0.0901	NS
		First difference	0.0001	S (I(1))
	PP	Intercept	0.6588	NS
LNIMS	ADF	Intercept	0.9110	NS
		Trend & intercept	0.6941	NS
		First difference	0.0000	S (I(1))
	PP	Intercept	0.9627	NS
LNFERTMZ	ADF	Intercept	0.8719	NS
		Trend & intercept	0.0444	S (I(0))
		First difference	0.0002	S (I(1))
	PP	Intercept	0.9824	NS
LNIRRGARMZ	ADF	Intercept	0.4940	NS
		Trend & intercept	0.4383	NS
		First difference	0.0001	S (I(1))
	PP	Intercept	0.5359	NS

Variables	Type of Test	Form of Test	P-Value	Conclusion
MEANRAIN	ADF	Intercept	0.0000	S (I(0))
		Trend & intercept	0.0000	S (I(0))
	PP	Intercept	0.0000	S (I(0))
MINTEMP	ADF	Intercept	0.0847	NS
		Trend & intercept	0.0040	S (I(0))
		First difference	0.0000	S (I(1))
	PP	Intercept	0.0847	NS
MAXTEMP	ADF	Intercept	0.6878	NS
		Trend & intercept	0.0358	S (I(0))
		First difference	0.0000	S (I(1))
	PP	Intercept	0.0840	NS

Critical val. at 5% sig level; NS- non stationery, S - stationery

Source: Authors' Computation

These were necessary to establish if the series are stationery and to ascertain the order of integration. Table 1 presents the results of the stationarity tests using ADF and PP approaches. The results in Table 1 indicate that at $p<0.05$, the log of fertilizer quantity used, log of mean rainfall in maize growing areas, and log of minimum and maximum temperatures were stationery at levels - I(0). However, the remaining variables were I(1). In order to avoid spurious results, and since the variable are mixture of I(0) and I(1), Auto-Regressive Distributed Lag (ARDL) model was used. However, for ARDL to be applied, two conditions must be satisfied. The first is that the dependent variable must not be I(0) and none of variables must be I(2). Cobb-Douglas production model can also be suited to mixture of I(0) and I(1) provided similar tests are conducted as ARDL model (Wooldridge, 2016). The estimated model was also examined for parameter stability using the VAR stability test, serial correlation (LM), multicollinearity test, heteroscedasticity, Wald F-statistic, stability and RESET Test. We tested for cointegration and the results showed presence of cointegration (see Table 2). The results also demonstrated presence of a long run relationship among the selected variables in the estimated models. It is, therefore, possible to estimate the log-run coefficients for the crop yield model.

Table 3 presents the results of normality, serial correlation and heteroscedasticity tests that were carried out on the residuals of the log of maize yields. Based on Jarque Bera test, it was confirmed that the residuals are normality distributed. Also, Breush-Godfrey Lagrange Multiplier (LM) test confirmed absence of no serial correlation in the residuals. LM test also confirmed the absence of autoregressive

Table 2. Result of Cointegration Test for Maize Output Data Series

Type of Test	Test Statistic	Critical Values	Conclusion
Wald Test	4.4477**	4.145	Long run cointegration exists

** implies significant at 5 % level

Table 3. Residual Properties of Maize Output Response Equation

Type of test	Test statistic	Test statistic	Probability
Normality test-histogram	Jarque Berra	0.6419	0.7254
Breusch-Godfrey Serial Correlation LM Test	Obs*R-squared	2.18476	0.3354
Heteroskedasticity Test: ARCH	Obs*R-squared	3.72449	0.0536

Table 4. Ramsey Reset Tests Results for Maize output

Dependent variable	F statistic	Probability	Conclusion
Log of maize output	3.34726	0.0780	No indication of misspecification error

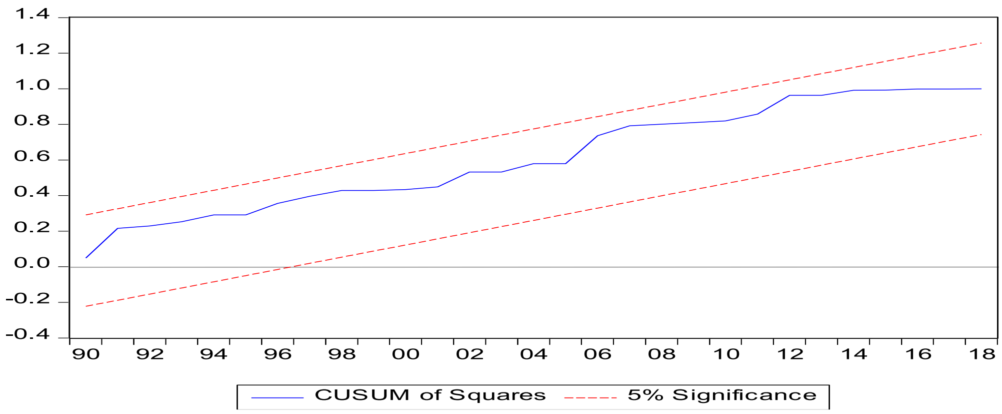

Figure 1. Recursive Residuals from the Maize Output Response Equation

conditional heteroscedasticity (ARCH).

In addition, Ramsey Reset test was carried out to confirm that the models were properly specified (see Table 4). In order to test for stability of estimated parameters, recursive coefficient tests were carried out. Figures 1 shows little divergence in all the plotted graphs. This implies estimated parameters are sufficiently robust.

Impact of Climate and Socio-Economic Variables on Yield of Maize

The explanatory variables included in the model are in their logarithmic form in order to provide convenient economic interpretations (elasticities) and to reduce heterogeneity of the variance. In the estimation of Cobb-Douglas production function, mean rainfall of growing season (F-S), *short-season* rain, *long-season* rainfall, mean minimum and maximum temperatures (Feb-Sept), and CO2 emission were included. From the socio-economic variables, the improved seed used, land area harvested, and irrigated area under maize cropping system were included in to the maize yield model. On the other hand, quantity of fertilizer used in maize production was tried to include in the model, but dropped since it exhibited high correlation with land area and maize yield data series. The quadratic form of climate variables were also considered for inclusion into the yield model, but excluded because of multicollinearity.

In this study, the maize yield model has been estimated by employing ordinary least square technique. The estimated coefficients of the Cobb Douglas functional model were significant as the F-value indicated that the overall regression model was fitted good and followed normal distribution for the present data. The adjusted R^2 values of 0.726 in the estimated maize yield model implies that 72.6 percent of the variations in maize yield model are explained by climate variables [mean rainfall (Feb-Sept), short-season rainfall and long-season-rainfall, mean minimum temperature and mean maximum temperature], fertilizer and improved maize seed consumed, and land area and irrigated area under maize cropping system. This indicates that only 27.4 percent of the variations in the maize yield are explained by other variables not included in the yield model.

The result of coefficient estimates of maize yield regression model is presented in Table 5. The estimated elasticity coefficients show that the climatic variables included in the model, except CO_2, showed negative relationship with maize yield, which are in line with the expected result. The elasticity coefficient of maximum temperature during crop growing period (February to September) is negative and significant at 10 percent level of significance. This implies that a 1% increase in maximum temperature during crop growing period diminishes maize yield by 3.09%, which is in line with the theory proposition. In practice, an increase in temperature above the optimum level during crop development phase will reduce the growth of shoots and roots of maize plant. High temperature also affects the flowering and grain filling process of crops, particularly maize crop (Waqas, et al. 2021). Air temperature above 35^0C suppresses maize ovary fertilization and the grain filling process, which is directly associated with the final grain yield. From this, it can be concluded that maize crop is very sensitive to high temperatures that are beyond optimum level as well as to the shortages in rainfall during the crop development process. This result is consistent with the study results of Chowdhury and Khan (2015) who in their study on the impact of climate change on rice yield in Bangladesh, found that maximum temperature has negative (-4.95) and significant (10% level) impact on the yield of rice. Kumar et al. (2015), in their study on the effects of climate change on the productivity of crops, also reported a negative influence of average rainfall (-0.0212) and average maximum temperature (-0.224) on the yield of the potato crop. However, only average rainfall was significant at a 1% level. They further reported that the average minimum temperature has a negative (-0.756) and significant (at 5% level) impact on cotton yield.

The elasticity coefficients of mean rainfall (F-S), short-season rainfall (F-M), and long-season rainfall (J-S) are all negative. However, only the elasticity coefficients for crop growing season mean and short season rainfall are statistically significant at 1 percent and 5 percent levels, respectively. The result signifies that a 1% increase in crop growing mean rainfall and short-season rainfall reduce maize yield by -0.79% and 0.43%, respectively. This effect may occur due to two extreme events which are excessive crop season rainfall and deficit rainfall. Excessive rainfall during crop growing season

Table 5. Estimates of Cobb-Douglas Production Function from maize yield model

Explanatory Variables	Coefficients	Expected sign	Std Errors	T-Ratio	P-Value	VIF
(Constant)	15.7269					
lnMzAr	0.531***	Positive	0.1826	2.905	0.0068	5.291
lnMzIS	0.290**	Positive	0.1307	2.219	0.0342	4. 838
lnIrrigMzAr	-0.0759	Positive	0.1081	-0.702	0.4885	3.878
lnCGSRain	-0.787*	Negative	0.4613	-1.706	0.0983	1.165
lnShort-Season	-0.4292**	Negative	0.1607	-2.670	0.0127	1.688
lnLong-Season	-0.2729	Negative	0.4084	-0.668	0.5097	1.595
lnMin-	-0.6395	Negative	0.8421	-0.759	0.4536	3.238
lnMax-	-3.0888*	Negative	1.6447	-1.878	0.0701	2.241
lnCO_2	0.1944	Negative	0.1677	1.159	0.2565	4.709
R^2	0.778					
Adjusted R^2	0.726					
F-ratio	15.017***					
Sample Size	38					

*** Significant at 1%, ** significant at 5% and * Significant at 10%
Source: Author’s computation

decreases maize yield significantly in more excellent areas in conjunction with poorly drained soils. Such yield loss gets exacerbated under high preseason soil water storage. Low or deficient rainfall associated with drought also decreases maize yield due to water deficiency and concurrent heat, with more significant yield loss for rain-fed conditions (Li et al., 2019). The result of this study aligns with the outcome of the research on the association between climate change and rice yield conducted by Chowdhury and Khan (2015). They have examined the effect of changes in climate on yield of rice in Bangladesh and reported that the crop season rainfall demonstrated negative and significant (at 10% level) impact on rice yields. As such, the result patently evinces that a 10% increase in crop season rainfall reduces rice yield by 1.83%. Oppositely, the elasticity coefficient estimates of area cultivated under maize crop exhibited positive and significant (at 1% level) impact on yield of maize, which supports the theory. The result signifies that a 1% increase in area cultivated under, maize crop boosts maize yield by 0.53%. Conversely, irrigated area under maize crop cultivation had negative impact on maize yield, but statistically non-significant. Furthermore, improved maize seed showed positive and significant (at 5% level) impact on yield of maize, indicating that an increase in use of improved maize seed would increase yield of maize by 0.29%. Summing up all the elasticity coefficients of explanatory variables included in the maize yield Cobb-Douglas model, the result becomes -3.639. This shows existence of decreasing returns to scale in maize crop production business in Ethiopia.

CONCLUSION AND SUGGESTIONS

This paper analyzed the impact of climate variables and other selected input variables on Ethiopia's maize crop yields. The study revealed that all climatic factors, except CO2, among the climate-related variables, maize yields were negatively influenced by all climatic factor, except CO_2. CGSR, short-season rainfall and maximum temperature had negative and significant impact on yield of maize crop. This implies that the short season rainfall is the main climatic factor affecting yield of maize because shortage of rainwater during this season affects seedbed preparation, sowing of seed, and even wilting of emerged seedlings. In addition, other input variables such as improved seeds and land areas had positive impact in increasing yield of maize. It can be concluded that persistent variability in some climate parameters has some grievous implications on Ethiopian maize productivity. Therefore, efforts to address the negative influences of climate change on maize production beckons on introduction of adequate adaptation strategies that considers rising temperature and seasonal rainfall variability. Such efforts can be pursued through provision of local weather information and routinely executing early warning services. In addition, Ethiopian research agendas should prioritize developing drought-resistant maize varieties along with the conscientious provision of fertilizers.

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