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Time Series Regression Analysis on Effects of Climatic Change and Variability on Production and Yield of Bean, Sweet Potato and Cassava Crops in Kenya

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Abstract

There is a much uncertainty in the prediction of production and yield for cereal and tuber crops in Kenya. These uncertainties can only be addressed and mitigated with the aid of accurately developed parsimonious statistical models which encompasses several important predictive variables. In this paper the effect of climatic factors and rural population on the production and yield of important food crops grown by poor households in Kenya are investigated. Secondary time series data on climate change factors, population, crop production, and yield were used in the study. The data was recorded from 1961 to 2020, obtained from (FAO, 2020) and (NASA, 2020). In addition, temperature and other climatic data were collected from Climate Change Knowledge Portal (2020). Time series regression model building approach was used in the analysis. First, all the variables were tested to find if they were stationary. In case the data was non-stationary, transformation methods of differencing, logarithm or the ratio method was applied. The study found that there was a strong correlation($r=0.9017$) between the rural population and the carbon dioxide emission. In the case of sweet potato, the four significant factors that affected production were floods (p-value=0.006), rural population (p-value=0.000), area under harvest (p-value=0.002) and drought (p-value=0.031). The sweet-potato-regression model had the highest predictive power, 82.4 percent. For beans, only one factor, the area under harvest (p-value=0.000) was significant; while for cassava, the only two significant factors were: area under harvest (p-value=0.001) and the cube-area under harvest (0.000). The significance of the area under harvest being a major factor pointed to lack of technology adoption by the small household farmers. The

study recommends that farmers should plant larger acreages of crops, employ technology, and adopt measures that can mitigate against incidences of drought.

Keywords: Time series mode1, rural population, stationarity, technology

Introduction

The Agricultural sector is a major backbone of Kenya's economic development. Agriculture contributes about 25 percent of Gross Domestic Product (GDP). It is the main source of food availability at the national level, and a primary source of livelihood for poorest households. Of the 70 percent of the population living in rural areas, 80 percent are dependent on rain-fed agriculture as a source of food and income (FAO, 2015). The area under agricultural crop cultivation is about 20 percent of the total land. Kenya has a structural production deficit for several staple food crops. Cereal imports have increased steadily in recent years, driven primarily by population growth and urbanization, (Kenya Food Security Brief, 2013). Agricultural productivity has been on the decline at a rate of 21.41 percent annually (Agesa et al., 2019). Understanding crop yield plays a major role in determining the overall annually production as well as crop prices.

Despite a few cases of intermittent increase in crop production and yield, agricultural development has faced numerous challenges including vulnerability to weather and climate related shocks, limited access to inputs by many farmers, pests and diseases, and lack of credit. Climate variability adversely impacts crop production and imposes a major constraint on farming, mostly under rain-fed conditions, across the world (Bannayan et al., 2011). The yield potential of a crop primarily depends on climate (TNAU, 2016). More than 50 percent of the variation in crop production is attributed to climate change and variability. Climate change has thus become the most important development and global governance issue in the 21st century (African Development Bank, 2010). Sidan et al. (2021) concluded that the impact of human-caused environmental pollution and global climate change on the economy and society can no longer be underestimated. They stated that Agricultural sector is the worst sector affected by climate change. The most important climatic factors that influence growth, development, and yield of crops are solar radiation, temperature, and rainfall.

The impact of climate change will pose a significant challenge to agricultural productivity, as the frequency of drought is expected to increase in occurrences and magnitude. Agricultural droughts are related to the availability of water for crops although some crops can withstand the reduced soil moisture conditions for a long duration, for example sesame, cassavas, and potatoes, while others dry up immediately there is a reduction in soil moisture. The Arid and semi-arid lands carry 30% of the country's total human population yet they are characterized by uncertainty of rainfall and high transpiration rates. The climate change may result in temperature variation, unreliability of amount and frequency of rainfall, floods, and droughts and high levels of carbon dioxide emissions.

Approximately 70 percent of Kenya's land mass is affected by drought, which may be extreme weather and climate events. Kenya experiences drought on a cyclic basis. The major ones coming every ten years and the minor ones happen almost every three to four years (Kenya National Disaster Profile, 2004). Severe droughts have been recorded in ten-year cycles in Kenya. These were experienced in 1974, 1984, 1994, and 2004. The 1983-84 and the 1999-2000 droughts were the most severe. After the El Nino rains of 1997 and 1998, prolonged droughts were experienced in many areas parts of Kenya leading to famine and starvation, (Kenya Natural Disaster Profile, 2004). From the aforementioned, it is evident that Kenya has been hit by repeated severe droughts. The drought cycle has become shorter, with droughts frequency and intensity increasing due to global climate change and environmental degradation. The cycle has reduced over the years from every ten years to every five years, and recently to about 2-3 years.

Essential for growth and development, optimum temperature is required for maximum dry matter accumulation and high night temperature growth of shoot. High temperature adversely affects mineral nutrition, shoot growth, and pollen development resulting in low yield. Crop growth and development is mainly a function of temperature if water is available in required amounts. Although weather and climate have always experienced changes either positive or negative, recent atmospheric warming is unprecedented (Rasul et al., 2011).

The changing climatic pattern has also resulted in severe flooding. Floods cause a lot of losses in Kenya, especially because they have become a perennial problem and seem to weaken the

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communities' ability to cope with it. This has been evident in parts of Western, Nyanza, and Tana River areas. It has led to the witnessing of destruction of crops and decline in agricultural production levels. The National Climate Change Response Strategy (NCCRS), (2010); National Climate Change Action Plan (NCCAP): 2013-2017; Government of Kenya (2010), and Climate Change Act 2016- Government of Kenya (2016); were documented to respond to the impacts in order to achieve national and global economic plans such as Medium-Term Plans, Vision 2030, and Sustainable Development Goals.

Other factors that affect production include carbon dioxide emission and population size. Carbon dioxide emission enhances climatic change, which poses a threat to food security (Ayyildiz & Erdal, 2021). The emission is caused by agricultural production activities. They stated that livestock breeding contributes more to carbon dioxide emission than agricultural production. They recommended the examination of the relationship between agricultural production and carbon dioxide emission to aid countries develop carbon dioxide emission-reducing measures. In addition, countries need to adopt agricultural production methods that minimize the positive association between vegetative and livestock production. Muyanga and Jayne (2014) studied the effects of rising rural population density on smallholder agriculture in Kenya using panel data. They developed a structural model for estimating the impact of population density on among other things for 1997 and 2010 on agricultural intensification. Generally, total household income per adult equivalent was found to decline significantly as population density rises.

Kenya produces a wide range of crops categorized into cereals, and pulse crops. The cereals and pulse crops include: maize, wheat, rice, sorghum, millet; beans, chick pea, beans, cow pea, and green gram. The other type is the roots and tuber crops, namely potatoes, cassava, yams, sweet potato, oil crops (ground nuts, sunflower). The main cash crops include tea, coffee, sugarcane, pyrethrum, and sisal. Kenya also produces several horticultural crops as well as flowers, both for consumption and also for export. Besides commodity crops, Kenya also produces a wide variety of seeds (Oseko & Ndienya, 2015, pp 19, 20).

The bean is a major source of protein for most farm households in Eastern and Southern Africa. Bean farming in Kenya is mostly practiced in Central, Nyanza, Eastern, and some parts of Western

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Kenya. Most farmers regard bean as a super crop because it is a good nitrogen source. It is often inter-cropped with the main crop such as maize for maximum absorption of nutrients. Bean require soil that is evenly moist soil for plant growth and production. A season which is dry can be remedied with supplemental water application from a drip hose. Dry soil can stunt plant growth or kill the plant. Too much water can also be detrimental. It can result in plants that are deformed or diseased with a fungal growth. That aside, excess rainfall may wash away soil nutrients or fertilizer before the plants have time to absorb them. The use of organic compost into the soil before planting improves the soil's water drainage and increases the nutrient value for better growth. It is regarded as a warm weather plant, grown especially in the spring. The soil temperature should not be above 60 degrees Fahrenheit. Bean will not germinate if the temperatures are too cool. Its consumption in Eastern and Southern Africa exceeds 50 kilograms per person per year (FAO, 2019).

Cassava (*M. esculenta*) is the main crop produced in Africa, contributing significant energy to the population, with an average 196 kcal/capita/day in 2008 (FAO, 2010; Smit and Skinner 2002). It is known for its drought tolerance stressful environments (El-Sharkawy, 2004). From the studies which have quantified the impacts or responses of cassava to climate change, Jarvis et al. (2012) found out that cassava is the crop least affected by climate change compared with other major staples.

Sweet potato (Ipomoea batatas Lam.) is an important food crop with an average per capita consumption of 24 kg per year. Its production and yield can be satisfactory under adverse climatic and soil condition. It gained prominence as a useful crop due to its adaptability to wide production ecologies and yield responses despite minimal external inputs (Sugiri et al, 2017). It also requires low or non-use of external inputs (Nungo et al., 2007). In addition, it is grown in mixed farming systems and takes short periods to mature, thus offering household food security for small-scale farmers. Besides being cooked and consumed as food, sweet potato vines are a good dairy animal feed supplement with high protein content (10 to 15 per cent) and are easily digestible. It has been noted that sweet potato has immense potential to improve household income and nutrition in sub-Saharan Africa (Issah et al., 2017).

Crop yield is used in determining overall production and supply of a crop (Hayes, 2021). It is standard measurement of the amount of agricultural production harvested per unit of land area. The most common units of measurements of yield is bushels per acre or tons per acre. Yield is used to determine how much a farmer or an area can produce. Once the total yield is known, and the acres planted, the total production of an area can be calculated. Ochieng et al. (2016) found that climate variability and change affect agricultural production with different impacts across crops. Further, they found that for tea, temperature has a negative effect, whereas rainfall has a positive effect. They also found that temperature has a greater impact on crop production than rainfall. Agesa et al. (2019) undertook a study on effects of climate change on crop production in Yatta sub-county. They found that most farmers in the region were aware of climate change (98%), and moderately uncertain low rainfall (50%), below average about drought (33%), and rising few about temperatures (14%). Several data types and models have been used to study crop production and yield. Schlenker and Lobell (2010) used panel data which combined historical crop production and weather to predict the drop in yield of five stable food crops. Anyaegbu et al. (2023) analysed the impact of climate change using Autoregressive Distributed Lag Bound approach and Error Correction Model.

This study aimed at developing parsimonious models for prediction of crop production and yield. The investigation of climatic variables and natural disasters is essential because inherent structures and patterns identified may be used in policies and decision making to curb the negative effects of climate change and variation in the environment.

Statement of the Problem

There is much uncertainty on the effects of climate change and variability, and rural population on crop production systems. These uncertainties can be addressed and mitigated using accurately developed parsimonious statistical models based several important predictive variables. However, the predictive power of the models developed for crop production and yield have been limited since these models have omitted important variables in their study. Most of the studies have ignored the effects of drought and floods in predicting production and yield of crops. The studies have also focused mainly on a single crop. Further, time series regression models have not been developed for analysing crops like cassava, sweet potatoes, and even bean for the Kenyan case. In modelling, the transformation used for achieving stationarity was based only on differencing and logarithmic transformation, and these again have been found inadequate in some cases.

This study has not only used the two methods of transformation, but included one based on the ratio of the consecutive values of the series. Therefore, this study has used more variables for prediction of crop yield and production. Their effects have also been analysed. The study focused on; assessing the effect of climate change factors on the production of beans, cassava and sweet potatoes in Kenya, investigating the effect of rural production on beans, cassava and sweet potatoes in Kenya and determining the effect of area of production on the production of beans, cassava and sweet potatoes in Kenya. Previous studies have shown that, mathematical modelling of crop production are invaluable tools for predicting crop growth and development, thus informing agronomic interventions (Tsuji et al., 1998). Crop models have been used globally especially in China and Africa, and to a less extent in Kenya. These models have been based on several factors that affect crop production and yield. These factors include: carbon dioxide emission, technical development, economic market, human planting behaviour, and fertilizer consumption, and annual-rainfall, price at harvest, humidity, and rural population. Prediction have also been based on different types of models and types of data collected. These studies have also differed in methodology where secondary or primary data has been used.

The effects of precipitation and temperature on crop production, with other variables incorporated have been studied. The studies include the inclusion of three climate indices as explanatory variables in historically observed rain-fed crop yields (1983–2005) of both barley and wheat in the northeast of Iran (Bannayan et al.,2011). The results revealed differences in the association between crop yield and climatic factors at different locations. The maximum temperature in south of the study area proved to be the key factor for determining crop yields while temperature variability resulted in variability in crop yield. This finding was implicit. In contrast to this, Kasimba (2014) carried out a study in Guruve district, Zimbabwe, on the impacts of climate change on crop production, and included disease. He used primary data. He argued that climate change affects crop productivity as a result of insufficient rains, high temperatures and sometimes too much rain causing crop diseases. The results of this study were more explicit. The study found out that rainfall variability causes decline in crop production. Further, drought, and occasional occurrence of extreme low temperature had the same effects as rainfall while frequent change in climate adversely lowers crop production.

A similar study was done by Mikova et al. (2015) in Rwanda. However, they included other variables such as fertilizer use in their model. In addition, Adamset al. (2015) did a similar study but included new explanatory variables, namely livestock production and carbon dioxide emission. The study found out that climatic factors such as temperature, precipitation change and high amount of carbon dioxide concentration in the atmosphere have greater effect on crop productivity. The findings were collaborated by Kasimba (2014), who revealed that increases in temperature generally reduced crop yields and quality of grains, while increase in precipitation was useful in drier areas for increasing soil-moisture. This study was not empirically explicit on the impact of carbon emission on crop yield. Yila (2023) also studied the impact of droughts, high temperatures and unreliable rainfall crop production in Moyamba District, Southern Sierra Leone. He found that felt that these major adverse weather events contributed significant loss in the yields of the crops cultivated.

Several studies have been conducted specifically on bean, cassava, and sweet potato crops. Mupakati and Tanyanyiwa (2017) assessed the impact of cassava production on rural livelihoods with respect to climate change adaptation strategy. They suggested that cassava has an extensive root system that can penetrate poor soils which may not support crops like maize. Cassava cultivation is not expensive since it can be produced without fertilizer. However, fertilizers can enhance yield. Siloko et al. (2021) studied the effects of some meteorological variables on cassava production in Edo State, Nigeria (2021). The study employed the nonparametric statistical approach in investigating the interactions between temperature and relative humidity and their direct effects on cassava production. The study investigated the interactions between temperature and relative humidity and their effects on cassava production for a period of six years which is from 2014 to 2019 in Edo State, Nigeria using kernel method. The results obtained revealed that quality cassava yields annually is associated with higher relative humidity and lower temperature and vice-versa.

A model that included climatic and environmental changes on the yields of bean cultivation in China was done by (Sidan et. al., 2021). The study focused on bean crop since it has the largest supply and demand gap in China. It established a panel spatial error model which included climate environment, economic market, human planting behaviour, and technical development level of 25 provinces in China from 2005 to 2019. The study shows that increase in precipitation has a significant positive effect on bean yield. On the contrary, the increase in temperature has a significant negative effect on bean yield. Carbon emissions do not directly affect bean production, at least presently. They recommended that bean cultivation should be based mainly on the overall impact of environmental changes on its production, rather than technical enhancements such as irrigation and fertilization. There are also studies that have involved livestock production.

Ayyildiz and Erdal (2021) undertook a study on the relationship between carbon dioxide emission, crop, and livestock production indices. They found that rapid increase in carbon dioxide emission triggers climate change which is a threat to food security. They concluded that examining the relationship between agricultural production and carbon dioxide emissions can help countries take emission-reducing measures and develop policies to ensure food safety. It has been reported that a 1% increase in crop production index had effect on carbon dioxide emission only in lower middle-income countries. It could be stated that livestock breeding has a higher effect on carbon emission in agricultural production. Extreme weather events have been witnessed to occur with high frequently and intensity (Yan and Alvi, 2022). These include floods, drought and storm surges which had devastating effect on livestock, crops and food supplies (Godde et al., 2021). Botero and Barnes (2022) reported that the most important climatic risk confronted by common bean production in Colombia is El Niño Southern Oscillation (ENSO) through its two extreme phases, El Niño and La Niña.

Kawaye and Hutchinson (2021) found out that climate change and variability in Malawi have negatively affected the production of maize, a staple food crop. However, they realized that there have been increases in growing area, production, yield, consumption, and commercialization of both cassava and sweet potato. Factors behind these increases include the adaptive capacity of these crops in relation to climate change and variability, structural adjustment programs, population growth and urbanization, new farming technologies, and economic development.

Cassava and sweet potato are seen to have the potential to contribute to food security and alleviate poverty among rural communities.

A study by Dhakal (2018) found that rural population has negatively affected rice production. He observed that inclusion of the predictor variable, area harvested in the model implied low uptake of technology in the agriculture system. However, he advocated for the inclusion of predictors such as fertilizer consumption, annual rainfall, and price at harvest in the model which could have a significant implication. Since the study wanted to use a large time series data, use of fertilizers was omitted since the data was inadequate. Several studies on the effect of climate change on crop production has have been done in Kenya. Muyanga and Jayne (2014) undertook a study to measure how Kenyan farmers and farming systems have responded to changes in population density and associated land pressures. They found out that farm sizes are declining gradually and inversely related to population density. Shrinking farms are associated with increasing land intensification; rural household income per adult declines as population density rises resulting in low productivity. According to Birch (2018), the average farm size is falling and land distribution is becoming more concentrated, leading to significant constraints on production, particularly for smallholders. He observed that inclusion of the predictor area harvested with its respective coefficient in the model implied low uptake of technology in the agriculture system.

Kabubo et al. (2015) studied the impacts of climate change on food security in Kenya and found out that climate variability reduces food security. They argued that high rainfall is necessary for increased crop yield while excess rainfall leads to flooding and water logging which is harmful to crops especially at infancy stage. The major crops such as beans, sorghum, and maize were studied while the climatic variables in the study were precipitation, temperature, and run-off and cloud cover over the years. They recommended that a study that considers the effect of relative humidity as a climatic variable on crop production be done. A slightly different study was done by Ochieng, et al. (2016). They estimated the effect of climate variability and change on revenue of maize and tea crops separately, using a household fixed effects estimator. They found that climate variability and change affect agricultural production with different impacts across crops. They recommended that strategies should be developed to mitigate the likely harmful effects of rising temperatures and increasing rainfall uncertainties.

Further, Agesa et al (2019) undertook studies on climate change effects on crop production in Yatta sub-county. They identified drought, unreliable rainfall, low soil fertility and low soil moisture, as well as pests and diseases (28%), lack of inputs (17%), planting of the wrong type of crop for the region (12%), and lack of funds (7%) as the main reason for the deteriorating performance. They opined that climate change and climate variability have a big impact on crop production in the region. Luedeling (2011) carried out a study on impacts of climate change on crop production in Homabay and Busia counties in the Lake Victoria Basin. He found out that climatic changes had a negative relationship with crop production. He used crop productivity as the response variable while rainfall, temperature and soil type were the independent variables. He concluded that the main climatic factor that affects crop productivity is temperature. This study did not include the soil as a factor because it is for the whole country and based on aggregated annual data.

Gaps in the Literature

From the above literature review, it is evident that no empirical study based on regression model has been undertaken to study the effect of flood and drought on crop production in Kenya, yet flood could have significantly influence on production. Further there is no evidence of predictive regression time series models being developed for beans, sweet potatoes, and cassava. Studies have indicated that cassava has been less studied compared to other crops despite its importance as a food crop in many of the developing countries. In Kenya, most of the studies done on crop production were based on a few particular counties and hence there is need for a study on how climate change affects crop production and yield nationally.

Conceptual Framework of the Study

In this study, a time series regression model was developed. The dependent variables were crop production and crop yield. The explanatory variables included temperature, precipitation, rural population, carbon dioxide emission, and area of production. From the literature review, these are the main factors that explain variation in the dependent variables. The relationship between the variables is indicated in the figure 1. The expected signs can be explained as follows: Increase in temperature has negative effect since it reduces the amount of moisture in the soil. This lowers

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productivity. Carbon dioxide emission leads to climate change that overall leads to floods and high temperature. As the rural population becomes larger, the area under cultivation is reduced. For most crops, high rainfall leads to high production. The higher the area planted the higher the expected output harvested.

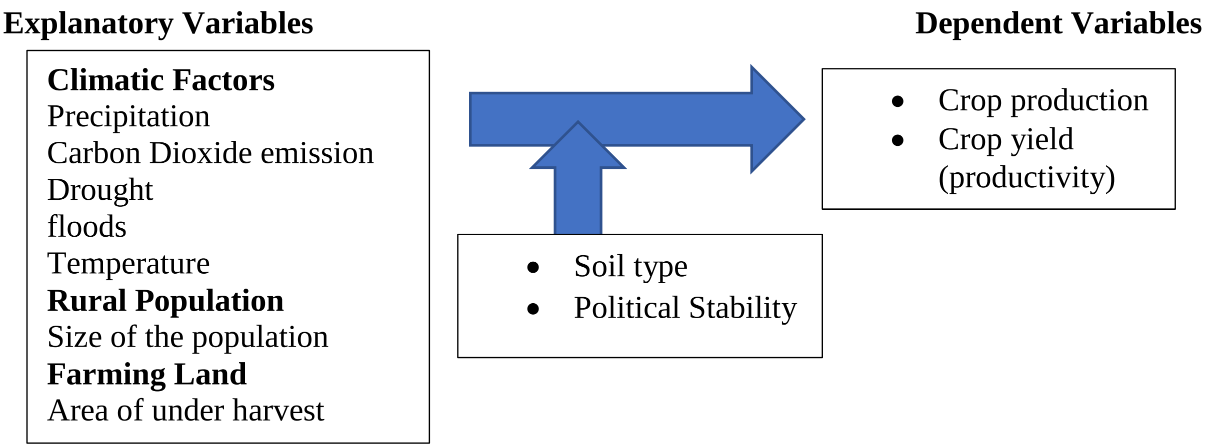

Fig. 1: Conceptual framework of the study (Source: Author, 2023)

Priori signs of the Explanatory variables

From the discussions in the literature, we expect the following signs for the effect of the explanatory variables on crop production and yield.

Table 1: Expected priori signs of predictor variables

Explanatory Variable	Effect on crop yield/crop productivity
Temperature	Negative
Precipitation	Positive
Carbon dioxide emission	Negative
Floods	Negative
Rural population	Negative
Area harvested	Positive

Methodology

Data Collection

A list of five predictor variables obtained from the literature thought to impact on the crops productivity and production were scanned based upon past literature, availability of the data and the researcher's insight were identified. The predictors included precipitation, temperature, drought, floods, rural population, and carbon dioxide. Temperature and precipitation data were obtained from Climate Change Knowledge Portal (2020). Time series data on crop production, area harvested and yield between 1961to 2020 was obtained from (FAO, 2020). Data was also collected on the years when there was flood and drought incidences, declared by the government as a major disaster. An indicator variable was used to model these cases as follows:

Flood = 1, if there was a major flood in the year, and =0, otherwise

Drought =1, if a major drought was reported, and =0, otherwise.

Parsimonious models are simple models with great explanatory and forecasting capability. They explain data with the least explanatory variables (Vandekerckhove et al, 2015). Accordingly, parsimonious models have the right number of predictors needed to explain the model properly. To obtain the best regression model, Draper, and smith (1998) p.327) have mentioned several model building and selection criteria. In this study, we use the adjusted coefficient of determination statistics to discriminate among the possible time series regression models in the selection of a parsimonious model for production and productivity.

Data Analysis

Regression model building procedure was followed in fitting the models. In time series regression, all the time series variables used must be stationary before they are fitted into the regression model. If a variable is not stationary, then a series of transformations may be conducted to make it stationary. The transformation approaches used include differencing (D), logarithmic (Log), or combining both Logarithmic and Differencing, abbreviated as (D.log), or using the ratio of consecutive values of the series (Xt /Xt-1). Once the series is stationary, the dependent variable, productivity, is examined for normality. Stationary test was determined using Dickey and Fuller Unit Root Test. Table1 and Table 2 show the results of the stationary test, the transformation undertaken in case the series was not stationary, and the new stationary variable created. The model was then fitted and diagnostic analysis conducted for normality, heteroscadasticity, linearity, and functional fit.

Results and Findings

Table 2 and table 3 show the results of stationarity tests and transformation performed for the variables used in predicting production and yield of beans, sweet potatoes, and cassava.

Table 2: Climatic factors and population size

Variable	Dickey-Fuller test for unit root-p-value	Remark	Transformation Done	Dick Fuller Test-Pvalue	Remark
Precipitation	p-value =0.0000				
Temperature	p-value=0.0511	Nonstationay	Log_difference _temperature	0.049	Stationary
Carbon (CO2) emmission	P-Value=1.00	Nonstationary	carbon_dioxide emision-difference		Stationary
			Log carbon Emmission	0.000	Stationary
			SQR_log_carbon Emmission	0.000	Stationary
Rural population	1.00	Nonstationary	Log_rural population	0.0000	stationary
			SQR_log rural population	0.0067	Stationary

Table 3: Stationarity: production and yield of bean, cassava and sweet potato crops

Variable	Dickey-Fuller test for unit root-p-value	Remark	Transformation	Variable	Dickey-Fuller test for unit root-p-value
Yield Sweet Potato	0.0375		Log_yield_sweet_potato	0.0000	Stationary
Area of Sweet potato	0.2865	Nostationary	D. Log_Area_sweet_potato	0.0000	Stationary
Production Sweet potato	0.5529		Difference Sweet Potato	0.0007	Stationary
			Difference_sweet_yield	0.0000	Stationary
Production sweet potato			Dlog_production_beans	0.000	Stationary

			Ratio_sweet_potato		stationary
Area_beans	0.8036	Nonstationary	Ratio_area_bean	0.000	Stationary
Productivity Beans	0.0459	Stationary			
Production beans	0.7657	Nonstationary	D.log_production_beans	0.000	Stationary
			Ratio_production_beans	0.000	Stationary
Area_cassava	0.9582	Nonstationary	Dlog_area_cassava	0.0000	stationary
Yield Cassava	0.0000	Stationary	Cassavayield	0.000	stationary
Production Cassava	0.7872	Nonstationary	Cassavaprod	0.0000	stationary

Models for Beans Production and Yield

First, stationarity and normality tests were done for the dependent variables, bean production and bean productivity. Both bean productivity and the transformed bean production (D.log production) were stationary and normally distributed. These variables were regressed on the explanatory variables. The regression model fitted for bean productivity was found inadequate, since there was no significant variable in the model. The ratio of beans production was regressed on the explanatory variables. The model was adequate. A new variable, area of maize was added because beans and maize are always intercropped. The intercropping was represented by the proxy variable, area of maize. In addition, it was also observed that there was very high correlation($r=0.9017$) between rural population and carbon dioxide emission. This was a sign of possible presence of multicollinearity and hence only only one of the two variables, rural population, was retained.

Diagnostic results indicated that the model fitted was adequate. The Ramsey reset test of the fitted values of Ratio-Beans production had a p-value = 0.4366 >0.05. This implied that the higher powers of the independent variables were not necessary in the model, and were excluded. The VIF test indicated no multicollinearity since the VIF values were all less than 10 .ie., VIF: drought, 1.17; precipitation, 1.14; log (rural population), 1.07; Floods, 1.06; Ratio Area harvested,1.04. From Shapiro-Wilk normality test, the p-value=0.47562>0.05 was obtained, indicating the normality of the residuals of the bean production. The Breusch-Pagan test for heteroskedasticity was also performed. The p-value of the test was P= 0.0866>0.05. This implied that there was no heteroscedasticy in the model. Ramsey reset test had a p-value=0.1423>0.05, implying there was no evidence of omitted variables in the model. The results of the regression model are shown in table 4 and table 5.

From table 4, it is apparent that the model is significant, with P-value=0.000<0.05. The coefficient of determination is 55.94 percent. This implies that the factors in the model explains 55.94 percent of the variation in bean production.

Table 4: ANOVA Table for regression model for predicting bean production

Source	SS	df	MS			
				Number of obs	=	51
				F (5, 45)	=	12.54
Model	1.50933786	5	.301867572	Prob > F	=	0.0000
Residual	1.08317574	45	.024070572	R-squared	=	0.5
				Adj R-squared	=	0.5358
Total	2.5925136	50	.051850272	Root MSE	=	.15515

From table 4, it is evident the only one factor, area of beans (p-value=0.000) harvested is significant. This result is consistent with the findings of Dhaka (2018) which found that area under rice production significantly affected the rice production. Carbon emission and temperature have also been found to have negative impacts on production of crops (Sidan et al., 2021; Adams, et al., 2015; Luedeling, 2011). Precipitation also had a positive effect on bean production. These results are consistent with findings of (Kabubo et al., 2015). The only departure from the findings is the significance of the temperature and precipitation on the production. This study found the variables to be insignificant.

Table 5: Coefficients of the Explanatory Variables for Bean production

Ratio_production_bean	Coef.	Std. Err.	t	P>t
Ratio_Area_bean	1.129073	.1533523	7.36	0.000
diff_temp	-2.254823	1.926673	-1.17	0.248
precipitation	.0000922	.0001996	0.46	0.646
log_area_maize	.1619883	.1656619	0.98	0.333
difference_carbon2_emission	-.000024	.0002084	-0.11	0.909
_cons	-2.459652	2.259932	-1.09	0.282

On the significance of temperature and precipitation, the results contradicted the findings of (Sidan et. al., 2021) who found that increase in precipitation has a significant positive effect on bean yield.

On the contrary, the increase in temperature has a significant negative effect on bean yield. Carbon emissions do not directly affect bean production.

Sweet Potato Productivity and Production

The two dependent variables, sweet potato production, and yield were tested for stationarity using the Dickey Fuller unit root test. Since both variables were non-stationary, they were transformed and the new variables created: D.log production, log yield potato, difference potato production, and ratio productivity potato. The stationary dependent variables were subjected to normality test, and the conclusion was that there was no evidence to indicate they failed to be stationary. The ANOVA for the regression of ratio-yield-sweet-potato is given in table 7 and the coefficients shown in table 8.

From table 6, it is evident that the model obtained was adequate since p-value=0.0000<0.05, implying we failed to reject the model obtained. The explanatory variables in the model explained 82.40 percent of the variation in the sweet potato production. The model obtained fitted well since p-value=0.000<0.05. There were several significant variables in the model. The model had a very high coefficient of determination, 82.4 percent. This implied that 82.4 percent of the variation in sweet potato production can be explained by temperature, area of harvest, precipitation, rural population, drought and floods.

The diagnostics tests performed had the following results: VIF for the explanatoy variables were: drought, - 1.24; precipitation, 1.20; diff_temp, 1.12; Floods, 1.11; D_log_area~potato, 1.07 and log_rural_population, 1.06. These values were less than 10 and hence we concluded that there was no evidence of multicollinearity. The Ramsey RESET test using powers of the fitted values of log_sweet_prod had a p-value=0.2658, indicating the model has no omitted variables. The Shapiro-Wilk test for normality had p-value= 0.05331, indicating normality of the residuals of log_sweet potato. The Breusch-Pagan for heteroskedasticity had a p-value of 0.2527>0.05. There was no heteroscasticity in the data.

Table 6: ANOVA table for regression of log_sweet_production

Source	SS	df	MS		
				Number of obs	= 52
				F (6, 45)	= 35.11
Model	10.9397573	6	1.82329289	Prob > F	= 0.0000
Residual	2.33693807	45	.051931957	R-squared	= 0.824
				R-squared	= 0.8005
Total	13.2766954	51	.260327361	oot MSE	= .22789

Table 7: Coefficients of the explanatory variables for predicting log_sweet_production

Variable	Coef	Std. Err.	t	P>|t|	[95%	Conf. Interval
diff_temp	-.8308401	2.782798	-0.30	0.767	-6.435683	4.774002
D_log_area_sweet_potato	.5501488	.1716276	3.21	0.002	.2044731	.8958245
precipitation	-.0000144	.0002971	-0.05	0.962	-.0006129	.000584
log_rural_population	1.042891	.0734859	14.19	0.000	.8948824	1.190899
drought	-.1567405	.0702976	-2.23	0.031	-.2983272	-.0151538
Floods	-.2847684	.0976383	-2.92	0.006	-.4814221	-.0881147
_cons	2.790915	.7541245	3.70	0.001	1.27203	4.309799

From Table 7, it is evident that four variables significantly affected sweet potato production. These included: Floods (p-value=0.006); drought (p-value=0.031) and rural population (p-value=0.000) and area of harvest (p-value= 0.002). As found from other studies, temperature and precipitation had a negative impact on sweet potato production, see (Kasimba, 2014; Sidan et al., 2021). However, on precipitation, it contradicted the findings by Sidan et al. (2021), which was done in China. The results are shown in table 8 and table 9.

The results of table 8 show that the model is adequate since p-value=0.0254<0.05. The explanatory variables, in the model included precipitation, temperature, rural population, area of sweet potato, the square of the Area of Sweet potato and the cube of area of sweet potato. These explanatory variables explained 26.44 percent in the variation in the productivity of sweet potato. From table 10, the significant variables on sweet potato yield are Area of sweet, Potato harvest, cube_of Area Potato.

Diagnostic tests were performed to validate the model. The VIF for independent variables were: cube_Dlog_Sweet potato, 6.56; Dlog_sweet Potato, 5.17; SQR_Dlog_sweet potato, 1.71; precipitation, 1.06; D_temp,1.05; log_rural_production,1.04. The Ramsey RESET test, indicated that there were no omitted variables in the model, p-value=0.8357>0.05. The Breusch-Pagan test for heteroskedasticity had a p-value=0.2052>0.05. This implied that there was no heteroscedasticity. The significant variables in the model were Difference logarithm of _Area_Sweet Potato: p-value=0.001 and cube_Area_Dlog of Sweet Potato.

Models for Cassava Production and Yield

The models for cassava production and yield were fitted after it was found that they were stationary and normality. The results are given in table 10 and table 11. In table10, it is clear the model for predicting cassava production is significant. The p-value=0.0313 <0.05. The coefficient of determination is 22.79 percent, which implies that 22.79 percent of the variation in cassava production is explained by variation in the explanatory variables. Table 11 shows the coefficients.

Table 8: The ANOVA regression of sweet potato

Source	SS	df	MS			
				Number of obs	=	52
				F (6, 45)	=	2.70
Model	.319694297	6	.053282383	Prob > F	=	0.0254
Residual	.889474821	45	.019766107	R-squared	=	0.2644
				Adj R-squared	=	0.1663
Total	1.20916912	51	.023709198	Root MSE	=	.14059

Table 9: Coefficients of multiple regression model for sweet potato yield

Ratio_yield_Sweet_~o	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
precipitation	.000192	.0001723	1.11	0.271	-.0001551	.000539
diff_temp	-1.214315	1.660949	-0.73	0.469	-4.559637	2.131008
log_rural_population	-.0008427	.0448949	-0.02	0.985	-.0912657	.0895804
Dlog_Area_SPotato	-.8275691	.232953	-3.55	0.001	-1.296761	-.3583777
SQR_Area_Dlog_SPotato	.2207632	.2954633	0.75	0.459	-.3743304	.8158568
cube_Area_Dlog_SPotato	3.006992	.9370921	3.21	0.002	119592	4.894393
_cons	.9229699	.4651337	1.98	0.053	-.0138574	1.8597

From table 11, the only significant variable for production was the area of harvest for the cassava (p-value=0.001). The other climatic variables and rural population are not significant. This is consistent with the findings of Dhaka (2018), and Jarvis, et. al. (2012) who found out that cassava is the crop least affected by climate change compared with other major staples such as maize, sorghum, and millets. The diagnostic tests revealed the following: The Ramsey RESET test had p-value= 0.7337>0.05, showing that the functional form of the model did not omit the higher power of the explanatory variables. VIF for drought, 1.27; precipitation.

Table 10: Regression model for cassava production

Source	SS	df	MS			
				Number of obs	=	52
(5, 46) = 2.71						
Model	.044865877	5	.008973175	Prob > F	=	0.0313
Residual	.152032339	46	.003305051	R-squared	=	0.2279
				Adj R-squared	=	0.1439
Total	.196898216	51	.003860749	Root MSE	=	.05749

1.20; diff_temp, 1.12; Dlog_areaof cassava, 1.06; log_rural_population, 1.04; the Breusch-Pagan for heteroskedasticity, P-value = 0.4775>0.05, implying the data was homosedastic. The Shapiro-Wilk test for normal data p-value= 0.33293>0.05. That implied that the residuals of the model were randomly and normally distributed.

Table 11: Coefficients of the explanatory variables for predicting Cassava production

cassavaprod	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Precipitation	.0000134	.0000751	0.18	0.859	-.0001378	.0001646
diff_temp	.6053178	.7006533	0.86	0.392	-.8050242	2.01566
Dlog_area_cassavaha	.5127884	.1500541	3.42	0.001	.2107453	.8148316
log_rural_population	-.0255276	.0183711	-1.39	0.171	-.0625068	.0114516
drought	.0292407	.0179663	1.63	0.110	-.0069236	.0654049
_cons	1.240509	.1883254	6.59	0.000	.8614294	1.619588

In table 12 and table 13, the results of the regression models for cassava yields are given. Table 12 shows that the model obtained for predicting cassava is significant, p-value=0.0049. The coefficient of variation is 29.8 percent. This implies that 29.8 percent of variation in cassava yield is explained the explanatory variables. The coefficients of the explanatory variables are shown in table 13. The main factor influencing the yield of cassava are: the area of cassava harvested, p-value=0.001<0.05. Precipitation, rural population.

The diagnostic results are given as follows: the Ramsey RESET had p-value=0.5752>0.05, implying that the functional form of the model did not leave out higher powers of the explanatory variables. The VIFs did not show multicollinearity since the VIF were: precipitation, 1.07; diff_temp, 1.04; log_rural_population, 1.04; Floods, 1.04; log_area_of cassava, 1. The Breusch-Pagan test for heteroskedasticity had p-value= 0.2462. This implied the data was homoscedastic.

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The Shapiro-Wilk test for normal data p-value=0.67391. The residuals were randomly and normally distributed.

Table 12: Regression model predicting cassava yield

Source	SS	df	MS			
				Number of obs	=	52
Model	.06441213	5	.012882426	F (5,46)	=	3.90
Residual	.151754549	46	.003299012	Prob > F	=	0.0049
Total	.216166679	51	.004238562	R-squared	=	0.2980

Table 13: Coefficients of the explanatory variables for predicting cassava yield

Cassava yield	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
precipitation	.0000143	.0000751	0.19	0.850	-.0001368	.0001653
diff_temp	.5766207	.7000129	0.82	0.414	-.8324322	1.985674
Dlog_area_cassavaha	-.4969113	.1499169	-3.31	0.002	-.7986784	-.1951442
log_rural_population	-.0254072	.0183544	-1.38	0.173	-.0623526	.0115382
drought	.0294925	.0179499	1.64	0.107	-.0066386	.065623
_cons	1.238763	.1881533	6.58	0.000	.8600296	1.617496

Conclusion

In this study time series regression models were fitted for predicting annual crop production and productivity. The crops presented were beans, sweet potato, and cassava. The explanatory variables included precipitation, temperature, rural population, drought, floods, and carbon dioxide emission. The study used time series regression analysis where the data had to be made stationary first and then the regression model building methodology used. The study found that there was a very high correlation between rural population and the carbon dioxide emission. Hence only one of the two variables was used during modelling. In addition, for all the three crops, area of harvest significantly affected the annual production and yield. For beans, drought was also a major factor that significantly affected its production. For sweet potatoes, the significant factors, apart from the area under production, included rural population and floods. This implied that beans are very sensitive to floods. The study recommends that farmers should be assisted to use improved farming input even as they increase their farming areas.

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