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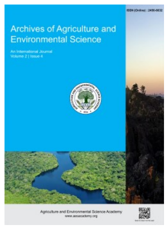

CASE STUDY

Impacts of rainfall and temperature variation on maize (*Zea mays* L.) yields: A case study of Mbeya Region, Tanzania

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ABSTRACT

Based on the multiple regression model the impacts of rainfall and temperature on maize (*Zea mays* L.) yields in Mbeya region have been analyzed. Overall, findings revealed that the seven selected variables, that is, January maximum temperature, February maximum temperature, April maximum temperature, Rainfall from February to April, Rainfall during growing season, December rainfall and October maximum temperature influenced maize yields in the region by 65.4%. Diversely, the results showed 34.6% wasn't explained by the model, meaning that there are other factors apart from temperature and rainfall could be used to explain the variation of maize (*Z. mays*) yield in the region. Furthermore, taking 1990 -2012 as baseline period, the model projection for a period of 2020-2042 shows that maize (*Z. mays*) yield may change from 1.5% to 2.3%, 2.6% to 3.6% and 2.4% to 3.5 %, as a result of separate future influence of 10% decrease in rainfall, 1^{0}C raise in temperature and combined influence of both temperature and rainfall change, respectively. Nevertheless, the findings from this study, reveals that Mbeya region may still be potential maize (*Z. mays*) growing region in the prescribed period provided the magnitude change of both future rainfall and temperature hold and other factors not explained by the model do not change significantly. Therefore, the government must focus to conduct more research on uses of appropriate maize (*Z. mays*) varieties to obtain the maximum maize (*Z. mays*) crop yield in the region.

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INTRODUCTION

A better understanding of the impacts of climate change and variability on crop yields to a stakeholder in the agricultural sector is of vital importance for proper planning in farming practices. One of the useful ways in enhancing such understanding is the use of models related results. Statistical and process based models are prominent in anticipating the effects of climate change and variability on crop production. Process based models usually simulate crop responses to specific weather, soil, management and crop factors governing agricultural productivity (White *et al.*, 2011). Despite of their contribution in examining the effects of climate change on agricultural productivity, there are some limitations associated to these models. For instance, the models are calibrated for individual sites and are assumed to be accurate to simulate crop responses over that particular site (Lobell and Field, 2007). Furthermore, the scarcity of reliable data on weather, soil and management limits the use of models as an extensive predictive tool in evaluation as well as for planning and thus models have ended up providing only 'best-guess' estimates (Jones *et al.*, 2003; Schlenker and Roberts, 2009). Statistical models employ historical data on crop yields and climate to develop statistical relationships. The main advantages of these models are on their limited dependence on field calibration data, transparence during model uncertainties assessment through the use of coefficients of determination and confidence intervals as well as their usefulness at large spatial scales. However, absence of adaptation responses in examining the future crop response projection is one of the limitations of statistical models; for instance, changes in varieties grown, planting and harvesting dates, and so on, are not taken into account (Lobell and Burke, 2010).

Different studies conducted to investigate the impact of climate change on crop production in Tanzania have reported mixed relationship between climate change and variability on crop production. Lema *et al.* (2014) reported the existence of positive relationship between rainfall and maize and beans; and negative relationship between temperature and maize and beans. Haji (2013) identified a positive correlation between rainfalls, mean minimum temperature and maize yield, but maximum temperature showed a negative relationship. Mongi *et al.* (2012); Mndeme (2016) and Majule (2015) reported that climatic variables, especially change of rainfall and temperature lead to the reduction of crop production. Rowhani *et al.* (2011), applied CERES (Crop Environment Resource Synthesis) model to examine the ability of statistical models to predict yield responses to changes in mean temperature and precipitation. The results reveal that both models projected maize yields decrease. This study assesses the impacts of rainfall and temperature variation on maize yields in Mbeya region in Tanzania using multiple regression model. The choice of the model is linked to the availability and nature of the data as well as transparence in assessing the model. Mbeya region is chosen as a case study area because; the region is the biggest maize producer in the country (URT, 2007). Maize (*Zea mays* L.) in the region as well as in the country is a major staple food, most marketed crop, and determinant of the national maize surplus. Furthermore, to the best knowledge of authors, there is no single study which has been conducted in the study area to assess the combined future impacts of rainfall and temperature variation on maize (*Z. mays*) yields using multiple regression models.

MATERIALS AND METHODS

Collection of data

The secondary data used in this study were collected from the Ministry of Agriculture and Cooperatives, Ministry of Livestock and Fisheries Development and Tanzania Meteorological Agency (TMA). The meteorological and maize (*Zea mays* L.) yield data included monthly rainfall and rainfall during growing season, minimum and maximum temperatures as well as maize (*Z. mays*) yields in Mbeya region. Time series data (1990 -2012) covered 23 years were used for this study. Table 1, shows the variables used in the study, namely, observed maize (*Z. mays*)yields (OMY) as response variable and explanatory variables were January maximum temperature (Tjanmax), February maximum temperature (Tfebmax), April maximum temperature (Taprmax), Rainfall from February to April (Rfa), Rainfall during growing season (Rgs), December rainfall (Rdec) and October maximum temperature (Toctmax). Table 1, shows the climatic and maize (*Z. mays*) yields data used in the study area.

About the study area

Mbeya region lies between latitude 7° and 9°31' south of the equator and between longitude 32° and 35° east of Greenwich. The region lies at an altitude of 500 metres above sea level with high peaks of 2981 metres above sea level at Rungwe higher attitudes. The region shares borders with countries of Zambia and Malawi to the South; Rukwa Region to the West; Tabora and Singida Regions to the North; while Iringa region lies to its East (URT, 2007). In 2015 Mbeya region was divided into two regions of Mbeya and Songwe. The region usually receives rainy from October to May ranging from 650mm to 2600 mm per annual while dry season starts from June to September. The region also experiences the temperatures range from about 16°C in the highlands to 30°C in the lowland areas (Figure 1) (URT, 2007). Southern highland zone in the major maize (*Z. mays*) producer, accounting for about 33% of the total maize production in the country. Mbeya region alone accounts for 11% of the maize produced in the zone (AGPTAP, 2015). Maize (*Z. mays*) in Mbeya region is both a major staple food and most marketed crop (in volume terms). This being the case, maize (*Z. mays*) is of vital importance to the region considering its level of production as well as an important determinant of the national maize surplus.

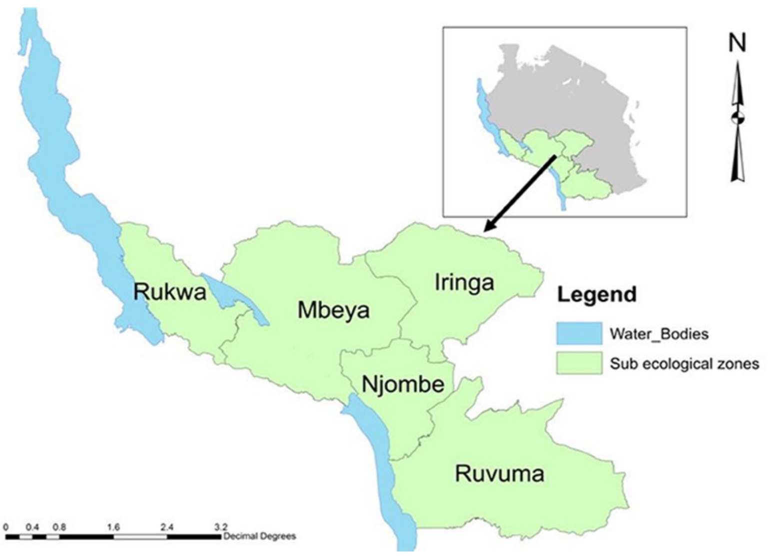

Figure 1. *Depicts major maize production regions in Tanzania, including the study area (Source: Luhunga, 2017).*

Table 1. Depicts the climatic and maize (*Z. mays*) yields data used in the study.

Year	OMY (tanne/ha)	Tjanmax (°C)	Tfeb (°C)	Taprmax (°C)	RFA (mm)	RGS (mm)	Rdec (mm)	Toctmax (°C)
1990	1.80	23.2	23.7	23.6	318.5	697.5	202.4	27.4
1991	1.90	23.2	24.5	23.5	390.5	797.2	215.8	25.6
1992	2.40	24.1	23.8	23.5	390.1	768.9	137.8	26.8
1993	1.70	22.6	23.2	23.1	428.9	846.3	20.4	26.6
1994	1.70	23.9	22.9	23.0	446.9	826.2	110.8	26.7
1995	1.70	23.7	23.1	23.3	507.3	881.5	106.6	27.6
1996	1.70	23.6	23.0	23.2	504.2	1061.9	235.9	27.5
1997	1.70	24.5	23.2	23.3	423.5	992.3	372.4	26.7
1998	1.90	23.4	23.4	23.4	442.0	743.2	76.6	27.0
1999	1.40	22.7	24.9	23.4	449.8	948.3	144.7	25.8
2000	2.00	24.0	23.9	23.6	461.2	918.1	252.6	27.1
2001	2.30	22.2	23.6	23.5	305.1	846.6	174.5	25.9
2002	1.20	22.8	24.0	23.4	396.1	766.1	153.9	27.3
2003	2.00	23.9	25.1	23.6	321.7	772.5	162.3	27.4
2004	2.30	24.6	23.9	23.4	388.3	896.6	286.9	26.7
2005	2.20	23.9	25.6	23.7	315.2	641.3	112.9	27.1
2006	2.00	24.8	24.6	23.0	369.3	991.6	319.6	27.7
2007	1.80	23.6	24.1	23.4	352.2	842.4	209.1	27.0
2008	2.20	23.3	23.3	23.4	432.7	905.5	167.4	27.3
2009	2.20	24.4	23.5	23.3	443.4	897.6	160.7	27.8
2010	1.90	24.6	24.2	23.4	400.8	677.3	93.1	28.1
2011	1.80	24.5	24.2	23.6	453.1	1058.4	356.3	27.3
2012	1.80	24.4	25.4	23.6	283.1	695.4	187.3	28.2

Regression model development

Model assumptions

In developing the multiple regression model to be used in predicting the impacts of future rainfall and temperature variation on maize (*Z. mays*) yields in Mbeya region, we first check the assumptions for multiple linear regression model.

Linearity assumption

The linearity assumption requires that the relationship between the dependent variable and independent variables is linear. Garson (2012) suggests that a proper method detect linearity is to run regression analysis.

In this study, if there is a significant linear relationship between the independent variables (climatic variables), xi, i=1,.......,7 and the dependent variable (maize yield), y_j, i=1,..., 23, the slope will not equal zero. The null hypothesis therefore states that the slope is equal to zero, and the alternative hypothesis states that the slope is not equal to zero. Table 2 indicates the results from analysis of variance for the test of goodness of fit of the model at significance level of 5%.

Analysis of Variance (ANOVA) (Table 2) indicates that p-value (0.011) < 0.05, in this case null hypothesis is rejected. The test provide evidence that the linear relationship between maize yields and January maximum temperature, February maximum temperature, April maximum temperature, rainfall from February to April, rainfall during growing season, December rainfall and October maximum temperature exists.

Normality assumption

Normality assumption considers that variables have normal distributions. When the variables are not normally distributed, they can distort relationships and significance tests (Osborne and Waters, 2002). Shapiro-Wilk test is useful in examining the normality assumption whereby comparison is done between pre -assigned significance level and Shapiro-Wilk Test value. Shapiro-Wilk test is used when the sample size is less than 2000 (Shapiro and Wilk, 1965). If the significance value of the Shapiro -Wilk test is greater than the pre-assigned significance level then the data is normal, and once it is below the pre – assigned significance level then the data significantly deviate from a normal distribution. The p-values of dependent and independent variables using Shapiro –Wilk test are shown in Table 3.

The Shapiro - Wilk p- value for each variable is greater than 0.005 (Table 3). The test suggests that the residuals are approximately normally distributed, meaning that the normality assumption is met. Therefore the variables used in this study are normally distributed.

Independence of errors assumption

This assumption requires that the regression model errors are independent; that is, the error terms are uncorrelated for any two observations (Mooi and Sarstedt, 2011). DW test is a prominent statistic test used in testing for the occurrence of serial correlation between residuals. The value of DW statistics ranges between 0 and 4. DW value below 1.5 or larger than 2.5 indicates a problem. We apply DW to test this assumption.

The model summary for this study indicates that the values of R, R square, Adjusted R square, Standard error of the estimate and DW are 0.809, 0.654, 0.493, 0.2065 and 1.953 respectively. The DW statistic is 1.953 which is between 1.5 and 2.5, in this case the data is not autocorrelated, implying that independence assumption is met and errors associated with the data used in this study are uncorrelated.

Homoscedasticity assumption

Homo (equal) scedasticity (spread) is the assumption that the error variance denoted by is equal for all observations. On the other hand, heteroskedasticity is the violation of the homoscedasticity assumption. Gelfand (2013) asserts that when this happens, the OLS estimates become inefficient, the regular standard errors of these estimates are wrong, leading to incorrect inferences. According to Chong (1993) the assumption of homogenous variance of residuals is highly affected by outliers because of large residuals. In this study we use the Glejser test method which is applied by performing the regression analysis and use the absolute residuals from the regression to test for the heteroskedasticity assumption.

The multiple regression equation relating the residuals and the climatic variables is given by;

$$\left|\hat{u}_i\right| = \delta_0 + \delta_1 X_1 + \delta_2 X_2 + \ldots\ldots\ldots\ldots + \delta_k X_k + e_i$$

where, δ_0 through δ_k are residuals parameters, X_1 through X_k are the explanatory variables, and e_i, $i = 1, 2, \ldots, k$ is an error term.

To test for heteroskedasticity , we have the following hypotheses:

$H_0 : \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = 0$

$H_1 : \delta_i \neq 0$, at least one of the δ_i's is not equal to zero, for i=1,2,....,7.

If the significant value of each of the explanatory variable is greater than the significant level (α), then, the null hypothesis is accepted (there is no problem of heteroskedasticity). On the other hand, if the significant value of each of the explanatory variable is greater than the significant level (α), the null hypothesis is rejected (there is problem of heteroskedasticity). The p-value (from Table 4) of each of the residual parameters X1 through X7 is greater than a preassigned significance level of 0.005. This means that null hypothesis is accepted and heteroskedasticity is not a problem.

Multicollinearity assumption

By definition, multicollinearity is a situation in which there is an exact or nearly relation among two or more of the input variables (Hawking and Pendleton, 1983). If the explanatory variables are highly correlated may result into inappropriate model, erroneous conclusion and sometimes insignificant parameters with significant model (Vaughan and Berry, 2005; Hawking and Pendleton, 1983). The VIF is widely used to test the extent of multicollinearity. The variance inflation factor for variable X_i is denote as VIF_i and is defined by the equation $VIF_i = 1/1\text{-}R_i^2$, where R_i^2 is the multiple coefficient of determination for the regression. There is no formal VIF cut off value for examining the existence of multicolinearity but (Alauddin and Nghiemb, 2010), recommend the VIF cut off point of 10, because a value greater than 10 is often used as an indication of potential multicollinearity problem.

The model

Suppose we denote X1=Tjanmax (0C), X2=Tfebmax (0C), X3 =Taprmax (0C), X4=Rfa (mm), X5= Rgs (mm), X6 = Rdec (mm), X7 = Toctmax (0C), and Y represents maize yields (tonne/ha), then the Regression Model relating these variables may be written as:

This system of n equations can be written equivalently in matrix format as:

$$y = \beta_0 +_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \varepsilon \qquad (1)$$

where,

β_0 is the intercept when all x are set equal to zero and β_1 through β_7 are regression coefficients population parameters. x_1 through x_7 are the explanatory variables and ε is the random error (residual) component.

Suppose n>k observations are available, and y_i denotes the ith observed response and x_{ij} denotes the ith observation of explanatory variable x_j. Then, the classical linear regression model is given by:

$$y_i = \beta_0 +_1 x_{1i} + \beta_2 x_{2i} + \ldots\ldots.. + \beta_k x_{ki} + \varepsilon_i \quad (i = 1, 2, \ldots.., n) \qquad (2)$$

we can write the equation for each observation as a sytems of n equations for the classical linear regression model (equation 2) as follows :

$$\begin{aligned}
y_1 &= \beta_0 + \beta_1 x_{11} + \beta_2 x_{12} + \ldots\ldots. + \beta_k x_{1k} + \varepsilon_1 \\
y_2 &= \beta_0 + \beta_1 x_{21} + \beta_2 x_{22} + \ldots\ldots. + \beta_k x_{2k} + \varepsilon_2 \\
&\vdots \\
y_n &= \beta_0 + \beta_1 x_{n1} + \beta_2 x_{n2} + \ldots\ldots. + \beta_k x_{nk} + \varepsilon_n
\end{aligned}$$

This system of n equations can be written equivalently in matrix format as :

$$y = X\beta + \varepsilon \quad (3)$$

where,

y is $n \times 1$ vectors

β is $m \times 1$ vectors and

X is $n \times m$ vectors.

where,

$m = k + 1$ is the number of parameters.

Let $\hat{\beta}$ be $k \times 1$ vector of estimates of β, then the estimated model (equqtion 3) may be written as:

$$y = X\hat{\beta} + e \quad (4)$$

e is $n \times 1$ vector of residues, computed as:

$$e = y - X\hat{\beta} \quad (5)$$

To determine the least square estimator, we write the sum of squares of the residues (a function of $\hat{\beta}$) as:

$$S(\hat{\beta}) = \sum_{i=1}^{n} e_i^2 = e^T e = \left(y - X\hat{\beta}\right)^T \left(y - X\hat{\beta}\right) \quad (6)$$

The minimum of $S(\hat{\beta})$ is obtained by setting the derivatives of $S(\hat{\beta})$ equal to zero.

$$\frac{S(\hat{\beta})}{S(\hat{\beta})} = -2X^T y + 2X^T X\hat{\beta} = 0$$

$$X^T y = X^T X\hat{\beta} \quad (7)$$

Multiplying both sides of equation (7) by we have;

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T y$$

$$\text{Since } k = 7, \text{ then } \hat{\beta} = \begin{bmatrix} \hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \\ \hat{\beta}_5, \hat{\beta}_6, \hat{\beta}_7 \end{bmatrix}$$

Where, $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$, $\hat{\beta}_4$, $\hat{\beta}_5$, $\hat{\beta}_6$ and $\hat{\beta}_7$ are the estimators of β_0, β_1, β_2, β_3, β_4, β_5, β_6, and β_7 respectively.

The estimated coefficients of the model generate the predicted values given by;

$$y = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \hat{\beta}_3 X_3 + \hat{\beta}_4 X_4 + \hat{\beta}_5 X_5 + \hat{\beta}_6 X_6 + \hat{\beta}_7 X_7 + \varepsilon \quad (8)$$

From table 6, $\hat{\beta}_0 = -23.716$, $\hat{\beta}_1 = +0.499$, $\hat{\beta}_2 = -0.289$, $\hat{\beta}_3 = +1.161$, $\hat{\beta}_4 = -0.006$, $\hat{\beta}_5 = +0.003$, $\hat{\beta}_6 = -0.004$, and $\hat{\beta}_7 = -0.219$.

Hence equation (8) becomes:

$$Y_i = -23.716 + 0.499 X_{1i} - 0.289 X_{2i} + 1.161 X_{3i} - 0.006 X_{4i} + 0.003 X_{5i} - 0.004 X_{6i} - 0.219 X_{7i} + \varepsilon \quad (9)$$

Equation (9) represents the model that describes the relationship between maize yields and climatic variables.

Testing the significance of the model

To be sure that the model works well and produces reliable results, testing its siginificance is vital importance. The significanceof the model is tested by formulating two hypotheses. The model hypotheses are stated below.

Null hypothesis

$H_0: \beta_1$ = 0; none of the explanatory variables is significant.

$$\beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 =$$

Alternative hypothesis

$H_A: \beta_i \neq$ 0, for i = 1, 2, 3, 4, 5, 6, 7; at least one of the explanatory variables is not equal to zero.

From analysis of variance (ANOVA) (Table 2), the Test statistic equal to 4.051 and its corresponding p- value (0.011) is less than 5%, implying that there is strong statistical evidence that at least one of the regression coefficient in non –zero. We use t-test to examine the significance of each (individual) explanatory variable. Since the p-value for each explanatory variable is less than 0.05 this implies that all climatic variables are non–zero. Therefore the developed model is significance.

RESULTS AND DISCUSSION

We focus on results from the regression model in assessing the impacts of rainfall and temperature variations on maize (*Z. mays*) yields in Mbeya region. We first show the predictive ability of the model by examining the coefficient of multiple determination and p- value in relation to the significance level. Then, we present the projection of the impacts of rainfall and temperature variation on maize (*Z. mays*) yields in the region in 2020 -2042 period, taking 1990- 2012 as the baseline period by considering the temperature increase of 1°C and rainfall decrease of 10% in the prescribed period. The choice of two climatic variable variations in future is based on result from climate models for Tanzania which project that future average annual temperature may increase between 1°C-3°C, and the areas which receive uni modal rainfall seasons, could experience annual rainfall decrease of 5% - 15% (United Republic of Tanzania, 2014).

Goodness of fit of the model

The result showed that predictive model for maize (*Z. mays*) yield was statistically significant with $\alpha \leq 0.05$ (Table 2). The value of R^2 = 0.654, indicating that 65.4% of the variation in maize (*Z. mays*) yield in Mbeya region is explained by the climatic variables. On the other hand, 34.6% could be attributed to other factors not captured by the model (Figure 2).

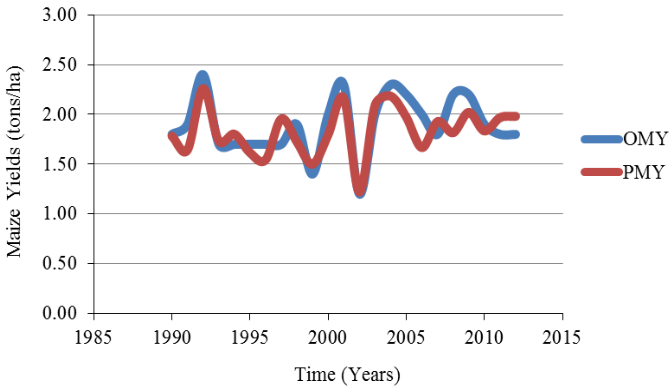

Figure 2. *Observed maize (Z. mays) yields (OMY) and predicted maize yields (PMY) in tonne/ha in Mbeya region of Tanzania.*

Maize yields change due to separate and combined future impact of rainfall and temperature

In this study, we consider the future rainfall decrease of 10% and 1°C increase in temperature to predict the separate and combine impact of both temperature and rainfall on maize (*Z. mays*) yields in Mbeya region. Lobell and Burke (2010) argue that time series models can extremely be useful for projections for the next 20-30 years. Therefore, taking 1990 -2012 as the baseline period, the study may predict the future influence of these climatic changes on maize (*Z. mays*) yields in 2020-2042 period taking the maximum projection of 30 years. Table 6, describes maize (*Z. mays*) yield change due to future separate and combined impact of rainfall and temperature variation.

Future impact of rainfall variation on maize (*Z. mays*) yield in Mbeya region

Considering the rainfall variable alone, the model indicates that the coefficients of total rainfall from February to April (Rfa), rainfall during growing season (Rgs) and December rainfall (Rdec) are -0.006, +0.003 and -0.004, respectively. This being the case, Rfa and Rdec impact maize (*Z. mays*) yields negatively. Importantly, Rgs, rainfall during the growing season is positive and favours maize (*Z. mays*) yields in the region. Generally, the rainfall decrease of 10% may cause the maize (*Z. mays*) yields in Mbeya region to change between 1.5% to 2.3% in 2020 -2042 taking 1992 -2012 as baseline period. Baijukya *et al.* (2016) suggest that maize usually needs about 500mm -1500 mm of rainfall per growing season although some maize types can do well with as little as 250 mm of rainfall. Examining the rainfall per growing season from the data, rainfall decrease of 10% may cause the rainfall during the growing season to fall into the range of 577mm and 956 mm inclusive. Thus, such decrease in future may not have substantial impact on maize yields in prescribed period, provided other factors not explained by the model do not change significantly.

Table 2. Analysis of variance (ANOVA) for the test of goodness of fit of the model α =5%.

Model	Sum of squares	Df	Mean square	F	Significance
Regression	1.210	7	0.173	4.051	0.011
Residual	0.640	15	0.043		
Total	1.850	22			

Table 3. Depicts the P- values for dependent and independent variables for Shapiro- Wilk at α =5%.

Variable	P-Value
Y	0.308
X_1	0.372
X_2	0.231
X_3	0.065
X_4	0.384
X_5	0.785
X_6	0.559
X_7	0.336

Table 4. Depicts the P-value corresponding to the residual parameters X_1 through X_7 at α =5%.

Variable	P-Value
X_1	0.972
X_2	0.154
X_3	0.164
X_4	0.631
X_5	0.549
X_6	0.590
X_7	0.572

Future impact of temperature variation on maize (*Z. mays*) yield in Mbeya region

Regarding the temperature variable, the model indicates that the increase of 1°C in 2020-2042, maize (*Z. mays*) yields in Mbeya region may change between 2.6% to 3.6% (Table 6) taking 1990-2012 as baseline period. This finding is in agreement with the result obtained by Mtongori *et al.* (2016). They found that increase in temperature favored maize yield in southern part of Tanzania for some cultivars. Importantly, Statistical studies have indicated that daily maximum temperature greater than approximately 30°C limit maize yields (Schlenker and Roberts, 2009; Lobell *et al.*, 2011). Commuri and Jones (2001) found that temperatures above 30°C increasingly impaired cell division and amyloplast replication in maize kernels, and thus reduced grain sink strength and yields. This being the case, considering the temperature data used in this study, the maximum temperatures in the region will not be beyond 30°C, implying that the future temperatures change in prescribed period by considering the increase of 1°C may still be in the limit that is suitable and not harmful for growing maize.

Future impact of combined variation on maize (*Z. mays*) yield in Mbeya region

The model results also indicate that the future combined effect of both temperature and rainfall may cause maize yields change between 2.4% and 3.5% in 2020 -2042, taking 1990 -2012 as the baseline period.

Table 5. Depicts unstandardized and standardized coefficients, t and p-values and VIF of climatic variables.

Variable	Unstandardized coefficients		Standardized coefficients	T	Significance	Collinearity statistics
	B	Std. Error	Beta			VIF
Constant	-23.716	8.482		-2.796	0.014	
Tjanmax (X_1)	0.499	0.110	1.242	4.521	0.000	3.273
Tfebmax (X_2)	-0.289	0.088	-0.763	-3.280	0.005	2.349
Taprmax (X_3)	1.161	0.348	0.763	3.340	0.004	2.265
Rfa (X_4)	-0.006	0.001	-1.220	-3.939	0.001	4.159
Rgs (X_5)	0.003	0.001	1.201	2.971	0.010	7.079
Rdec (X_6)	-0.004	0.001	-1.281	-3.460	0.003	5.941
Toctmax (X_7)	-0.219	0.088	-0.507	-2.495	0.025	1.793

The VIF of all independent variables, that is, VIF of X_1, X_2, X_3, X_4, X_5 and X_6, and X_7 are less than 10. This indicates the absence of multicollinearity and implies that variables are not highly correlated.

Table 6. Shows maize (*Z. mays*) yields change in Mbeya region due to future separate and combined impact of rainfall and temperature variation.

Years	OMY (tons/ha)	Maize yields in % due to temperature rise by 1^{0}C	Maize yields change in % due to temperature rise of 1^{0}C and rainfall decrease of 10%	Maize yield change in % due to rainfall decrease of 10%
1990	1.80	3.2	3.0	1.8
1991	1.90	3.0	2.9	1.7
1992	2.40	3.6	3.5	2.3
1993	1.70	3.1	2.9	1.7
1994	1.70	3.2	3.0	1.9
1995	1.70	3.0	2.9	1.7
1996	1.70	2.9	2.8	1.6
1997	1.70	3.3	3.2	2.1
1998	1.90	3.1	2.9	1.8
1999	1.40	2.9	2.7	1.5
2000	2.00	3.2	3.0	1.9
2001	2.30	3.5	3.3	2.2
2002	1.20	2.6	2.4	1.3
2003	2.00	3.5	3.3	2.1
2004	2.30	3.6	3.4	2.3
2005	2.20	3.3	3.2	2.0
2006	2.00	3.0	2.9	1.7
2007	1.80	3.3	3.1	2.0
2008	2.20	3.2	3.0	1.9
2009	2.20	3.4	3.2	2.1
2010	1.90	3.2	3.1	1.9
2011	1.80	3.3	3.2	2.1
2012	1.80	3.4	3.2	2.0

Conclusion

This study has demonstrated that multiple regression model might provide more insight on assessing the effects of rainfall and temperature variation on maize (*Z. mays*) yields at regional level. Since the model has revealed that change in temperature and rainfall may have impacts on maize (*Z. mays*) yields in the region, the following recommendations are useful: Factors other than temperature and rainfall variables should be included in the model. This may provide a deep understanding on how various factors affect maize (*Z. mays*) yields in the region. Such variables could include market access, input use, and extension services and so on. A comparison study using different type of models should be applied in the study area. The result may provide solid standing for informing policy and decisions making process which may be useful to agricultural stakeholders in improving maize (*Z. mays*) yield. Since, temperature and rainfall variables have impact on maize (*Z. mays*) yields in the region, the government through the responsible ministry should insist in conducting research frequently in order to come up with suitable maize (*Z. mays*) varieties that maximize yield in the region.

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