Arima and Arimax Analysis on the Effect of Variability of Rainfall, Temperature, Humidity on Some Selected Crops in Nasarawa State

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***Abstract*: Crops production are highly sensitive to climate change. They are affected by long-term trends in average rainfall temperature and humidity. This study examines the effects of the variability of rainfall, temperature and humidity on some selected crops (rice and yam) in Nasarawa using autoregressive integrated moving averages (ARIMA) and autoregressive integrated moving averages with exogenous variables (ARIMAX). This research compare ARIMA modeling method which make forecast in univariate data and ARIMAX as multivariate method which include independent variables such as rainfall, temperature and humidity. The data for the study were collected from the Nasarawa Agricultural Development programme (NADP) for the period of twenty-three years from (1998 – 2020). The data collected were analyzed using ARIMA and ARIMAX models. The results from the analysis indicates that rainfall and humidity has negative and significant effect on yam production. However, rainfall and humidity has insignificant effect on rice production. Also, the forecast performance evaluation revealed that ARIMAX model performed better in modelling production of yam while the ARIMA model performed better in modelling production of rice in the study area.**

***Keywords*: ARIMA, ARIMAX, Forecasting, NADP, Modeling, variability**

I. INTRODUCTION

Agriculture is the main economic activity in Nasarawa state. Nasarawa state agricultural development programme observes that farming in the state is subsistence and generally rain fed cultivation of annual crops (Victor, 2018). Crops grown include grains such as rice, wheat, soybeans, maize and millet and tubers crops such as yam and cassava. The bulk of crop production in Nasarawa state is undertaken by small scale farmers most of whose labour force, management and capital originate from the household. Agriculture employs the large percentage of working population in the state. However, Climate change and variability are becoming a strong threat for food security in the twenty first century, particular for the agriculture dependent Sub-Saharan African countries (Eva, 2019).

Crop production is highly sensitive to climate change. It is affected by long-term trends in average rainfall temperature, intern-annual climate variability, shocks during specific phonological stages, and extreme weather events (ICPP, 2012). Some crops are more tolerant than other to certain types of stresses, and at each phonological stages, different types of stage affect each crop specifies in different ways (Simpson, 2017). As climate change, crop production strategies must change too. There will always be some uncertainty associated with modeling the complex relationships between agricultural yield and future climate scenarios.

Global warming is projected to have a significant impact on factors affecting agriculture, including temperature, carbon dioxide and precipitation. Identifying the agricultural effect of climate change might help to properly anticipate and adapt farming to maximize agricultural productivity (Fraser, 2008). Because most African countries lack the capacity of adapting to this problem, minor changes can spark a significant effect on the agriculture capacity of any nation.

For any particular crops, the effect of climate affects the crops optimal growth and production. In some areas, warming may benefit the types of crops that are typically planted and allows farmers to shift to crops that are currently grown in warmed areas. Conversely, if higher temperature exceeds a crops optimum temperature, yields may decline. In addition, climate changing is leading to more occurrence of extreme events such as droughts (moisture deficits) and floods (moisture surpluses), which have a negative impact on crop growth and can reduce yields. It is against this background that this study seeks to examine the effects of the variability of rainfall, temperature and humidity on some selected crops in Nasarawa using autoregressive integrated moving averages (ARIMA) and autoregressive integrated moving averages with exogenous variables (ARIMAX). The specific objective of the study is to compare the two different models (i.e Auto Regressive Integrated Moving Average and Auto Regressive Integrated Moving Average with Exogenous Variables); to investigate the significant effect of rainfall, temperature and humidity on some selected crops and, to evaluate the forecasting performance of the models.

The study findings of this study will create awareness to the farmers on the effect of climate on agricultural activities in

Nigeria. also, it will also create awareness to the government on the implementation of policies on climate change.

II. LITERATURE REVIEW

The effects of climate change have been evaluated by several scholars. According to Fosu-Mensah (2012), when temperature exceeds the optimum level for biological processes, crops often respond negatively with a steep drop in net growth and yield. Gornall *et al*. (2010) in a study in Australia opined that extreme air temperatures higher than 38°C led to lower maize grain yields, while similar temperature for rice led to high productivity. Other studies have also shown that a 1°C to 2°C rise in mean temperature causes large percentage yield loss in maize (Chijioke et al., 2011).

Considering the yield losses from the findings, the inherent complexity of crop production systems requires integrating many factors to ensure maximum crop yields. One of the most important factors is soil temperature. It has long been recognized that an increase in temperature stimulates the rate of microbial decomposition in the soil which in turn diminishes organic matter content along with nutrient and moisture holding capacity. This indirectly affects total land area suitable for permanent cultivation (Khan et al., 2009 and McCarl, 2006). Crop yield is influenced by the growth, spread and survival of crop pathogens, pests and diseases. These pests and diseases are sustained by temperature. Most analyses show that in a warmer climate, pests may become more active and may expand their geographical range. For instance, recent warming trends in the United States and Canada have led to earlier insect activity in the spring and proliferation of some species, such as the mountain pine beetle (Gornall et al., 2010). The evident trend is that temperature variation affects the behavior of crop pathogen, plants and diseases.

Generally, rainfall regime is the most important climatic factor influencing crop production. This is because rainfall has the biggest effect in determining the crops that can be grown in different environments, the type of agricultural system to be practiced in different parts of the world, the farming system, the sequence and timing of farming operations.

In respect to the above, Fosu-Mensah (2012) have identified some important factors guiding rainfall in relation to crop production. According to him, the number of rainy days (the length of the rainy season), time of fall (onset) and total amount of fall, cessation and the type of soil are some of the important factors guiding rainfall in relation to crop production. Therefore, an interruption in the onset, length of the rainy season and cessation will affect soil moisture (soil moisture deficit and enhanced soil moisture), hence, crop development. According to Fosu-Mensah (2012), soil moisture deficit and also the timing of moisture deficits during growing seasons cause crop damage in stages of plant development. As such, water use for a given crop is a function of both the amount of water available to the crop and when that water is available relative to crop demand.

Moreover, increases in rainfall intensity in other regions could lead to higher rates of soil erosion, leaching of soil nutrients and agricultural pollutants, and runoff that carries soil and associated nutrients into surface water bodies leaving the soil impoverished to support plant growth (Gornall et al., 2010). If erosion and leaching of soil rates go unchecked, continued soil impoverishment would eventually force farmers to abandon their lands (Khan *et al.*, 2009). From the foregoing, both direct and indirect effects of moisture stress make crops more vulnerable to damage by pests, especially in the early stages of their development. According to Gornall *et al*, (2010), rainfall variability has the tendency to cause pest migration. A typical example is the migration pattern of locusts into Sub-Saharan Africa which Mowa & Lambi (2006) believe is influenced by variability in rainfall patterns, The migration of these locusts into Sub-Sahara Africa poses danger to food security and livelihoods in the region.

Chaleampon & Tapanee (2013) considered a univariate time series model to forecast Thailand exports to major trade partners, they compared autoregressive integrated moving average (ARIMA) and ARIMA with explanatory variable. The results from the analysis revealed that for exports to china, European union (27 countries) and the United States, the ARIMA model with leading indicator outperformed the ARIMA model.

Christopher *et al* (2014) conducted a study which aimed at identifying the significant variables which affect residential low voltage (LV) network demand and develop next day total energy use (NDTEV) and next day peak demand (NDPD) forecast models for each phase. The models were developed using autoregressive integrated moving average with exogenous variables (ARIMAX) and neural network (NN) techniques. It was observed that temperature accounted for half of the residual LV network demand. The inclusion of the double exponential smoothing algorithm, autoregressive terms, relative humidity and day of the week dummy variables increased model accuracy. In terms of R^2 and for each modelling technique and phase, NDTEU hindcast accuracy ranged from 0.77 to 0.87 and forecast accuracy ranged from 0.74 to 0.84. The NN models had slight accuracy gains over the ARIMAX models. A hybrid model was developed which combined the best traits of the ARIMAX and NN techniques, resulting in improved hind cast and forecast fits across the all three phase.

In another study by Prity *et al* (2014) who considered different Autoregressive Integrated Moving Average (ARIMA) models developed to forecast the rice yield by using time series of sixty years. The performances of these developed models were assessed with the help of different selection measure criteria and the model having minimum value of these criteria considered as the best forecasting model. Based on findings, it has been observed that out of eleven ARIMA models, ARIMA (1,1,1) is the best fitted models in predicting efficiency of rice yield as compare to others.

Mohammed (2014) developed the best Box-Jenkins autoregressive integrated moving average with external regressor, that is, ARIMAX model for examining the temperature and rainfall effects on the major spice crops production in the Bangladesh and forecasting the production using the same model. Due to time sequence data set, ARIMAX model is considered as a measuring tool of cause-effect relation. Among the spice crops and climatic variables (temperature and rainfall) under study. From the study, it is found that ARIMAX (2,1,2), ARIMAX (2,0,1) and ARIMAX (2,1,1) are the best model for chili, garlic and ginger crop respectively.

Uyodhu and Isaac (2016) conducted a study to find the appropriate ARIMAX model for the Nigerian non-oil export using exchange rate (in dollars) as the exogenous variable by adopting the Box –Jenkins iterative three – stage modelling approach – identification, estimation and diagnostics checking. The time plot of the two series at level shower that the mean and variance are not consist but variant with time. The augmented Dickey – Fuller (ADF) test conformed both series are not stationary hence the two series were differenced ones. Results of the unit roots test in the first difference rejected null hypothesis at 5% level of significance of non-stationary after first difference. The autocorrelation function (PACF) combined patterns suggested AR(2) and MA(6) respectively. By comparing their various Akaike information criteria (AIC) the parsimonious model was estimated as ARIMAX (2,1,5). The goodness of fit test confirmed the adequacy of the estimated model. All the roots of the estimated ARIMAX process lie inside the unit circle. The plots of the residuals are mostly serial non-correlation. The result from the estimated model implies that exchange rate has no impact on Nigerian non-oil as exchange rate has no impact on Nigerian non-oil as exchange rate failed to be significant.

Sanjeer and Urmil (2016) developed ARIMA and ARIMAX models for sugarcane yield prediction in Karnal, Ambala and Kurukshetra districts of Haryana. The weather data over the crop growth period were utilized as input series along with the sugarcane yield for building the ARIMAX models. The predictive performance of the contending models was observed in terms of the percent deviations of sugarcane yield forecast in relation to the real time yields and root mean square errors as well. The ARIMAX models performed well with lower errors metrics as compare to the ARIMA models in all time regimes.

Victor *et al* (2018) in their study focused on getting the crop yield trends of maize, yam and rice which are staple crops in Nasarawa state. The yields were subjected to simple regression analysis in order to determine the trends of the yield. The results show that maize and yam are on the positive trend while rice yield is on the decrease all over the state. Urbanization is seen as one of the factors hampering high yield of rice while more effort should be intensified for both dry and wet farming in the state.

Relan *et al* (2018) study the several linear time series forecasting models, one of the important and widely used technique for analysis of univariate time-series data is Box and Jenkins autoregressive integrated moving average (ARIMA) methodology. The study found that addition of the other exogenous variables sometimes increases the prediction accuracy of ARIMA model (ARIMAX). Among the linear models, the ARIMAX model performed better as compared to ARIMA model. However, the performance of machine intelligence techniques likes hybrid of linear and nonlinear model is better as compared to linear time models.

Ray & Bhattacharyya (2020) carried out a study on statistical modelling and forecasting of ARIMA and ARIMAX models for food grains production and Net availability of India. The study is designed with specific objectives to study the trend analysis of rice, heat and total food grain in India for the period starting from 1950 to 2019. For stochastic trend model estimation, time series parametric regression models i.e. Linear model, Quadratic model, Exponential model, Logarithmic model, Auto Regressive Integrated Moving Average (ARIMA) and Auto Regressive Integrated Moving Average with explanatory variables (ARIMAX) were analyzed for estimating an appropriate econometric model to capture the trend of major food grain viz. rice, wheat, total food grain production and net availability of the country. The study showed that ARIMA and ARIMAX performed better in forecasting the data under the study.

In another study by Obi and Okoli (2021) whose study compare the performance of ARIMA, ARIMAX and Single Exponential Smoothing (SES) model for Estimating Reported cases of Diabetes Mellitus in Anambra State, Nigeria. Secondary data used in this study was obtained from records of Anambra State Ministry of Health. The Akaike Information Criterion was used in assessing the performance of the model. The study showed that the data of the study satisfied normality and stationarity test. The findings of the study revealed that ARIMA model performed better with AIC = 1177.92 followed by ARIMAX model with AIC = 1542.25 and SES model has the highest value of AIC = 1595.67.

III. METHDOLOGY

3.1 Source Of Data

The data used in this research work was obtained from Nasarawa agricultural development programme (NADP) for the period of twenty-three years from (1998 – 2020).

3.2 Techniques For Data Analysis

Unit Root Test for Stationarity

Sometimes, time series data are not in their stationery form, hence there is need to transform it into a stationary form, an easy way of achieving this is to difference the time series data. One way of doing this is to use the Augmented Dickey-Fuller (ADF) t-statistic. The ADF test constructs a parametric correction for higher-order correlation by assuming that the y series follows an autoregressive of order p process and adding p lagged difference terms of the dependent variable y to the right-hand side of the test regression as follow:

$$\Delta y_t = \alpha y_{t-1} + x_t^{'}\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + v_t$$

where x_t are optional exogenous regressors which may consist of constant, or a constant and trend.

Arima Model

The ARMA model consists of two parts, an AR part and a MA part. The model is usually then referred to as ARMA (p, q) model where p is the order of the autoregressive part and q is the order of the moving average part. The mixed model is given as:

$$y_t = \delta + \emptyset_1 y_{t-1} + \ldots + \emptyset_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q}$$

or using the B-operator

$$\emptyset(B) y_t = \delta + \emptyset(B)\varepsilon_t$$

The model is referred to as ARMA (p, q) scheme. The ARMA model both stationary and invertible. In practice p and q are not greater than 3 and often less than or equal to 2 (Cooray, 2008).

If differencing is necessary to produce a stationary series, so that

$w_t = \nabla^d y_t$ and

$$\emptyset(B) w_t = \delta + \emptyset(B)\varepsilon_t$$

we then refer to it as Autoregressive Integrated Moving Average of orders p, d, q or ARIMA (p, d, q). Note that when d>0, many time series analyst would set $\delta = 0$ rather than retain a constant drift element corresponding to a d^{th} order polynomial. Indeed, Box and Jenkins (1976) in their ground breaking book on ARIMA model building refer to this as the principle of parsimony and use it as a major touch stone in model development. The Box-Jenkins forecasting procedure consists of the three main stages: Model identification, Parameter Estimate, Diagnostic checking and Forecasting.

Model Identification

It is not always easy to determine the appropriate model to fit to a time series data even after the time plot have been properly examined. It is also necessary to examine the two models identification tools. That is, the autocorrelation function (ACF) and partial autocorrelation function (PACF). The first approach to solving this problem is the use of the traditional Box – Jenkins approach which applied the combination of the ACF and PACF functions.

The behavior of the ACF and PACF can be used to help in identifying which model describes the time series value. The summary of the behavior of ACF and PACF for each of the general non-seasonal models is presented in Table 1.

Table 1: Table 1: The behavior of ACF and PACF for each of the general models

Model	ACF	PACF
Moving Average (MA) of Order q	Cuts off after lag q	Dies down
Autoregressive (AR) of order p	Dies down	Cuts off after p
Mixed autoregressive-moving average (ARMA) of order (p, q)	Dies down	Dies down

According to the principle of parsimony, parsimonious models are more preferred to over parameterized model when all things being equal (Hanke et al., 2001).

Model Estimation

After selecting the tentative models, the parameters for that model must be estimated. The parameters in ARIMA models are estimated by minimizing the sum of squares of the fitting errors. In general, the least squares estimates must be obtained using a nonlinear least squares procedure. A nonlinear least squares procedure is simply an algorithm that finds the minimum of the sum of squared errors function. Once the least squares estimates and their standard errors are determined, t-values can be constructed and interpreted in the usual way. Parameters that differs significantly from zero are retained in the fitted model while parameters that do not are dropped from the model.

Diagnostic Checking

Before a model is been used for forecasting, it must be checked for adequacy. Basically, a model is adequate if the residuals cannot be used to improve the forecasts. That is the residuals should be random. An overall check of model adequacy is provided by a χ^2 test based on the Ljung-Box Q-statistic. The test considers the sizes of the residual autocorrelations as a group. If the p-value associated with the Q-statistic is small, the model is considered inadequate. One should consider a new or modified model and continue the analysis process until a satisfactory model has been determined. However, if the p-value associated with the Q-statistic is not small, the model is considered adequate

Forecasting

Forecasting in time series involves predicting the future values of a series given its previous values of an error term. If the magnitudes of the most recent errors tend to be consistently larger than previous errors, it may be time to re-evaluate the model. Although ARIMA models involve differences, forecasts for the original series can be always computed directly from the fitted model.

ARIMAX Model

The ARIMAX model is an extension of autoregressive integrated moving average (ARIMA) model. It is an ARIMA model with exogenous variables. The time series modeling which is carried out by adding some variables are considered to have a significant contribution on the variables under study. It is done to increase the forecast accuracy of the model. The ARIMAX model is a generalization of ARIMA model and is capable of incorporating an external variables (X). given a (K + 1) time –series process $\{y_t,\ X_t\}$, where $y_t,\ and\ k$ components of X_t are real valued random variables, ARIMAX model assumed the form:

$$y_t\left(1-\sum_{j=1}^{p}\propto_s L^s\right)=\mu+\sum_{s=1}^{q}\beta_s^{'}L^sX_t+$$

1+s=1pγsLset

Where L is the usual lag operator

$L^s y_t = y_{t-s} L^s X_t = X_{t-s}$ e t c

$\mu\epsilon R, \alpha_s\epsilon R, \beta_s\epsilon R^k\ and\ \gamma_s\epsilon R$ are parameters, $e_t{'}$s errors, and p, q and r are natural numbers specified in advance. The first step in building an ARIMAX model consists of identifying a suitable ARIMA model for the endogenous variable. The ARIMAx model concept requires testing for stationarity of exogenous variable before modelling.

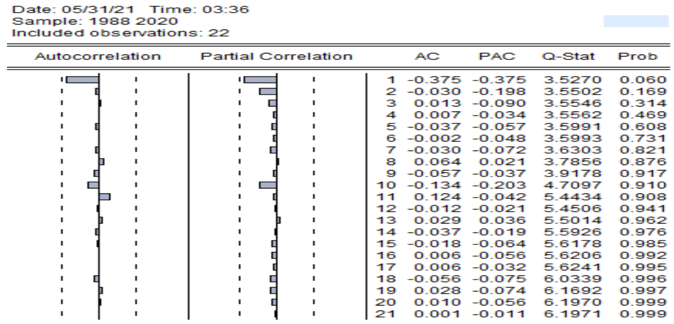
IV. RESULT AND DISCUSSION

IV.1 Unit Root Test

The application of most time series models requires data to be stationary (Prabakaran & Sivapragasm, 2014). The ADF test is applied for testing the stationarity for all the data sets considered in this study. It can be observed that all the data set are not stationary at level (p-values > 0.05). However, the data sets were stationary after first difference (p-values < 0.05) (Table 2). Thus confirmed that first differencing for all series are perfect for modelling and forecasting.

IV.2 Model Identification

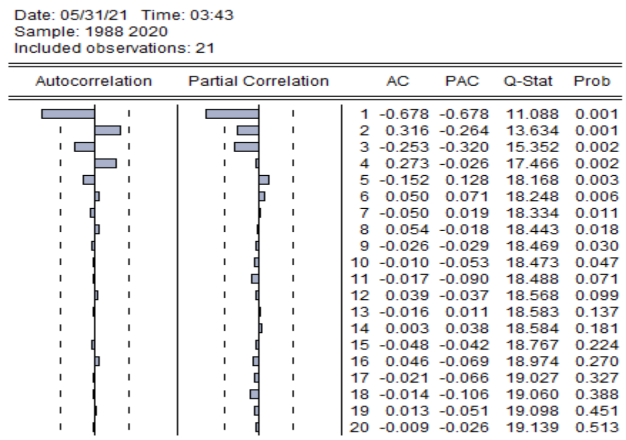
The autocorrelation function (ACF) and partial autocorrelation function (PACF) was used as a tools for identifying the parameter of the model. The ACF and PACF at first difference is presented in Figures below:



	AC	PAC	Q-Stat	Prob
1	-0.375	-0.375	3.5270	0.060
2	-0.030	-0.198	3.5502	0.169
3	0.013	-0.090	3.5546	0.314
4	0.007	-0.034	3.5562	0.469
5	-0.037	-0.057	3.5991	0.608
6	-0.002	-0.048	3.5993	0.731
7	-0.030	-0.072	3.6303	0.821
8	0.064	0.021	3.7856	0.876
9	-0.057	-0.037	3.9178	0.917
10	-0.134	-0.203	4.7097	0.910
11	0.124	-0.042	5.4434	0.908
12	-0.012	-0.021	5.4506	0.941
13	0.029	0.036	5.5014	0.962
14	-0.037	-0.019	5.5926	0.976
15	-0.018	-0.064	5.6178	0.985
16	0.006	-0.056	5.6206	0.992
17	0.006	-0.032	5.6241	0.995
18	-0.056	-0.075	6.0339	0.996
19	0.028	-0.074	6.1692	0.997
20	0.010	-0.056	6.1970	0.999
21	0.001	-0.011	6.1971	0.999

Figure 1: First Order difference of LNY

The tentative model identified from the correlogram is ARIMA (1,1,1) and ARIMA (10, 1,1)



	AC	PAC	Q-Stat	Prob
1	-0.678	-0.678	11.088	0.001
2	0.316	-0.264	13.634	0.001
3	-0.253	-0.320	15.352	0.002
4	0.273	-0.026	17.466	0.002
5	-0.152	0.128	18.168	0.003
6	0.050	0.071	18.248	0.006
7	-0.050	0.019	18.334	0.011
8	0.054	-0.018	18.443	0.018
9	-0.026	-0.029	18.469	0.030
10	-0.010	-0.053	18.473	0.047
11	-0.017	-0.090	18.488	0.071
12	0.039	-0.037	18.568	0.099
13	-0.016	0.011	18.583	0.137
14	0.003	0.038	18.584	0.181
15	-0.048	-0.042	18.767	0.224
16	0.046	-0.069	18.974	0.270
17	-0.021	-0.066	19.027	0.327
18	-0.014	-0.106	19.060	0.388
19	0.013	-0.051	19.098	0.451
20	-0.009	-0.026	19.139	0.513

Figure 2: Second order difference of LNR

The tentative model identified from the plot above is ARIMA (1, 2, 1) and ARIMA (1, 1, 1).

After identifying the tentative models using autocorrelation and partial autocorrelation function, the best fitted model was selected on the basis of least value of AIC of the tentative models identified. It was found that ARIMA (10, 1, 1) and ARIMA (1,1,1) were conserved as the best model for LNY and LNR respectively. In addition, ARIMAX (1, 1, 1) and ARIMAX (1,1,1) were considered as the best ARIMAX model for LNY and LNR respectively (Table 3). From the residuals ACF and PACF plots of ARIMA and ARIMAX, it was clear that all autocorrelations and partial autocorrelations lie between 95% control limits as shown in Figure 3 – 6. This also confirmed the goodness of fit of this selected models.

IV.3 Parameter Estimates of ARIMA and ARIMA Model

Table 4 presents the parameter estimates of ARIMA model. The R-square value of 0.2901 indicates that 29.1% of the variation in the dependent variable is account for by the independent variable. The model was significant at 10% prob(F-statistics) = 0.095733. This suggest that current values of LNY can be predicted from its previous values. However, none of the parameters was found to be significant.

Furthermore, the R-square value of 0.277970 for LNR indicates that the independent variables accounted for 27.8% of the variation in the dependent variable. This indicates that the passed values of LNR accounted for 27.8% of the variation in the current values of LNR. The prob(F-statistics) = 0.01077) indicates that the model is significant at 5% in predicting the future values of LNR. The AR(1) significantly contribute to the model.

Table 5 present the results of parameter estimates of ARIMAX model. It can be observed that R-square value of 0.620375. This suggest 62% of the variation in the current values of LNY is accounted for by the passed values of LNY and the changes in climates. The prob(F-statistics) = 0.012546 indicates that the overall model is significant. The model found that LNH and LNRA have negative and significant effect on of LNY at 10% and 5% level of significant. This implies that the higher the rainfall and humidity the less the values of LNY. The finding of the current study is in line with previous study by Fosu-Mensah (2012) who established that when temperature exceeds the optimum level for biological process, crops often respondents negatively with step drop in net growth and yield. Gornall et all (2010) also opined that extreme temperature leads to lower yields.

In addition, the parameter estimates of LNR revealed a R-square value of 0.385690 indicating that previous values of LNR and the explanatory variables considered in this study accounted for 38.6% of the variation in the current value of LNR. The prob(F-statistics) = 0.023426 indicates that the overall model is significant. The AR(1) term was found to be significant in predicting the current values of LNR.

4.5 Forecast Evaluation

The result of the forecast evaluation performance indicates that ARIMAX (1,1,1) performed better in forecasting the future values of LNY since it has the least values of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). However, ARIMA (1, 1, 1) performed better in forecasting the future values of LNR.

Table 2: Unit Root Test using ADF

Variables	Difference Order	ADF	P-value	Remark
LNR	0	-1.051113	0.7124	Not Stationary
	1	-5.229064	0.0007	Stationary
LNY	0	-1.895035	0.3283	Not Stationary
	1	-6.460630	0.0000	Stationary

Source: generated using EVIEWS

Table 3: Tentative ARIMA and ARIMAX Models

Variables	ARIMA MODEL	AIC	ARIMAX	AIC
LNY	(1, 1, 1)	1.313694	(1, 1, 1)	0.991562
	(10, 1, 1)	1.250401	(10, 1, 1)	1.088868
LNR	1, 2, 1)	0.407689	1, 2, 1)	0.276334
	(1, 1, 1)	0.144341	(1, 1, 1)	0.254907

Source: Computed using EVIEWS

Table 4: parameter Estimate of ARIMA Models

Variables	Parameters	Coefficient	Std Error	t-statistics	Prob
LNY	C	0.079405	0.090887	0.873671	0.3938
	AR(10)	-0.368184	1.230403	-0.299239	0.7682
	MA(1)	-0.526844	0.340349	-1.547952	0.1390
	SIGMASQ	0.1311052	0.095179	1.376898	0.1854
	R-square	0.290904			
	Adj R-square	0.172721			
	Prob(F-statistics)	0.095733			
LNR	C	0.004407	0.065440	0.067349	0.9470
	AR(1)	-0.943549	0.351072	-2.687620	0.0150
	MA(1)	0.646504	0.716526	0.902276	0.3788
	SIGMASQ	0.045202	0.013245	3.412734	0.0031
	R-square	0.277970			
	Adj R-square	0.157632			
	Prob(F-statistics)	0.01077			

Source: Computed using EVIEWS

Table 5: parameter Estimate of ARIMAX Models

Variables	Parameters	Coefficient	Std Error	t-statistics	Prob
LNY	C	23.40749	13.95432	1.677437	0.1142
	LNT	-0.637817	4.747094	-0.134360	0.8949
	LNRA	-2.504855	1.308178	-1.914766	0.0748
	LNH	-1.460100	0.660022	-2.212197	0.0429
	AR(10)	-0.345875	0.485964	-0.711729	0.4876
	MA(1)	-1.000000	12620.79	-7.92E-05	0.9999
	SIGMASQ	0.070161	19.61250	0.003577	0.9972
	R-square	0.620375			
	Adj R-square	0.468526			
	Prob(F-statistics)	0.012546			
LNR	C	5.991519	12.65825	0.473329	0.6428
	LNT	-4.243557	3.794073	-1.118470	0.2810

	LNRA	-0.097372	0.637785	-0.152672	0.8807
	LNH	2.129459	2.644475	0.805248	0.4333
	AR(1)	-0.943648	0.389369	-2.423529	0.0285
	MA(1)	0.652017	0.916169	0.711678	0.4876
	SIGMASQ	0.038458	0.015760	2.440245	0.0276

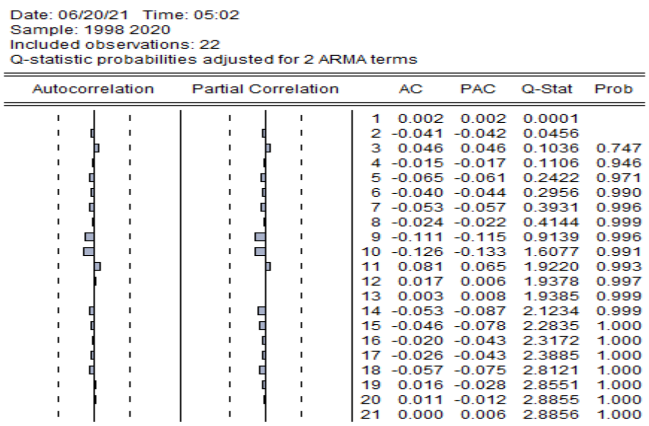
	R-square	0.385690			
	Adj R-square	0.139966			
	Prob(F-statistics)	0.023426			

Source: Computed using EVIEWS

Table 6: Forecast Performance Evaluation

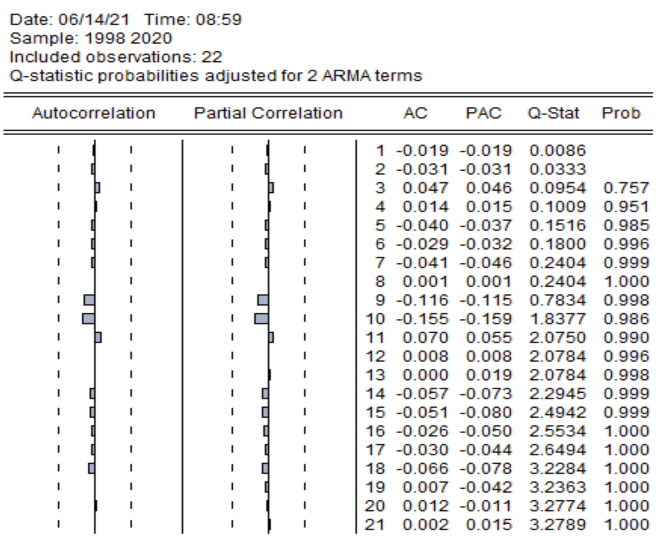
Variable	ARIMA	RMSE	MAE	MAPE	ARIMAX	RMSE	MAE	MAPE
LNY	(10, 1, 1)	0.4728	0.3740	8.6384	(1, 1, 1)	0.3149	0.2061	5.2246
LNR	(1, 1, 1)	0.4437	0.3611	6.5664	(1, 1, 1)	0.4489	0.3798	6.9580

Source: Computed using EVIEWS


Date: 06/20/21 Time: 05:02
Sample: 1998 2020
Included observations: 22
Q-statistic probabilities adjusted for 2 ARMA terms

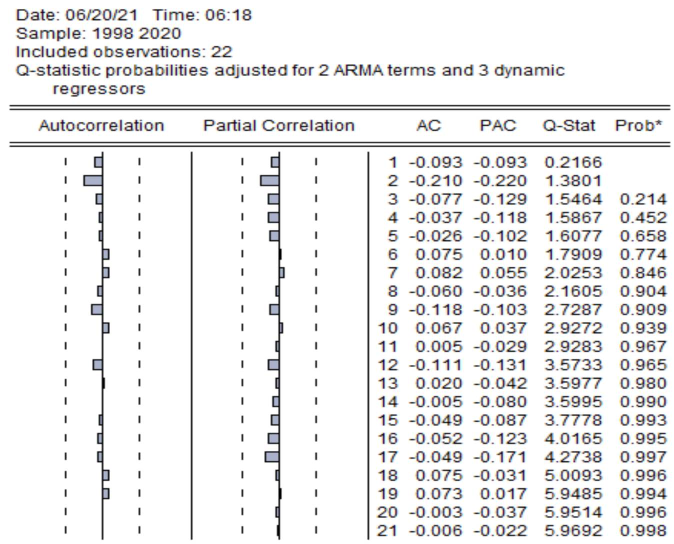
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.002	0.002	0.0001	
		2	-0.041	-0.042	0.0456	
		3	0.046	0.046	0.1036	0.747
		4	-0.015	-0.017	0.1106	0.946
		5	-0.065	-0.061	0.2422	0.971
		6	-0.040	-0.044	0.2956	0.990
		7	-0.053	-0.057	0.3931	0.996
		8	-0.024	-0.022	0.4144	0.999
		9	-0.111	-0.115	0.9139	0.996
		10	-0.126	-0.133	1.6077	0.991
		11	0.081	0.065	1.9220	0.993
		12	0.017	0.006	1.9378	0.997
		13	0.003	0.008	1.9385	0.999
		14	-0.053	-0.087	2.1234	0.999
		15	-0.046	-0.078	2.2835	1.000
		16	-0.020	-0.043	2.3172	1.000
		17	-0.026	-0.043	2.3885	1.000
		18	-0.057	-0.075	2.8121	1.000
		19	0.016	-0.028	2.8551	1.000
		20	0.011	-0.012	2.8855	1.000
		21	0.000	0.006	2.8856	1.000

Figure 3: Correlogram Residual Test of ARIMA (10, 1, 1)


Date: 06/14/21 Time: 08:59
Sample: 1998 2020
Included observations: 22
Q-statistic probabilities adjusted for 2 ARMA terms

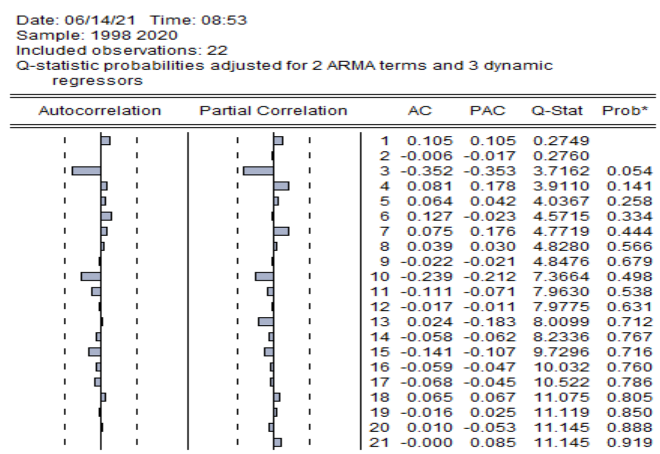
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.019	-0.019	0.0086	
		2	-0.031	-0.031	0.0333	
		3	0.047	0.046	0.0954	0.757
		4	0.014	0.015	0.1009	0.951
		5	-0.040	-0.037	0.1516	0.985
		6	-0.029	-0.032	0.1800	0.996
		7	-0.041	-0.046	0.2404	0.999
		8	0.001	0.001	0.2404	1.000
		9	-0.116	-0.115	0.7834	0.998
		10	-0.155	-0.159	1.8377	0.986
		11	0.070	0.055	2.0750	0.990
		12	0.008	0.008	2.0784	0.996
		13	0.000	0.019	2.0784	0.998
		14	-0.057	-0.073	2.2945	0.999
		15	-0.051	-0.080	2.4942	0.999
		16	-0.026	-0.050	2.5534	1.000
		17	-0.030	-0.044	2.6494	1.000
		18	-0.066	-0.078	3.2284	1.000
		19	0.007	-0.042	3.2363	1.000
		20	0.012	-0.011	3.2774	1.000
		21	0.002	0.015	3.2789	1.000

Figure 4: Correlogram Residual Test of ARIMA (1, 1, 1)


Date: 06/20/21 Time: 06:18
Sample: 1998 2020
Included observations: 22
Q-statistic probabilities adjusted for 2 ARMA terms and 3 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.093	-0.093	0.2166	
		2	-0.210	-0.220	1.3801	
		3	-0.077	-0.129	1.5464	0.214
		4	-0.037	-0.118	1.5867	0.452
		5	-0.026	-0.102	1.6077	0.658
		6	0.075	0.010	1.7909	0.774
		7	0.082	0.055	2.0253	0.846
		8	-0.060	-0.036	2.1605	0.904
		9	-0.118	-0.103	2.7287	0.909
		10	0.067	0.037	2.9272	0.939
		11	0.005	-0.029	2.9283	0.967
		12	-0.111	-0.131	3.5733	0.965
		13	0.020	-0.042	3.5977	0.980
		14	-0.005	-0.080	3.5995	0.990
		15	-0.049	-0.087	3.7778	0.993
		16	-0.052	-0.123	4.0165	0.995
		17	-0.049	-0.171	4.2738	0.997
		18	0.075	-0.031	5.0093	0.996
		19	0.073	0.017	5.9485	0.994
		20	-0.003	-0.037	5.9514	0.996
		21	-0.006	-0.022	5.9692	0.998

Figure 5: Correlogram Residual Test of ARIMAX (1, 1, 1)


Date: 06/14/21 Time: 08:53
Sample: 1998 2020
Included observations: 22
Q-statistic probabilities adjusted for 2 ARMA terms and 3 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.105	0.105	0.2749	
		2	-0.006	-0.017	0.2760	
		3	-0.352	-0.353	3.7162	0.054
		4	0.081	0.178	3.9110	0.141
		5	0.064	0.042	4.0367	0.258
		6	0.127	-0.023	4.5715	0.334
		7	0.075	0.176	4.7719	0.444
		8	0.039	0.030	4.8280	0.566
		9	-0.022	-0.021	4.8476	0.679
		10	-0.239	-0.212	7.3664	0.498
		11	-0.111	-0.071	7.9630	0.538
		12	-0.017	-0.011	7.9775	0.631
		13	0.024	-0.183	8.0099	0.712
		14	-0.058	-0.062	8.2336	0.767
		15	-0.141	-0.107	9.7296	0.716
		16	-0.059	-0.047	10.032	0.760
		17	-0.068	-0.045	10.522	0.786
		18	0.065	0.067	11.075	0.805
		19	-0.016	0.025	11.119	0.850
		20	0.010	-0.053	11.145	0.888
		21	-0.000	0.085	11.145	0.919

Figure 6: Correlogram Residual Test of ARIMAX (1, 1, 1)

V. CONCLUSION

The study aimed at investing the effect of the variability of rainfall, temperature, humidity on some selected crops in Nasarawa State using ARIMA and ARIMAX models. The forecast evaluation carried out using RMSE, MAE and MAPE revealed that ARIMAX model performed better in forecasting the future values of yam. However, ARIMA model performed better in forecasting the future value of rice. The ARIMAX model revealed that high rainfall reduces the yield of yam in the study area.

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