MODELLING AND FORECASTING OF MILLET PRODUCTION IN NIGERIA

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ABSTRACT:

Millet is one of the most extensively cultivated cereals in the world, ranking fourth after rice, wheat and sorghum. In Nigeria since independence it has been noticed that the area under millet production has been gradually decreased, even though there is increase of productivity in some areas. However, millet production hampered with numerous problems which drastically decreased yields of millet production from about 8 million tonnes in the year 2008 to about 5 million, 1 million and even 0.9 million tonnes in 2009/2010, 2011/2012 and 2013 respectively. There is slight increase in production of 2014, 2015, 2016 and 2017 of 1.3, 1.4, 1.5 and 1.5 million tonnes respectively. There is need to examine the trend of millet production in Nigeria. Therefore, this research modelled millet production in Nigeria for the period of 55 years from 1962 to 2017 using the secondary data from Food and Agriculture of United Nations (FAO). The result shows that ARIMA (1,1,0) is the model that best fit and describe the reality among the 10 postulated ARIMA models because it has the least Akaike information criteria (AIC) and Bayesian information criteria (BIC), the model evaluated its performance and forecast five years observations for 2018 to 2022, and the results shows expected (increase in) millet production of 2,079,942; 2,522,333; 2,842,501; 3,074,214; and 3,241,909 tonnes for the year 2018; 2019; 2020; 2021; and 2022 respectively. Finally, The ARIMA model is suggested for modelling millet production in Nigeria.

Key Words: Millet Production, ARIMA, Model Evaluation Criteria, Forecasting, Nigeria

INTRODUCTION

Millet is one of the most extensively cultivated cereals in the world, ranking fourth after rice, wheat and sorghum in terms of area planted to these crops (Economy affair, 2017). Millet is second in importance only to sorghum as a staple food crop in the northern Nigeria, over 40% of land sown annually to cereals is devoted to millet. Thus, millet is sown annually of about five million hectares of land between latitude 70N and 140N with a yield of about 4 million metric tonnes of grain (Aminu-Kano et al., 1998). It is a principal cereal cultivated in drought-prone semi-arid regions of Africa and the Indian subcontinent, mostly for food uses. Millet is also known as “Bajra” (India), “Gero”

(Nigeria, Hausa language), "Hegni" (Niger, Djerma language), "Sanyo" (Mali), "Dukhon" (Sudan, Arabic), and "Mahangu" (Namibia). Millet is a popular crop for food and fodder grown under limited moisture supply. Millet crop has wide adaptability to local environments. It is a hardy crop and can be grown in areas which are very hot and dry and on soils too poor for crops like maize and sorghum. Millet is considered more efficient in utilization of soil moisture and has a higher level of heat tolerance than sorghum and maize. As reported by Aminu-Kano *et al*. (1998), Nigeria is among the leading millet producing country. Within the last two decades, the country has become increasingly in the production of the crop, accounting for 14% of average annual global production in the period 1992 – 1994 in comparison with only 9% in the period 1979 -1981 period. The importance of Millet productivity forecasting is more relevant in semiarid state like Nigeria where the precipitation is confirmed to short period of four months. It is important foods in many underdeveloped countries because of their ability to grow under adverse weather conditions like limited rainfall. Millets ranks as the sixth most important cereal and feeds one third of the total world population (Khairawal, Rai, Andrew and Harrnarayana, 1999; FAO, 2007). They are easy to cultivate, inherently bio-diverse and can be grown together with varied crops. Another attributes of millets that make them a preferred choice in areas where they are cultivated, are their short harvest period. In African and Asian countries, millets serve as the main ingredient for preparation of traditional foods and beverages (Chopra, 2001). Millet is the major source of energy and protein for millions of people in Africa. It has been reported that millet has many nutritious and medical functions. Nigeria is the 3rd largest millet producing country in the world after India and China, and the leading producer in Africa followed by Niger and Mali. The areas of production in Nigeria are mostly; Kaduna, Yobe, Kano and Borno states. FAO (2009) stated that, in 2007 global millet production reached about 32 million tonnes with the top producing countries being: India (10,610,000), Nigeria (7,700,000), Niger (2,781,928), China (2,101,000), Burkina Faso (1,104,010), Mali (1,074,440), Sudan (792,000), Uganda (732,000), Chad (550,000) and Ethiopia (500,000). According to Chopra (2001) Pearl millet is the sixth most important cereal annually cultivated as rain fed crop in arid and semi-arid areas of Africa and the Indian sub-continent (Khairawal, Rai, Andrew and Harrnarayana, 1999; FAO, 2007). It is grown in over 40 countries predominantly in Africa and Asia as a staple food grain and source of feed and fodder, fuel and construction material (FAO, 2007). Pearl millets have excellent nutritional quality and are comparable to some commonly consumed cereals like wheat and rice (Ragaee et al. 2006). Pearl millets also offer several health benefits to consumers. Millet consumption can also lower glycemic response, which can be helpful for the treatment of type II diabetes (Choi et al. 2005). Inclusion of pearl millet in the human diet can also lower the risk of duodenal ulcers, anemia and constipation. They are valuable sources of some essential minerals such as potassium, magnesium, calcium, iron and zinc. Despite their beneficial nutritional properties and tolerance for adverse growing conditions, pearl millet consumption has been less compared to major cereals such as rice, wheat and corn. Pearl millet responds well to management inputs, therefore it has high potential of becoming an important component of intensive agriculture especially in arid and semi-arid regions (Izge, 2006). Pearl millet production attained approximately 54% of the global production in 2004. India is the largest producer of pearl millet in Asia, both in terms of area and production with an average productivity of 930kg/ha (ICRISAT report of 2011). Within the last two decades, Nigeria has become increasingly important in the production of millet even with the numerous problems involved in its cultivation. Nigeria has moved from the third to the present second largest producer in the world (Aminu, Ajayi, Ikwelle and Anaso, 1998). However, yields of pearl millet have over the years decreased. Izge (2006) reported that the purpose for expanding pearl millet production in Nigeria has actually been deliberate to meet the growing demand for food. Pearl millet production is hampered by numerous problems and as such there is a need to find ways of improving its productivity. Paul *et al.*(2013) applied Seasonal ARIMA (SARIMA) model for forecasting of total meat export from India. Gibert (2005) used ARIMA time-series models to present multistage supply chain model. Given an ARIMA model of consumer demand and lead time at each stage, it was showed that the orders and inventories at each stage are also ARIMA Ahmad *et al*. (2001) analyzed water quality data using an ARIMA model. ARIMA model has been frequently employed to forecast the future requirements in terms of internal consumption and export to adopt appropriate measures (Muhammed *et al*., 1992; Shahur and Haque, 1993; Kahforoushan*et al*., 2010; Sohail*et al*., 1994).

MATERIALS AND METHODS

Autoregressive (AR) Process

Let Y_t represent a time series, then

$$(Y_t-\delta) = \alpha_1 (Y_{t-1}-\delta) + \varepsilon_t \qquad (1)$$

Where δ is the mean of Y and ε_t which is an uncorrelated random error term with mean zero and constant variance σ^2 (it's a white noise) then we say that Y_t follows a first order autoregressive, or AR(1), stochastic process. Here the value of Y at time t depend on its value in the previous time period and random term but if we consider this model

$$(Y_t-\delta) = \alpha_1 (Y_{t-1}-\delta) + \alpha_2 (Y_{t-2}-\delta) + \varepsilon_t \qquad (2)$$

Then we say that Y_t follows a second-order autoregressive AR (2) process. That is the value of Y at time t depends on its value in the previous two time periods, where the Y value are being expressed around their mean value δ.

In general, we can have

$$(Y_t-\delta) = \alpha_1 (Y_{t-1}-\delta) + \alpha_2 (Y_{t-2}-\delta) + \ldots + \alpha_p (Y_{t-p}-\delta) + \varepsilon_t \qquad (3)$$

In which case Y_t is a p^{th}-order, or AR (p) process.

Equation (3) can also be written as

$$Y_t = \text{Ʈ} + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \varepsilon_t$$

Where $\text{Ʈ} = (1-\sum_i^p \alpha_i) \delta$

Therefore, an AR model is simply a linear regression of the current value of the series against one more prior value of the series. The value of P is called the order of the AR model. The model can be analyzed with one of various methods, including standard linear least square (OLS) techniques.

Moving Average (MA) Model

Another common approach for modeling univariate time series data is the MA model. Suppose we model Y_t as follows

$$Y_t = Ø + \beta_o \varepsilon_t + \beta_1 \varepsilon_{t-1} \quad (4)$$

Where Ø is a constant and ε_t, is the random error shock. Here Y_t is equal to a constant plus a moving averages of the current and past error term. Thus, we say that Y_t follows a first-order moving averages, or an MA (1) process. If Y_t is model as

$$Y_t = Ø + \beta_o \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2}$$

Then. it is an MA (2) process. More generally

$$Y_t = Ø + \beta_o \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \ldots + \beta_p \varepsilon_{t-p} \quad (5)$$

Then Y_t is an MA (p) (i.e moving averages of order p). Therefore an MA process is simply a linear combination of white noise error terms.

Autoregressive and Moving Averages (ARMA) Process

It is quite likely that Y_t has characteristics of both AR and MA process and is therefore ARMA. Thus, Y_t follows an ARMA (1, 1) process if it can be written as

$$Y_t = w + \alpha_1 Y_{t-1} + \beta_o \varepsilon_t + \beta_1 \varepsilon_{t-1} \quad (6)$$

That is Y_t is linear of one AR and one MA term, where w is a constant term. In general, in an ARMA (p,q) process; there will be p autoregressive and q moving averages terms.

Autoregressive Integerated Moving Averages (ARIMA) Model

The Univariate Autoregressive Moving Average (ARMA) model is a time series medel that uses past and current values of the dependent variable to produce forecasts of the variable. The technique generates that this identified correlation will continue into the future. In this way, it becomes possible to obtain good approximation of the behavior of a variable by a purely statistical approach. Based on the Box-Jenkins (1976) modeling technique, ARMA methodology seeks to establish a parsimonious relationship, using as few parameters as possible. For example to forecast the values of a series y, using the ARMA technique, the general model specification for the series is expressed as

$$y_t = (a_1L + a_2L^2 + \ldots + a_pL^P)\, y_t + (1 + b_1L + \ldots + b_q L^q)\, e_t \quad (7)$$

and can be expressed as

$$y_t = \sum_{i=1}^{p} (a_i L^p) y_t + \sum_{i}^{q} (b_i L^q) e_t + e_t$$

Where P and q = the number of lags for autoregressive (AR) and moving average (MA) processes respectively; e_t = an error process, with $e_t \sim N(0,1)$

L =the lag operator on the processes; defined as $L^n y_t = y_{t-n}$ or $L y_t = y_{t-1}$

The specification can be further extended to include explicit modelling of seasonal factors observed in the data. Apart from specifying seasonal dummy variables, the pure time series ARMA Specification is extended to the Seasonal Autoregressive Moving Average (SARMA). Detail definition of ARIMA models are stated as follows. To determine the appropriate lag lengths of the processes, examination of the autocorrelation (ACF) and Partial autocorrelation (PACF) functions is necessary, as these functions give the relationship between data points, and indicates the memory of the data generation process.

An ARIMA-seasonal model is denoted ARIMA(P,D,Q) , where P is the order of auto regression in the seasonal model, D is the order of differencing, Q is the order of the moving average in the seasonal model and S is the seasonal length.

A seasonal-ARIMA (P, D, Q) *S* model is given by

$$(1-\beta_1-\ldots-\beta_p L^{sp})(1-L^s)^D y_t = (1-\Phi_1 L^s-\ldots-\Phi_Q L^{QS})\,\varepsilon_t \quad (8)$$

Statistical Test

Augmented Dickey Fuller (ADF) Test

This test was first introduced by Dickey and fuller (1979) to test for the presence of unit root (s)

$$\Delta y = \alpha y_{t-1} + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} \quad (9)$$

The hypothesis testing:

Ho: $\alpha = 0$ (the series contains unit roots)

H1: $\alpha < 0$ (the series is stationary)

Decision Rule:

Reject the null hypothesis (Ho) if the test statistic is less than the asymptotic critical values.

KPSS Test (Kwiatkowski Phillips Schmidt Shin Test)

This test is used to test for stationary in level (i.e. mean) by considering

$$Y_t = X_t + Z_t \quad (10)$$

The integration properties of a series Y_t may be investigated by testing:

Ho: $Y_t \sim t$

H1: $Y_t \sim t$

That is, the null hypothesis that the data generating process (DGP) is stationary is tested against a unit root and KPSS.

Model Selection Methods

The most famous Information Criteria are Akaike Information Criteria (AIC), the Bayesian Swartz Information Criteria (SIC) are considered for model selection. These criteria are computed using the log-likelihood estimates. Given the criteria values of two or more models, the model satisfying minimum AIC or SIC is most representatives of the true model and, may be interpreted as the best approximating model among those being considered (Dayton 2003, Hamadu and Adeleke, 2009). Let r, k, n and *ll* be response variable, the number parameters, the number of observations and the maximum likelihood function respectively. The Akaike Information Criteria is

$$AIC = -2\left(\frac{ll}{n}\right) + \frac{2k}{n} \quad (11)$$

The Schwartz Bayesian information criteria is an alternative the AIC that imposes a large penalty for additional coefficients. It is given as:

$$SIC = -2\left(\frac{ll}{n}\right) + \frac{k \ln n}{n} \quad (12)$$

The main reason for preferring the use of a model selection procedure such as SIC in comparison to traditional significance tests is the fact that, a single holistic decision can be made concerning the model that is best supported by the data in contrast to what is usually a series of possibly conflicting significance test. Moreover, models can be ranked from best to worst supported by the data at hand, thus, enlargeing the possibilities of interpretation (for more insights see Dayton, 2003, Hamadu and Ibiwoye, 2010).

Empirical-Analysis

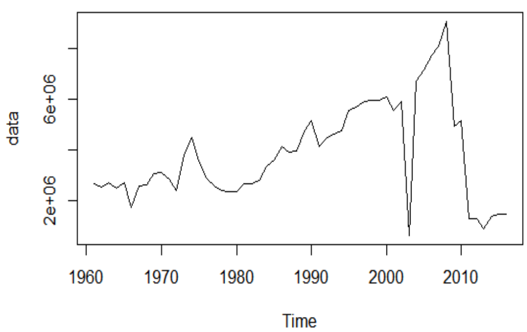

Figure 1: A plot of millet production in Nigeria (1962-2017)

Data source: *Food and Agriculture of United Nations (FAO)*

From the above figure the pattern exhibits trend behaviour why? because the trend pattern exist when the data generally exhibit random fluctuations, a time series may also show gradual shifts to relatively higher particularly between 2004 to 2010 and fall in 2011.If a time series plot exhibits this type of behaviour, we say that trend pattern exists. Therefore the above figure delineate that trend pattern exist.

Figure 2: a plot of the first order difference of millet production (1962-2017)

Data source: *Food and Agriculture of United Nations (FAO)*

The above figure depicts that the series is stationary in terms of mean and variance that is, this portrait that there is no any variability between the pattern of the series. This implies that the series is stationary at integrated of order one. A time series is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time period depends only on the distance or gap or lag between the two times periods and not the actual time at which the covariance is computed. In short, if a time series is stationary, its mean, variance and auto covariance (at various lags) remain the same no matter at what point we measure them.

Unit Root Test

Table 1; Augmented Dickey-Fuller Test (ADF)

Dickey-Fuller	-3.7771
Lag order	3
p-value	0.02645

Since p value = 0.02645<α= 0.05 then we reject the null hypothesis and conclude that the series is stationary.

Table 2: KPSS test statistics and critical values

KPSS Level	0.10288
Truncation lag parameter	1
p-value	0.1

Since p value = 0.1> α= 0.05 we do not reject the null hypothesis and conclude that the unit root is reliable.

Plot of Autocorrelation (ACF) and Partial Autocorrelation (PACF) Function

Before we can determine the estimate of the parameter for the time series we first of all identify the order of the model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) factor plot which can help to identify the pattern in the stationary series of millet production, the idea is to identify the presence of AR and MA components in the residuals

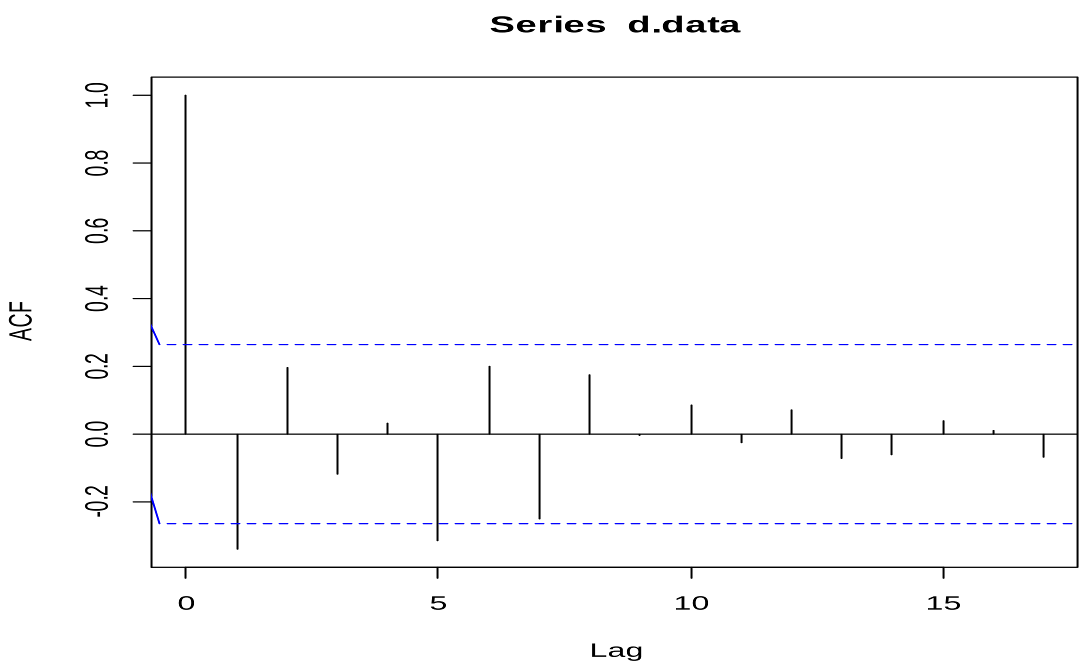

Figure 3: Autocorrelation function (ACF) of millet production

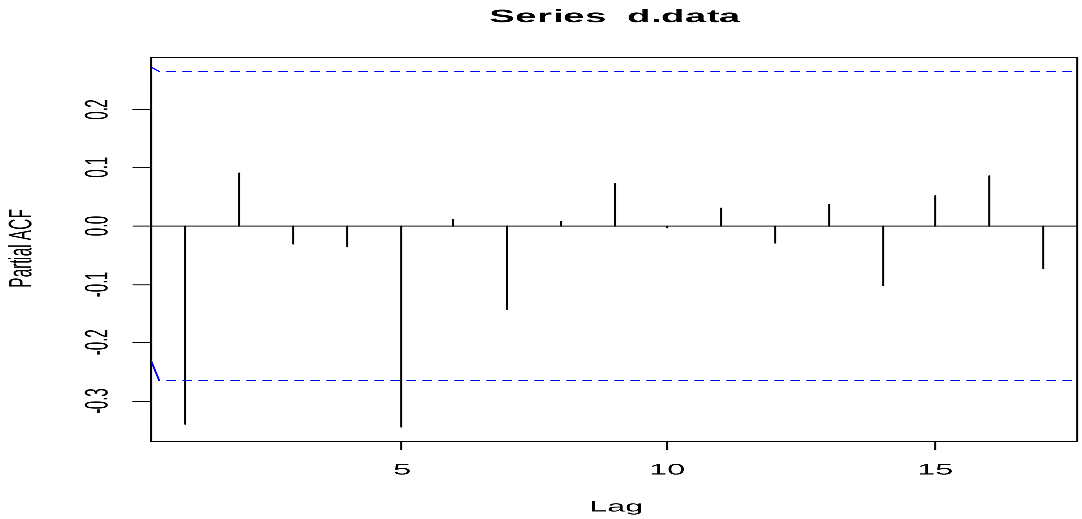

Figure 4: Partial Autocorrelation function (PACF) of millet production

From the plot of ACF AND PACF above we notice that there is spikes in the plots outside the insignificant zones, therefore we conclude that the residuals are not random.

Table 4. Postulated Model and Evaluation

MODEL	AIC	BIC
ARIMA (1,1,0)	1711.1	714.89
ARIMA(1,1,1)	1720.3	716.67
ARIMA(1,1,2)	1717.1	721.23
ARIMA(1,1,3)	1714.7	730.43
ARIMA(2,1,1)	1720.2	733.56
ARIMA(2,1,2)	1718.4	735.78
ARIMA(2,1,3)	1729.8	741.48
ARIMA(3,1,1)	1735.5	745.37
ARIMA(3,1,2)	1740.6	749.79
ARIMA(3,1,3)	1743.7	757.23

This implies that there is information available in the residuals extracted by ARIMA models. Based on the model selection criteria of AIC and BIC, the appropriate model is selected. The models together with selection criteria are presented in table below. ARIMA(1,1,1), ARIMA(2,1,3), ARIMA(3,1,1), ARIMA(3,1,2), ARIMA(3,1,3) respectively. And under BIC: still ARIMA (1,1,0) has the minimum value, but followed by ARIMA(1,1,1), ARIMA(1,1,2), ARIMA(1,1,3), ARIMA(2,1,1), ARIMA(2,1,2), ARIMA(2,1,3), ARIMA(3,1,1), ARIMA(3,1,2), and ARIMA(3,1,3) respectively. From both the two selection processes ARIMA (1,1,0) has the minimum value and therefore it is the parsimonious model that fits the data.

Table 5. A Forecast of the millet production (2018 – 2022)

Years	Forecast point
2018	2079942
2019	2522333
2020	2842501
2021	3074214
2022	3241909

The above table shows the forecast of millet production from 2018 to 2022 using the best fitted model i.e ARIMA (1,1,0) that Nigeria will have an estimated millet production of 2,079,942; 2,522,333; 2,842,501; 3,074,214; and 3,241,909 metric tonnes for the year 2018; 2019; 2020; 2021; and 2022 respectively. We observed a gradual increase in the production from 2014 to 2022 despite the series of decreased in 2009 to 2013.

CONCLUSION

Millet is one of the most extensively cultivated cereals in the world, ranking fourth after rice, wheat and sorghum. In Nigeria since independence it has been noticed that the area under millet production has been gradually decreased, even though there is increase of productivity in some areas. However, millet production hampered with numerous problems which drastically decreased yields of millet production from about 8 million tonnes in the year 2008 to about 5 million, 1 million and even 0.9 million tonnes in 2009/2010, 2011/2012 and 2013 respectively. There is slight increase in production in 2014, 2015, 2016 and 2017 of 1.3, 1.4, 1.5 and 1.5 million tons respectively. Therefore, this research modeled millet production in Nigeria for the period of 55 years from 1962 to 2017 using the secondary data from Food and Agriculture of United Nations (FAO). It was obtained that ARIMA (1,1,0) is the model that best fit and describe the reality among the 10 postulated ARIMA models because it has the least Akaike information criteria (AIC) and Bayesian information criteria (BIC). Empirical analysis confirmed that trend pattern exist even though the data generally exhibit random fluctuations, a time series also show gradual shifts to relatively higher and lower particularly in between 2004 to 2011. If a time series plot exhibits this type of behavior, we say that trend pattern exists. The model evaluated its performance and forecast five years observations for 2018 to 2022, and the results shows expected (increase in) millet production of 2,079,942; 2,522,333; 2,842,501; 3,074,214; and 3,241,909 tonnes for the year 2018; 2019; 2020; 2021; and 2022 respectively. Finally, The ARIMA model is suggested for modeling millet production in Nigeria.

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