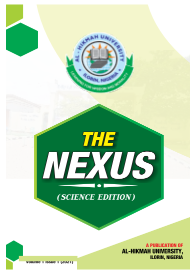
P-ISSN: 2811-2512
E-ISSN: 2811-2520

THE NEXUS
A Publication of Al-Hikmah University, Ilorin, Nigeria
(Science Edition)

Available online at https://www.alhikmahuniversity.edu.ng



AN AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODELING OF CROP PRODUCTION INDEX IN NIGERIA

[1]Gatta, N.F., [1]Afolayan, R. B., [2]Bakare, N. G., [3]Awotunde, D. R., *[4]Olawepo, G. K., [2]Kehinde, J. O.

[1]*Department of Statistics, University of Ilorin, Ilorin, Nigeria*
[2]*Department of Mathematics, University of Ilorin, Ilorin, Nigeria*
[3]*Nigerian Stored Product Research Institutes, Kano State, Nigeria*
[4]*Department of Plant Biology, University of Ilorin, Ilorin, Nigeria*

ARTICLE INFO

Article history:
Received: March 25, 2022
Revised: September 16, 2022
Accepted: October 14, 2022
Published online: November 15, 2022

Citation:
Gatta, N.F., Afolayan, R. B., Bakare, N. G., Awotunde, D. R., Olawepo, G. K., Kehinde, J. O. (2022). An Autoregressive Integrated Moving Average Modeling of Crop Production Index in Nigeria. The Nexus (Science Edition). 2(1): 37 - 43

***Corresponding Author:**
Olawepo, G. K.
Department of Plant Biology,
University of Ilorin, Ilorin, Nigeria
e-mail: olawepo.gk@unilorin.edu.ng
+2348064568024

ABSTRACT

In univariate time series econometrics model, forecasting is an important tool for assessing the performances of any single-variable time series such as the Crop Production Index (CPI). This study therefore, forecast the expected or future values of the CPI series in Nigeria using Box-Jenkins (1976) methodology. Pre-tests of the annual CPI series extracted from the World Governance Index spanning 1961 to 2018 (58 years) confirmed that the CPI was a difference stationary series of order one {I(1)}.The CPI data set was divided into train and test sets. The train set, 80% of the CPI series which is approximately 46 years covering 1961 to 2006 was used to develop the model. ARIMA (1,10), ARIMA (1,1,2) and ARIMA (1,1,1) models are suggested and all were used on the test data covering 2007 to 2018. ARIMA (1, 1, 0) was found to be the best among the competing models under model identification, parameter estimation, diagnostic checking and forecasting evaluation of the test data Using RMSE, MAE and MAPE performance indicator indices. Post-estimation test using a simple residual correlogram further disclosed that the residual obtained from the fitted model was white noise (i.e. all spikes of the plot are within the 95% confidence bounds). Lastly, The Out of sample forecast of the CPI using ARIMA (1,1,0) for the next 12 years (2019 to 2030) shows an upward trend with a constant growth of 1% to 2% annually. It is therefore recommended that efforts should be geared towards improving agricultural productivity by all stake holders in Nigeria to overcome the challenges of food security by the year 2030.

Keywords: *Crop Production Index; ARIMA; Residual Correlogram; Difference Stationary Series; Forecast; Nigeria.*

INTRODUCTION

Production of crops, especially cereals crops production is undeniably one of the major sub-sectors of agricultural sectors that can contribute significantly to the economic growth of a developing country if well-harnessed (Akanni and Adeniyi, 2020). Crop production includes all the feed sources that are required to maintain the dairy herd and the resource inputs used to produce the crops (Tomasula and Nutter, 2011). One major determinant or factor that stimulates the quantity of crop production or agricultural produce is the size of cultivated land used for planting the crops (Akanni *et al.,* 2021; Ciaian *et al.,* 2018; Lu *et al.,* 2018). Apart from the size of cultivated land, other factors that influence crop production include; agro-climatic, edaphic, biotic, socio-economic, and crop management. Consequently, the best way to increase the rate of crop production in any nation is to understand the forecasting of the Crop Production Index (CPI). By CPI, we refer to a measure of crop production for each year relative to the base period and include all crops except folder crops (World Bank Repository, 2019).

When there is one time series variable (i.e. usually low-frequency series) to be investigated in a study, the best approach to adopt for the series is the univariate time series techniques widely known as Box-Jenkins methodology or Autoregressive Integrated Moving Average {ARIMA (p, d, q)}modeling (Box and Jenkins, 1976). However, the best model for any single-observation time series in a study can either be AR(p), MA(q), ARMA (p, q), or ARIMA (p, d, q) depending on the chosen values of the orders p, q, and level of differencing d of the series respectively. If q and d assume value zero and p is non-zero, then AR(p) is the best model for modeling that time series. But if p and d assume zero values and q is non-zero, the MA(q) model is the best model to fit such series. Moreover, when the series is stationary at level (i.e. d is zero) and the values of p and q are non-zero, ARMA (p, q) is the appropriate model for the series. Lastly, when p, d and q are non-zeros, the ARIMA (p, d, q) model is the appropriate model for the series. The main goal of this technique is to predict the future values of the time series using its past values (Yaffee and McGee, 2000; Gujarati, 2009).The forecasted values from a univariate time series further will go a long way in assisting the sellers, farmers, investors, government, policymakers etc. to make good decisions regarding their investments or realizations.

Most of the related published works on crop production forecasted a particular type of crop using either the univariate or multivariate time series techniques. For example, Ali *et al.* (2015) forecasted the production and yield of sugarcane and cotton crops in Pakistan using ARIMA techniques. The results from their study showed that production and yield for sugarcane and cotton crops will continue to increase within the forecasted time frame. In a study, Akanni and Adeniyi (2020) used ARIMA (1, 1, 1) model to show that the production of cereal crops in Nigeria will continue to increase for the foreseeable future. Smil (1999) examined the impacts of nitrogen fertilizer on global crop production. His results proved that only 30-40% of applied nitrogen fertilizer is taken up by crops. Akanni *et al.,* (2021) applied the Vector Autoregressive (VAR) model to investigate the Crop Production Index-Permanent Cropland relationship in Nigeria. Their findings showed that Nigeria's crop production index is predictable by Nigeria's permanent cropland and vice versa. Garba *et al.* (2020) used Toda-Yamamoto techniques to show that cereal yields in Nigeria are predictable by both cereal production and the size of farmland used for planting cereal crops. To understand the dynamics of some determinants of agricultural land expansion in Nigeria, Oyekale (2007) used Error Correction Model (ECM) technique to confirm that cropland growth rates, agricultural production index, livestock population, human population, other lands,and cereal cropland growth rates have a significant impact on agricultural land expansion. Tóth (2012) studied the impact of land-take on the land resource base for crop production in the European Union using spatial techniques. Results from the spatial analysis later revealed that increasing landtake due to urbanization threatens the availability of fertile soils throughout Europe. Epule *et al.* (2014) applied structural equation modeling techniques to analyze the relationship between arable production per capita index, arable production, and permanent cropland and forest area. They found that the arable production per capita index is impacted more by population while the influence of rainfall on the arable production per capita index is weak.

The goal of the study is to forecast the future values of the Crop Production Index (CPI) series in Nigeria using the Box-Jenkins (1976) methodology.

MATERIALS AND METHODS

The data used for this study are second data on yearly CPI of Nigeria from 1961 to 2018.The data was obtained from the repository of World Governance via their website http://data.worldbank.org. An ARIMA model was used analyzing the data.

This work employed Box-Jenkins's (1976) methodology to model and forecast the CPI of Nigeria. Mathematically, the general form of the ARIMA (p, d, q) model for the CPI series is given by equation (1):

$$CPI_t = \mu + \sum_{i=1}^{p} \phi_i CPI_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (1)$$

Where: $I = 1, ..., p$, $j = 1, ...q$, CPI_t = CPI at current time t, CPI_{t-p} = CPI at lag p (past period ***t-p***), ε_{t-q} = Random shock at lag q (past period ***t-q***), ε_t = Random shock at current time period t, μ = a constant ϕ_i and θ_j autoregressive and moving average parameters respectively.

The four-step procedures for fitting a good ARIMA model to a univariate time series dataset are: identification, estimation, diagnostic checking, and forecasting.

Identification of order p and q components

Here, the orders p and q of the AR and MA components of the ARIMA (p, d, q) model werefirst pre-determined by observing the sample correlogram which is made up of the Sample Partial Autocorrelation Function (SPACF) and Sample Autocorrelation Function (SACF) plots for CPI_t.

In practice, the SACF determines the order q of the MA term while the SPACF determines the order p of the AR term from the sample correlogram.

Gujarati and Porter (2009) defines the sample correlogram as a plot of SPACF ($\hat{\rho}_k$) against the lags k. The mathematical expression for $\hat{\rho}_k$ is of the form:

$$\hat{\rho}_k = \frac{\Upsilon_k}{\Upsilon_o} \qquad (2)$$

Where: $\hat{\Upsilon}_k$ is the sample covariance at lag k and $\hat{\Upsilon}_o$ is the sample variance. To compute $\hat{\rho}_k$, the values of $\hat{\Upsilon}_k$ and $\hat{\Upsilon}_o$ are first computed from the following equations stated as equations (3) and (4):

$$\hat{\Upsilon}_k = \frac{\sum_{t=1}^{n-k} (Y_t - \overline{Y})(Y_{t-K} - \overline{Y})}{n} \qquad (3)$$

$$\hat{\Upsilon}_o = \frac{\sum_{t=1}^{n} (Y_t - \overline{Y})^2}{n} \qquad (4)$$

Where: n is the sample size and $\overline{Y}$ is the sample mean.

If the spikes of the SACF are decaying exponentially and that of the SPACF is statistically significant at lag p, then AR (p) is suggested. The MA(q) process occurs if the SACF is significantat lag q and SPACF decreases geometrically. However, if both SACF and SPACF exhibit a gradual decreasing pattern ARMA(p,q)is considered for modelling the series. Gujarat & Porter, 2009). The spikes of the SPACF and SACF are statistically significant if they are not within the 95% confidence bounds. Otherwise, they are insignificant.

The appropriate or best value for the p and q is further determined by subjecting the values reported by p and q to Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and Hann-Quinn Criteria (HQC).

Model estimation

The gretl software will be used to fit an Arima (p, d, q) model with a specify value of p, d and q parameters. After which the best competing models will be selected based on smallest values of Akaike's Information Criterion (AIC) and Bayesian's Information Criterion (BIC).

Diagnostic checking

Now, the residuals of the estimated model are further subjected to post-estimation tests using simple plots of residual correlogram. The model is good if the spikes of both the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are within the 95% confidence bounds. Otherwise, the model is not good.

Forecasting and Evaluation

Finally, forecasting is then made from the fitted model. This can either be out-of-sample or in-sample forecast depending on the objective of the study.

To evaluate the forecast accuracy of the competing models, this study will employ three error forecast accuracy measures, viz. Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAE). The precision of the models is measured based on the lower value of these output measures. The formula to compute RMSE, MAPE and MAE are given in equations 5, 6 and 7 respectively.

$$RMSE = \sqrt{\frac{1}{n}\Sigma(A_i - f_i)^2} \tag{5}$$

$$MAPE = \frac{1}{n}\Sigma\left|\frac{A_i - f_i}{A_i}\right| * 100 \tag{6}$$

$$MAPE = \frac{1}{n}\Sigma|A_i - f_i| \tag{7}$$

DATA ANALYSIS AND RESULTS

This section presents the results of the analyses carried on the CPI series using Gretl 1.2

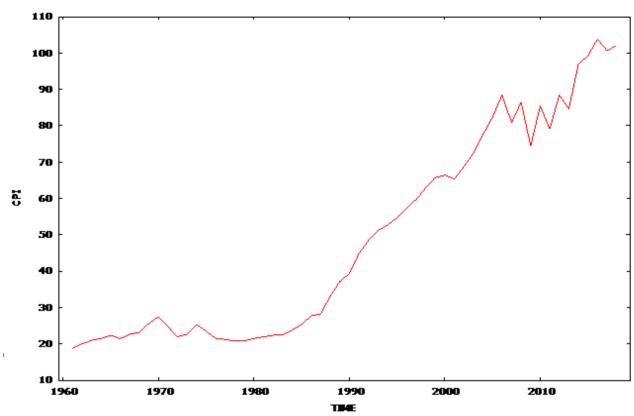


Figure 1: Crop Production Index (CPI) series, 1961-2018 (yearly)

exhibits an upward trend with fluctuations. As a result, the CPI is suggested to be a difference stationary series of some order d. Hence, the true value of d is however determined by subjecting the series to unit root analysis using Augmented Dickey-Fuller (ADF) test approach.

The Table 1 present the results of the Unit root test. The test shows that the CPI series is not stationary at level using Augmented Dickey-Fuller test of stationarity (ADF). The p-values (0.993) is greater than the significance level = 005, hence the null hypothesis of non-stationarity of CPI data is not rejected at 5% levels of significance. Therefore, the CPI data is not stationary at level, hence a difference of the series is required.

Table 1: Unit root tests results for CPI series

		ADF at level		
Variable	ADF-Stat	Critical Val	P-val	Remarks
CPS	0.792644	-2.916566	0.993	NS
		ADF at 1st difference		
Variable	ADF-Stat	Critical Val	P-val	Remarks
CPS	-3.279689	-2.915522	0.0207	S

The ADF unit root test at first difference in Table 1 further confirmed that the true order of integration of the CPI series is one {I(1)} since the 5% critical value of -2.9155 is greater than the ADF statistic of -3.2797. This is also evidence from the p-value (= 0.0207) which is less than the chosen level of significance (α = 0.05). Hence, the CPI data is stationary at first differencing.

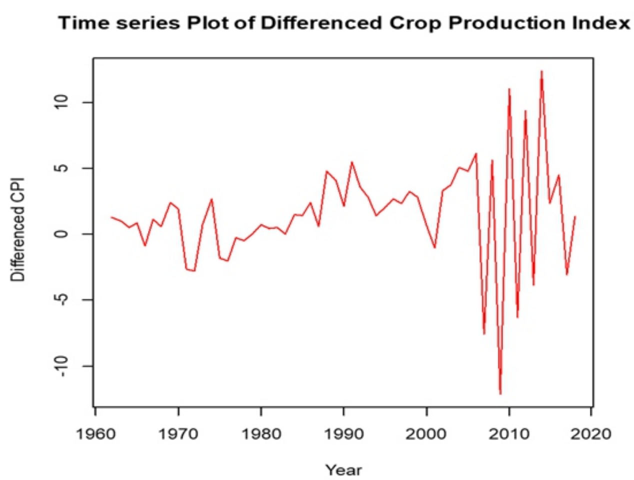


Figure 2: Time Plot of First Difference of Yearly Crop Production Index (CPI) series

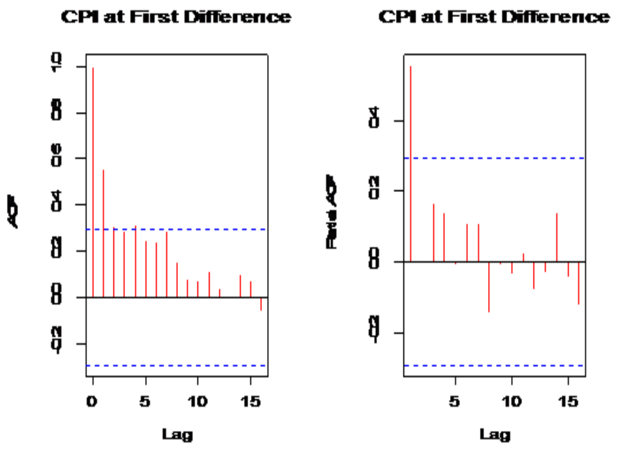


Figure 3: Correlogram of the CPI series at first differencing

The correlogram of the first difference of CPI data in figure 3, ACF dies out slowly after lag 1 and PACF dies out after lag 0. Therefore, the values of p and q of Arima (p, 1, q) model are set at 1 and 0 respectively. However, the best values of p and q for the AR and MA parts of the ARIMA (p,1,q) model are further determined using the selection criteria such as Akaike Information Criterion (AIC), Bayesian Information Criteria (BIC) and Hann-Quinn Criterion (HQC) respectively.

Table 2: Possible fitted ARIMA models

S/N	(p,d,q)	AIC	BIC	HQC
1	**(1,1,0)**	310.1714	316.3005	312.5534
2	**(1,1,1)**	298.4378	**298.4378***	301.6138
3	**(1,1,2)**	**290.0463***	300.2615	**294.0163***
4	(1,1,3)	292.046	304.3043	296.81
5	(1,1,4)	293.942	308.2433	299.4999
6	(1,1,5)	295.8032	312.1477	302.1552
7	(1,1,6)	297.7561	316.1435	304.9021

The summary results of the model selection criteria presented in Table 2 further reveal that ARIMA (1, 1, 2) was chosen by AIC and HQC selection criteria as the best model whereas BIC chose ARIMA (1, 1, 1) as the best model. However, ARIMA (1, 1, 0) model was not chosen by any of the selection criteria. Conversely, based on the lag 0 spike of the ACF, ARIMA (1, 1, 0) will also be considered for forecasting the CPI series.

Table 3: Competing models for the trained CPI series,1961 to 2006

	Coefficient	std. error	Z	p-value
ARIMA (1,1,0) model estimates				
Const	1.68694	0.622636	2.709	**0.0067**
AR(1)	0.607734	0.124372	4.886	**<0.0001**
AIC=181.0647, SIC=186.4847				
HQC=183.0852 ,**M.S.E=2.7753**				
ARIMA (1,1,1) model estimates				
	Coefficient	std. error	Z	p-value
Const	1.76606	0.872024	2.025	**0.0428**
AR(1)	0.761396	0.579067	1.315	0.1886
MA(1)	-0.247763	1.00618	-0.2462	0.8055
AIC=182.9898, SIC=190.2164				
HQC=185.6838				
ARIMA (1,1,2) model estimates				
	Coefficient	std. error	Z	p-value
Const	1.90017	1.04403	1.82	0.0688
AR(1)	0.923076	0.09352	9.87	**<0.0001**
MA(1)	-0.350675	0.181525	-1.932	0.0534
MA(2)	-0.265727	0.157983	-1.682	0.0926
AIC=182.3425, SIC=191.3758				
HQC=185.7100				

$$\mathrm{CPI}_t = 1.68694 - 0.607734\mathrm{CPI}_{t-1} + \varepsilon_t \qquad (8)$$

Based on the results from Table 3, the best model is ARIMA (1, 1, 0) since only AR (1) term is statistically significant since itsp-value (<0.0001) < (α=0.05). This means that the immediate past period (t-1) has a significant impact on CPI in the current time period t. However, the AR (1) and MA(1) terms of ARIMA (1, 1, 1) and MA(1) and MA(2) terms ofARIMA (1, 1, 2) models are not statistically significant (i.e. p-values > 0.05).

The competing Arima models built on the train CPI data are used to forecast test CPI data (2007-20018) that was set aside to evaluate the accuracy of the fitted models. The performances of each model in predicting the test data set was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE). If the actual (test data) values and forecast values are closer to each other, a small forecast error will be obtained. Thus, the smaller the values of RMSE, MAE and MAPE the better the model in forecast the future values of the series.

Table 4: Performance Evaluation Results of the three competing Arima Models

ARIMA	RMSE	MAE	MAPE
Arima (1,1,0)	**7.8789**	**6.5334**	**10.2898**
Arima (1,1,1)	7.9358	6.4963	10.3506
Arima (1,1,2)	7.9666	6.5807	11.2835

From Table 4, it can be observed that all the forecast errors from Arima (1,1,0) is smaller than that from both Arima (1,1,2) and Arima (1,1,1) except for MAE measures where Arima (1,1,1) value is smaller. Therefore, we can conclude that Arima (1,1,0) perform best among the three models and it's the most appropriate model for forecasting the future values of CPI.

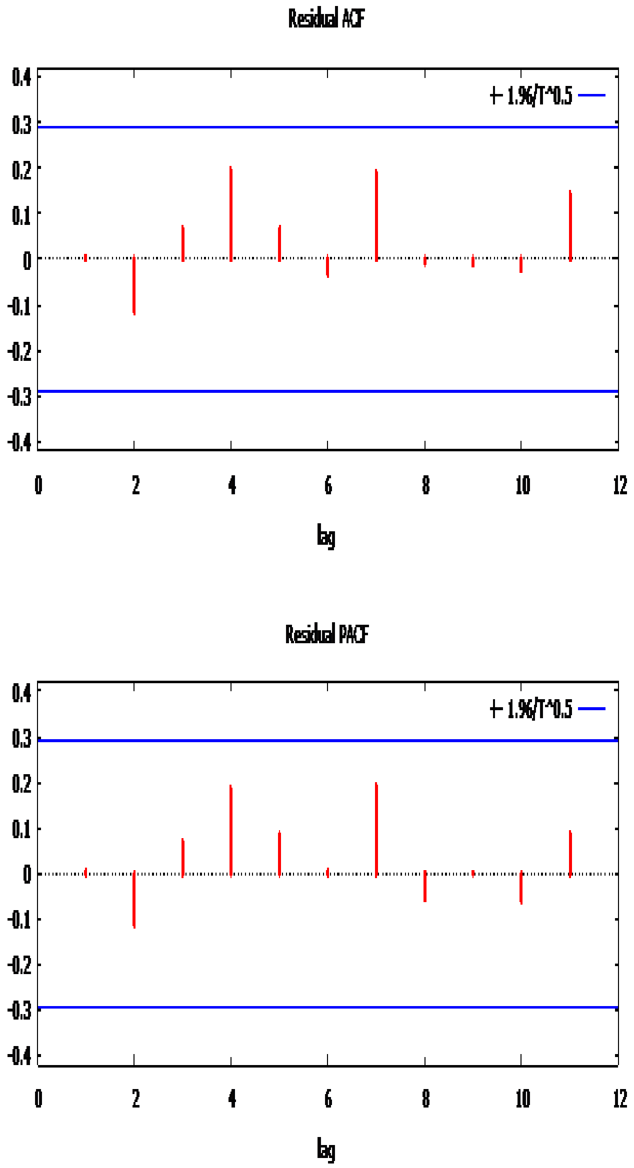


Figure 3: Residual correlogram for the trained ARIMA (1, 1, 0) model

After estimation of model parameters, diagnostic check on the adequacy of Arima (1,1,0) model is observed by plotting the ACF and PACF of the standardized squares of Residual. The ACF and PACF in Figure 3 reveal that ARIMA (1, 1, 0) model best fit the CPI series since all the spikes of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are within the 95% confidence bounds.

Table 5: 20% forecast for the CPI series, 2007 to 2018

Year	CPI	Prediction	Std. Error	95% Confidence Bounds
2007	80.86	92.84	1.684	89.54 - 96.14
2008	86.51	96.17	3.188	89.93 - 102.42
2009	74.41	98.86	4.61	89.83 - 107.90
2010	85.43	101.16	5.915	89.56 - 112.75
2011	79.11	103.21	7.106	89.29 - 117.14
2012	88.47	105.12	8.192	89.07 - 121.18
2013	84.6	106.95	9.188	88.94 - 124.95
2014	96.95	108.72	10.108	88.90 - 128.53
2015	99.27	110.45	10.963	88.97 - 131.94
2016	103.77	112.17	11.763	89.12 - 135.23
2017	100.68	113.88	12.515	89.35 - 138.41
2018	102.05	115.57	13.227	89.65 - 141.50

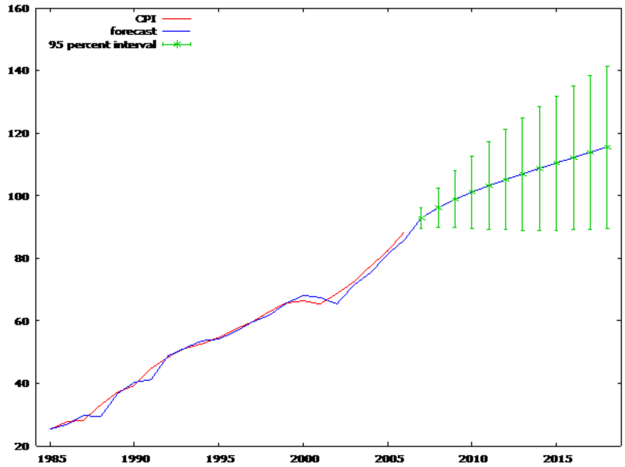


Figure 4: Within sample forecast plot of the CPI series from 2007 to 2018

Table 6 and Figure 4 jointly showed that the trained ARIMA (1, 1, 0) model adequately forecasted the remaining 20% of the series in that the forecasted values are very close to the true value of CPI series for the forecasted periods. Besides, the forecasted series are within the 95% confidence bounds; which shows that the forecasted values are good.

Table 6: 12 years out-sample forecast for the CPI series

Year	Prediction	Std. Error	95% Confidence Bounds
2019	117.27	13.905	90.02 - 144.52
2020	118.96	14.551	90.44 - 147.48
2021	120.65	15.170	90.92 - 150.38
2022	122.34	15.765	91.44 - 153.24
2023	124.03	16.339	92.00 - 156.05
2024	125.71	16.894	92.60 - 158.82
2025	127.40	17.430	93.24 - 161.56
2026	129.09	17.951	93.90 - 164.27
2027	130.77	18.457	94.60 - 166.95
2028	132.46	18.950	95.32 - 169.60
2029	134.15	19.430	96.07 - 172.23
2030	135.84	19.898	96.84 - 174.84

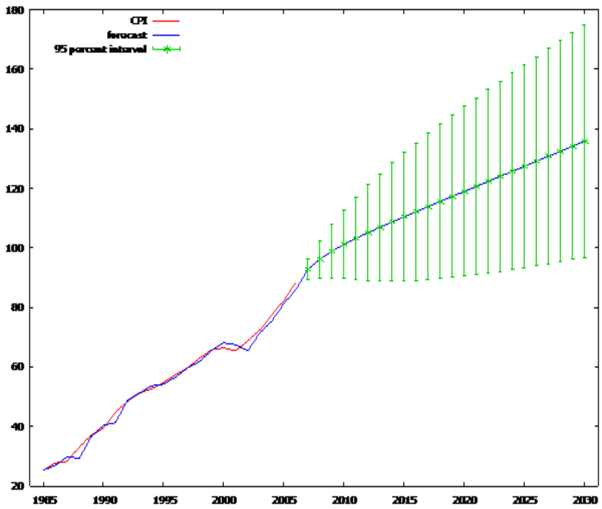


Figure 5: Out of sample forecast plot for CPI series from 2006 to 2030

Based on the forecasted results in Table 6 and Figure 5, the CPI is expected to increase within these forecasted time periods. Also, the forecasted series are within the 95% confidence bounds; which shows that the forecasted values are also good.

DISCUSSION OF FINDINGS

This study has used univariate time series techniques to forecast the Crop Production Index (CPI) for the next twelve (12) years as described by Box and Jenkins (1976). Pre-test analysis results reported in Table 1 confirmed that the hypothesis of non-stationarity was rejected for the series after first difference (i.e. I(1)). In order to obtain a good forecast, 80% of the series which is approximately 46 observations (i.e. 1961 to 2006) was first used to train the CPI data. Hence, the best models among the competing models was then fitted to the CPI series. Further pre-test results in Table 2 and Figure 2 revealed that ARIMA (1, 1, 2) was chosen by AIC and HQC selection criteria as the best model whereas BIC chose ARIMA (1, 1, 1) as the best model. Though, the best model which is ARIMA (1, 1, 0) was not chosen by the selection criteria but chosen based on experience since there is possibility of having no spike at lag 0 of the ACF; which represents the MA component of the ARIMA. (p, d, q) model. However, estimates of the ARIMA (1, 1, 0) model reported in Table 3 proved that the AR part of the model, CPI in immediate past period t-1(2017) has a significant impact on CPI in current time period t (2018). Also, the performance of the models in forecasting the future values of CPI was evaluated using forecast error measures such as RMSE, MAE and MAPE. The results which was presented in Table 4, further confirmed that Arima (1,1,0) as the best model for forecasting the future values of CPI data. Post-estimation test results obtained from the ARIMA (1, 1, 0) model is stationary or white noise since the spikes of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the residual correlogram in Figure 3 is within the 95% confidence interval. Moreover, 20% forecasted results of Table 5 and Figure 4 jointly showed that the trained ARIMA (1, 1, 0) model adequately forecasted the remaining 20% of the series in that the forecasted values are very close to the true value of CPI series for the forecasted periods (i.e. 2006 to 2018). Besides, the forecasted series are within the 95% confidence bounds; which shows that the forecasted values are good. Lastly, the results of an out-sample prediction presented in Table 6 and Figure 5 established that the CPI is expected to increase at a constant rate of 1% to 2% yearly from 2019 to 2030; which is the forecasted time periods.

CONCLUSION

In this study, we gave a detailed report on the future patterns or realizations of Crop Production Index (CPI) in Nigeria; which measures the rate of annual crop production of the country. Based on the results of the examination and outline of findings, we therefore conclude that the CPI is expected to increase arithmetically from 2019 to 2030; which is the forecasted time periods. This study agrees with the submission of Akanni and Adeniyi (2020) which recommends that Governments at all levels should formulate better policies that will harness the Nigerian crop potentials as tools for boosting the Nigerian economy and an avenue for job creation.

References

Akanni, S. B. and Adeniyi, O. I. (2020).On the forecast of cereals production in Nigeria.Federal University Wukari Trends in Science and Technology Journal (FTSTJ). 5 (2): 331-335.

Akanni, S. B., Kareem, K. Y., Grace, A. O., Alabi, M. O., Jabaru, S. O., Muhammed, M. T., Adeniyi, O.I., Peter, M and Oyerinde, O. J. (2021). Vector autoregressive modeling of crop production index-permanent cropland relationship in Nigeria. Annals.Computer Science Series, 19(1):92-97.

Ali, S., Badar, N. and Fatima, H. (2015).Forecasting production and yield of sugar cane and cotton crops of Pakistan for 2013-2030. Sarhad Journal of Agriculture, 31(1), 1-10.

Box, G.E. and Jenkins, G.M. (1976).Time series analysis, forecasting and control. San Francisco, Holden-Day Inc., USA.

Ciaian, P., Guri, F., Rajcaniova, M., Drabik, D. andPaloma, S. G. (2018). Land fragmentation and production diversification: A case study from rural Albania. Land use policy, 76, 589-599.

Epule, E. T., Bryant, C. R., Akkari, C., Sarr, M. A. and Peng, C. (2014). An assessment of the predictors of the dynamics in arable production per capita index, arable production and permanent cropland and forest area based on structural equation models. SpringerPlus, 3(1), 1-10.

Garba, M. K., Akanni, S. B., Yahya, W. B., Kareem, K. Y. and Afolayan, R. B. (2020). Modelling Effects of some Factors that Contribute to Cereals Yields in Nigeria using Toda-Yamamoto Techniques. SLU Journal of Science and Technology, 1(1), 50-56.

Gujarati, D. N. and Porter, D. C. (2009).Basic econometrics, 5th edition. McGraw-Hill/Irwin, New York.

Lu, H., Xie, H., He, Y., Wu, Z.and Zhang, X. (2018). Assessing the impacts of land fragmentation and plot size on yields and costs: A translog production model and cost function approach. Agricultural Systems, 161, 81-88.

Oyekale, A. S. (2007). Determinants of agricultural land

expansion in Nigeria: Application of Error Correction Modeling (ECM). Journal of Central European Agriculture. 8(3): 301 - 310.
Smil, V. (1999). Nitrogen in crop production: An account of global flows. Global biogeochemical cycles, 13(2), 647-662.
Tomasula, P. M.and Nutter, D. W. (2011). Mitigation of greenhouse gas emissions in the production of fluid milk. Advances in food and nutrition research, 62, 41-88.
Tóth, G. (2012). Impact of land-take on the land resource base for crop production in the European Union. Science of the Total Environment, 435, 202-214.
World Bank Repository (2018). Data on Food Production Index. Retrieved from http://data.worldbank.org
Yaffee, R. A. and McGee, M. (2000). An introduction to time series analysis and forecasting: with applications of SAS® and SPSS®. Elsevier.