
**Asian Journal of Probability and Statistics**

**2(1): 1-12, 2018; Article no.AJPAS.45035**

# Modeling Agricultural Gross Domestic Product of Kenyan Economy Using Time Series

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***Authors' contributions***

*This work was carried out in collaboration between all authors. Author MMN designed the study and performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors OJ and WN managed the analyses of the study. All authors read and approved the final manuscript.*

***Article Information***

DOI: 10.9734/AJPAS/2018/v2i124563

*Editor(s):*
(1) Dr. Manuel Alberto M. Ferreira, Professor, Department of Mathematics, ISTA-School of Technology and Architecture, Lisbon University, Portugal.

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Complete Peer review History: http://www.sciencedomain.org/review-history/27154

***Received: 16 August 2018***
***Accepted: 01 November 2018***
***Published: 12 November 2018***

***Original Research Article***

## Abstract

The agriculture sector is the mainstay of the Kenyan economy. Thus, the sector has a significant role and contribution to GDP. In this study, Box-Jenkins seasonal ARIMA time series modeling approach is used to develop a model that best describes the quarterly agricultural gross domestic product of Kenyan economy. Agricultural gross domestic product data collected quarterly from 2000-2014 at constant 2001 prices is used for modeling. From the analysis, SARIMA$(1, 0, 0)(1, 1, 0)_4$ was found to be the best model describing the quarterly agricultural gross domestic product of Kenyan economy.

*Keywords: Agriculture; seasonal ARIMA; GDP; time series.*

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**2010 Mathematics Subject Classification:** 53C25; 83C05; 57N16.

# 1 Introduction

Agriculture is the art and science of growing plants (crops) and the raising of animals for food, for economic gain or other human needs. The Agriculture sector is the mainstay of the Kenyan economy. The sector provides sustenance for more than 80% of the Kenyan population in terms of employment and food security [1]. The sector contributes directly upto 24% to the national GDP and 27% indirectly through linkages with manufacturing, distribution and other related sectors [1]. In addition, the sector employs more than 40% of the total population and more than 70% of Kenya's rural people. The sector accounts for 65% of revenue from exports [1]. The agriculture sector includes industrial crops, food crops, horticulture, livestock, fisheries and forestry sub sectors. However its key to note that there are several factors which affect agriculture which in turn affects the economy hence the GDP. Such includes land use, improvement of water resources and irrigation development, governance, macroeconomic stability, science & technology and infrastructure. The agriculture sector is large with multitude of actors such as private, non-governmental, parastatal and public.

Gross domestic product (GDP) is the basic measure of the overall economic performance of a country. It is the market value of all final goods and services produced within the borders of a nation in a year. Information on GDP is regarded as an important index for assessing the national economic development and for judging the operating status of macro-economy as a whole [2].

There exists a high correlation between the Kenyan economic growth rate and agricultural growth rate [1]. Improving agricultural performance is at the heart of improved economic development and growth. NEPAD [3] points out that there are several fundamental mutual reinforcing pillars on which to base the immediate improvement of agriculture and even food security. Such include; Extending the area under sustainable land management, improving rural infrastructure and agricultural research, technology dissemination and adoption.

Techniques of analysing time series data have been widely applied on different areas (sectors) namely; tourism, climate, GDP, crop yields among others. However, focus on the impact of agriculture sector to a country's economy is crucial. For instance, Enu [4] undertook a study to determine the impact of the agricultural sector on Ghana's economic growth using time series data from 1996-2006. He found that agricultural output had a significant positive impact on the nation's growth. Rahman [5] undertook a study to fit the best ARIMA model to be used to make efficient forecast of boro rice production in Bangladesh from fiscal year 2008-09 to 2012-13. Usman [6] undertook a study on contribution of agriculture sector in the GDP growth rate of Pakistan. He used time series data from 1990-2014 and fitted a regression model. From the model, he found that the agricultural variables considered had a strong relationship with the GDP growth rate. Sayedul and Mina [7] developed ARIMA(1,2,1) model as a reasonable model to forecast the yearly growth rate of GDP of Bangladesh using time series data which would aid in decision making process. Udah et al. [8] undertook a study to analyse contribution of various agricultural sub-sectors to Growth in Nigeria Agricultural sector.

In this paper, effort is made to analyse the contribution of agricultural sector to the Kenyan economy (at constant 2001 prices) from 2000 to 2014 to come up with the model that best describes quarterly agricultural gross domestic product of Kenya. This is because we are not able to assess the contribution of the sector to the Kenyan economy despite the effort made by the Government of Kenya. This will enable decision makers and policy makers especially in the Ministry of Agriculture and Kenya Agricultural & National Planning identify where policies can rightly be channelled towards improving the performance of the sector which has been identified by *The Vision 2030* as one of the key sectors to deliver the 10% annual economic growth rate under the Economic Pillar. Box-Jenkins Seasonal Autoregressive Integrated Moving Average (SARIMA) modeling approach is applied.

# 2 Methods and Materials

A time series is a set of observations $x_t$ each one being recorded at a specific time t [9]. Agricultural gross domestic product when taken at equal time intervals over a period of time constitute a time series data which can then be analysed using time series techniques. Basically, the purpose of time series is to describe the observed time series data, construct a model that fits the data and to forecast future values of the time series process.

Time series exhibit different types of components namely; trend seasonality and random component. A time series in terms of the three components can be written as;

$$x_t = S_t + T_t + E_t \tag{2.1}$$

where $x_t$ is the data at period t, $S_t$ is the seasonal component at period t, $T_t$ is the trend component at period t and $E_t$ is the error component at period t. However, the series can also be expressed in multiplicative form given as;

$$x_t = S_t * T_t * E_t \tag{2.2}$$

[10] Time series ARIMA models were first introduced by Box and Jenkins in 1960 [11]. They popularized the use of ARMA models including guidelines of transforming nonstationary time series into stationary by differencing to bring about the ARIMA models. In time series analysis, a stationary time series is one whose statistical properties remain unchanged over time. Thus for every $t$ and $t-s$: $E(x_t) = E(x_{t-s})$ (constant mean), $E(x_t - \mu)^2 = E(x_{t-s} - \mu) = \sigma_x^2$ (constant variance). If its not stationary it has to be transformed to stationary through differencing by use of the operator $\nabla$ defined by $\nabla^d = (1-B)^d$ and B is the backward shift operator defined by $B^j x_t = x_{t-j}$ [9][11].

Box and Jenkins methodology involves the three key iterative steps namely; model identification, parameter estimation and diagnostic checking. However, further development was done to add a preliminary stage of data preparation and a last step of forecasting [12]. Data preparation involves transformations and differencing if the data in consideration require this be done to meet Box and Jenkins assumptions before modeling.

Mathematical transformations also provided simple means of modeling seasonality which resulted into the general multiplicative seasonal ARIMA process of order $(p, d, q)(P, D, Q)_s$ which has been useful to date [13], where p is the order of non-seasonal AR, d is the order of non-seasonal differencing, q is the order of non-seasonal MA, P is the order of seasonal AR, D is order of seasonal differencing, Q is the order of seasonal MA and s is periods in a season.

SARIMA models are formed by adding the seasonal terms in the usual ARIMA model. More formally, a SARIMA model is expressed as,

$$\Phi(B^s)\phi(B)x_t = \Theta(B^s)\theta(B)\omega_t \tag{2.3}$$

where s is the number of periods per season, $x_t$ is the time series observation at time t, $\omega_t$ is white noise, $\Phi$ is the seasonal AR parameters, $\phi$ is the non-seasonal AR parameters, $\Theta$ is the seasonal MA parameters, $\theta$ is the non-seasonal MA parameters and B is the back shift operator. With presence of regular and seasonal differencing, equation 3 becomes;

$$\Phi(B^s)\phi(B)(1-B)^d(1-B^s)^D x_t = \Theta(B^s)\theta(B)\omega_t \tag{2.4}$$

where d is the order of non-seasonal differencing and D is the order of seasonal differencing [9][14]. The non-seasonal autoregressive (AR) and non-seasonal moving average (MA) components are;

$$\phi(B) = 1 - \phi_1 B^1 - \cdots - \phi_p B^p \tag{2.5}$$

and

$$\theta(B) = 1 - \theta_1 B^1 - \cdots - \theta_q B^q \tag{2.6}$$

respectively.

On the other hand, the seasonal autoregressive (SAR) and seasonal moving average (SMA) are;

$$\Phi(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{Ps} \tag{2.7}$$

and

$$\Theta(B^s) = 1 + \Theta_1 B^s + \cdots + \Theta_Q B^{Qs} \tag{2.8}$$

respectively.

SARIMA models have extensively been used in modeling time series data collected either weekly, quarterly or even monthly. For instance, Mwanga et al. [15] used SARIMA approach to model and forecast sugarcane yields in Kenya Sugar Industry. They found that seasonal ARIMA$(2, 1, 2)(2, 0, 3)_4$ to be the best model that fits quarterly sugarcane yields from 1973-2015. Otieno et al. [16] developed a SARIMA model to describe the tourist accommodation demand in Kenya using quarterly data. They found SARIMA$(1, 1, 2)(1, 1, 1)_4$ to be the suitable model. Kibunja et al. [17] undertook a study to forecast precipitation in Mt. Kenya region. They used SARIMA approach using monthly data and concluded that SARIMA$(1, 0, 1)(1, 0, 0)_{12}$ to be the best model to do forecasting of precipitation in the region.

In the agricultural contribution to Kenyan GDP, use of SARIMA models is not evident. Ong'ala and Mwanga [18] used time series to predict future adoption of sugarcane variety but did not consider the contribution of sugarcane to Kenyan GDP. In their research, Musundi et al. [19] developed an ARIMA model to describe and forecast the Kenyan GDP. However, this study did not consider analyzing quarterly agricultural gross domestic product data of the Kenyan economy (at constant 2001 prices) which is key for decision makers especially in the Ministry of Agriculture and Kenya Agricultural and National Planning to know where policies can rightly be channeled to improve the performance of the sector.

Data on quarterly agricultural gross domestic product of the Kenyan economy was obtained from Kenya National Bureau of Statistics office in Nairobi from January 2000 to January 2014 (at constant 2001 prices) at quarterly intervals. The data consisted of 57 observations and had no gaps. It was then entered into a spreadsheet in Excel and saved as CSV format. R statistical software was then used to read the data and for further analysis. The time series was explored to identify any underlying patterns. This was achieved through decomposing the series through classical approach to extract trend, seasonality and the random components.

Box-Jenkins SARIMA modeling approach was adopted as outlined in Box and Jenkins modeling technique. The Box-Jenkins approach used involved the following stages: data preparation which involved differencing to make the data stationary, model identification, model selection & parameter estimation, diagnostic checking and finally forecasting. Model identification was done by studying the ACF and PACF plots of the stationary series. The best SARIMA$(p, d, q)(P, D, Q)_s$ model was then selected based on Akaike Information Criteria (AIC) for the data up to 2011. Maximum likelihood method was used to estimate the parameters of the model. The data remaining for the nine quarters was used to check for the adequacy of the forecast. Model diagnostic checking was done by examining the ACF of residuals and the Ljung-Box test of residuals to check if the residuals look like white noise. In addition, Jarque Bera test and Shapiro-Wilk test were used to check for normality of residuals.

# 3 Results and Discussion

Quarterly agricultural gross domestic product data has a mean of ksh 77,720 million. The time series plot is as shown in Fig. 1.

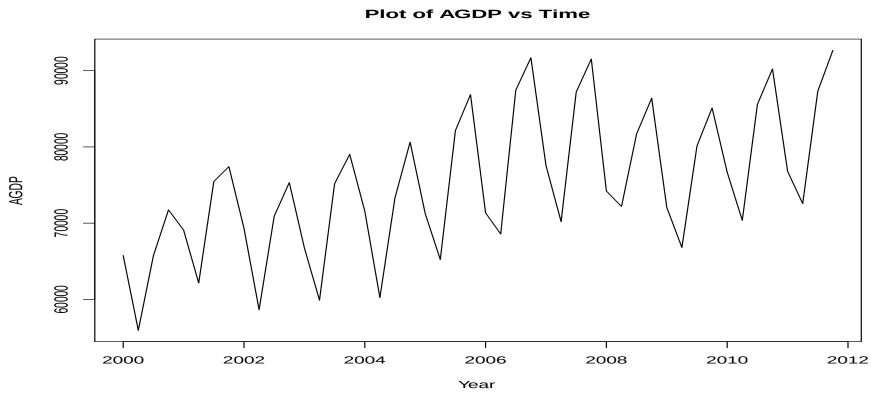


**Fig. 1. Time plot of AGDP at constant prices**

Upon decomposing using classical approach we have the output as in Fig. 2

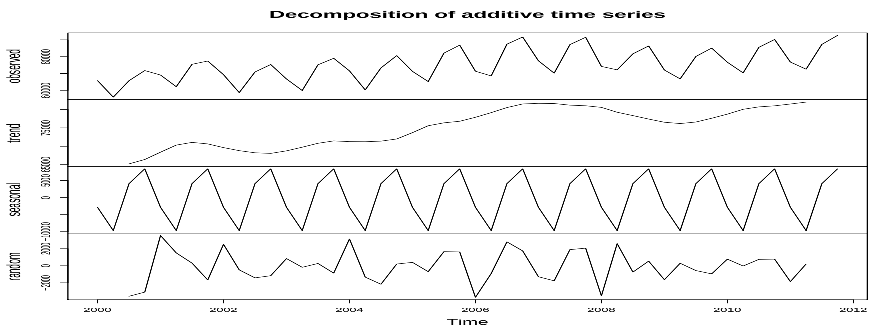


**Fig. 2. Decomposed Series of AGDP**

From the plot in Fig. 2, we observe that the series shows presence of an increasing trend (second from top) and a pattern repeating itself every year implying seasonality at period four quarters of a year. The Augmented Dickey-Fuller test confirmed that the series is non stationary ($Dickey - Fuller = -1.6212, lag = 3, p = 0.7268$). To achieve stationarity, seasonal and regular differencing were applied on the non stationary time series and the result is shown in Fig. 3.

From Fig. 3, it is observed that the series is stationary. This is confirmed by Augmented Dickey-Fuller test which gave ($Dickey - Fuller = -4.9253$, lag =3, $P = 0.01$).

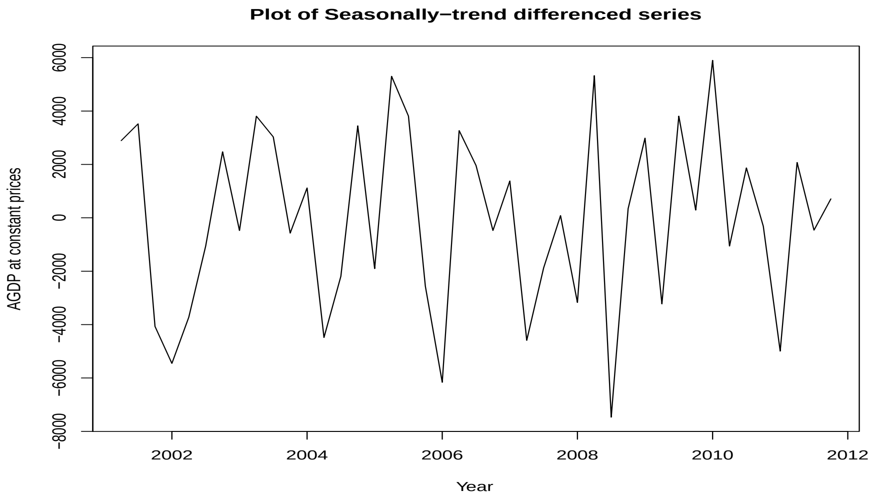


**Fig. 3. Plot of Seasonally-trend Differenced series**

### Model Identification

The autocorrelation and partial autocorrelation plots for the stationary series are shown in Figs. 4 and 5. The two were used to identify the order of AR, MA, SAR and SMA terms.

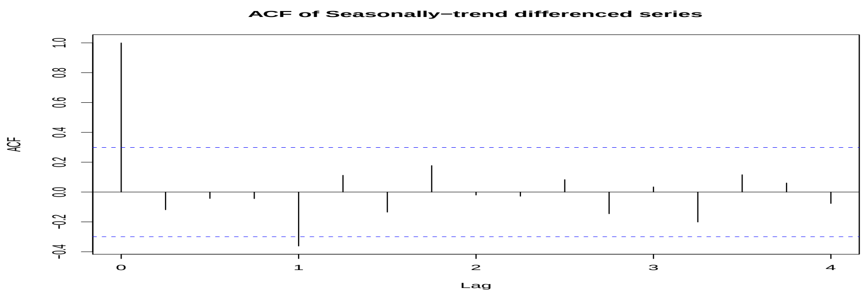


**Fig. 4. ACF of Seasonaly-trend differenced Series**

From the ACF plot, autocorrelation at lag 1 is significant while autocorrelation at other lags lie within the confidence bounds hence not significant. The PACF plot shows a significant spike at lag 1 while the rest are insignificant. Investigating the ACF and PACF at lags $s = 4, 8, 12, \cdots$ to identify the order of the seasonal components, we observe that the autocorrelations in both ACF and PACF are insignificant. Since both regular and seasonal differencing were each done once, this indicates that SARIMA$(1, 1, 1)(0, 1, 0)$ are the possible models for the quarterly agricultural gross domestic product data.

### Parameter Estimation and Selection

To select the best model, we consider the model with the minimum value of AIC. The values of AIC for the candidate models are given in Table 1.

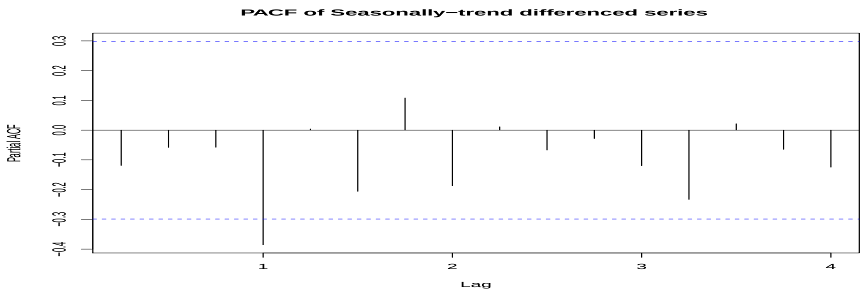


**Fig. 5. PACF of Seasonally-trend differenced series**

**Table 1. AIC values for the models**

| Model | AIC | RMSE | MAE |
|---|---|---|---|
| $(0,1,0)(0,1,0)_4$ | 821.86 | 3163.219 | 2498.119 |
| $(0,1,1)(0,1,0)_4$ | 823.16 | 3136.798 | 2446.501 |
| $(1,1,0)(0,1,0)_4$ | 823.25 | 3140.413 | 2454.115 |
| $(1,1,1)(0,1,0)_4$ | **819.24** | 2850.201 | 2259.952 |

From Table 1, it is observed that SARIMA$(1,1,1)(0,1,0)_4$ seems to be the best model to describe the quarterly agricultural gross domestic product of the Kenyan economy. The model has a minimum value of AIC which is 819.24.

The estimates of the parameter for the selected model are as in Table 2.

**Table 2. Parameter estimates for SARIMA**$(1,1,1)(0,1,0)_4$

| Model | Parameter | Parameter estimate | Std Error |
|---|---|---|---|
| $(1,1,1)(0,1,0)_4$ | $\phi_1$ | 0.6422 | 0.1229 |
| | $\theta_1$ | -1.0000 | 0.0665 |

When written in form of equation (4) with the estimated coefficients, the model becomes

$$x_t - 0.64x_{t-1} + 0.64x_{t-2} - x_{t-4} + 1.64x_{t-5} - 0.64x_{t-6} = \omega_t - \omega_{t-1} \tag{3.1}$$

where $x_t$ is the quarterly agricultural gross domestic product at time t and $\omega_t$ is the error term.

**Model Diagnostic Checking**

Model checking involves checking whether the residuals look like white noise. The Ljung-box test for autocorrelation indicates that the residuals are white noise ($X^2$=18.8661, df=19, p-value=0.4655). Shapiro-Wilk test showed that the residuals are normally distributed ($W = 0.9768$, p-value=0.4535). The ACF of residuals and the p-values for Ljung-Box test statistic are as in Fig. 6 from which we observe that the residuals are white noise.

Using the 'auto.arima' function in R software, SARIMA$(1,0,0)(1,1,0)_4$ emerged to be another possible model to describe the data. The estimates for the parameters of the SARIMA$(1,0,0)(1,1,0)_4$ model are $\phi_1 = 0.6616$ and $\Phi_1 = -0.3702$.

The SARIMA$(1,0,0)(1,1,0)_4$ model had an AIC value of 756.7 which is less than that for SARIMA

$(1,1,1)(0,1,0)_4$. The SARIMA$(1,0,0)(1,1,0)_4$ model was then subjected to diagnostic checking to test if the residuals are white noise. The Ljung-Box test gave a p-value of 0.6499 which is greater than 0.05 ($X^2 = 16.1107, df = 19, p - value = 0.6499$) implying that the residuals are random. The Jarque Bera test also gave a p-value greater than 0.05 an indication that the residuals are normally distributed ($X^2 = 1.1518, df = 2, p - value = 0.5622$). Shapiro-Wilk normality test produced a p-value of 0.4646 which is greater than 0.05 also implying that the residuals are normal. The diagnostic plots for the model is shown in Fig. 7.

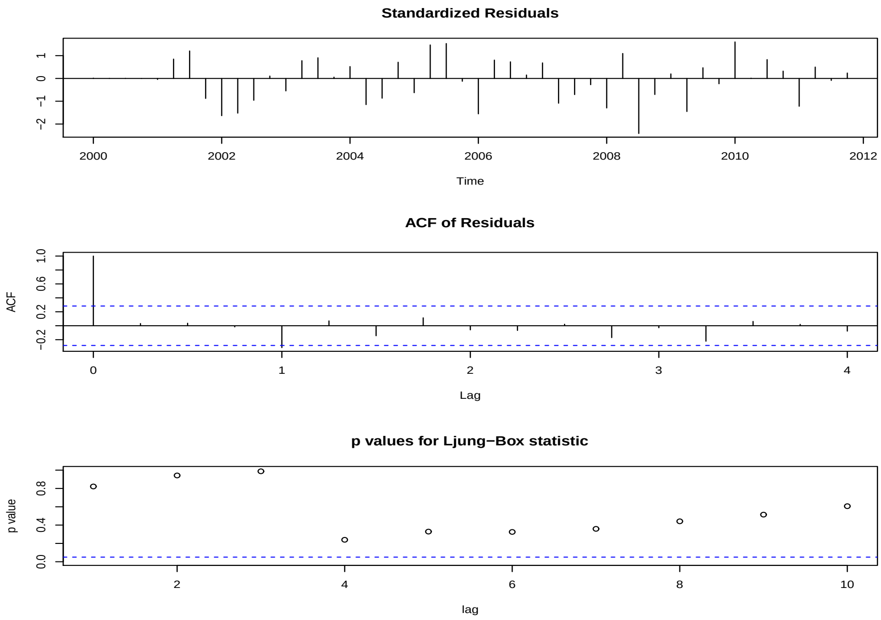


**Fig. 6. ACF of residuals and Ljung-Box p-values**

The two models seemed appropriate and thus to select best model, we consider the model with minimum value of AIC and MAE. The values for the two models are shown in Table 3a and Table 3b.

**Table 3a. AIC values for the 2 models**

| Model | AIC |
|---|---|
| $SARIMA(1,1,1)(0,1,0)_4$ | 819.24 |
| $SARIMA(1,0,0)(1,1,0)_4$ | **757.7** |

**Table 3b. MAE values for the 2 models**

| Model | ME | RMSE | MAE | MPE | MAPE | MASE |
|---|---|---|---|---|---|---|
| SARIMA$(1,1,1)(0,1,0)_4$ | -230.95 | 2850.20 | 2259.95 | -0.36 | 3.10 | 0.67 |
| SARIMA$(1,0,0)(1,1,0)_4$ | 33.73 | 2656.21 | **2052.69** | -0.01 | 2.78 | 0.60 |

From Table 3a and Table 3b, we conclude that SARIMA$(1,0,0)(1,1,0)_4$ is the best model for forecasting since it has the least value of MAE. When the SARIMA$(1,0,0)(1,1,0)_4$ model is

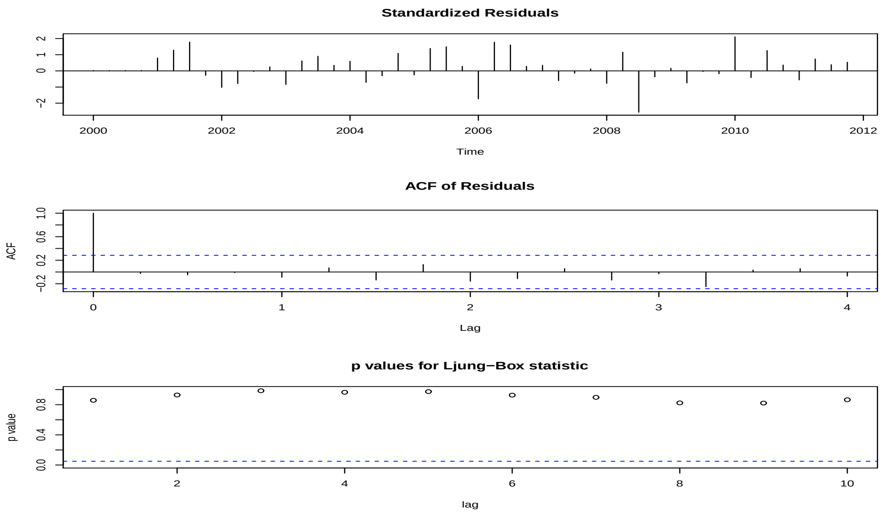


**Fig. 7. Diagnostic plot**

expressed in form of equation 4 with the estimated coefficients of the model, we have;

$$x_t - 0.66x_{t-1} - 0.63x_{t-4} + 0.42x_{t-5} - 0.37x_{t-8} + 0.24x_{t-9} = \omega_t \tag{3.2}$$

where $x_t$ is the quarterly agricultural gross domestic product at time t and $\omega_t$ is the error term.

**Forecasting**

Upon forecasting using the selected SARIMA$(1,0,0)(1,1,0)_4$ model from 2012 to 2019, the plot in Fig. 8 was obtained.

When the forecasted values from 2012 quarter 1 to 2014 quarter 1 are compared with the actual values (Table 4), all the actual values lie within the confidence interval indicating high accuracy level of forecasting of the model.

Fig. 9 shows a plot to compare the actual values with the forecasted values from 2012 quarter 1 to 2014 quarter 1. From the plot, it is observed that there is no much deviation of the forecasted values (blue line) from the actual values (black dotted line) indicating that the selected model is adequate.

**Table 4. Forecasts from SARIMA$(1,0,0)(1,1,0)_4$ model**

| Year | Actual | Point Forecast | Lo 80 | Hi 80 | Lo 95 | Hi 95 |
|---|---|---|---|---|---|---|
| 2012 Q1 | 78317 | 80369.24 | 76686.04 | 84052.45 | 74736.26 | 86002.23 |
| Q2 | 74052 | 74872.25 | 70456.00 | 79288.50 | 68118.18 | 81626.32 |
| Q3 | 93401 | 89471.41 | 84770.17 | 94172.66 | 82281.48 | 96661.35 |
| Q4 | 97188 | 94368.30 | 89547.62 | 99188.97 | 86995.71 | 101740.89 |
| 2013 Q1 | 84873 | 81502.72 | 75811.54 | 87193.90 | 72798.81 | 90206.63 |
| Q2 | 77741 | 76376.55 | 70343.78 | 82409.32 | 67150.22 | 85602.88 |
| Q3 | 94428 | 90969.47 | 84793.14 | 97145.80 | 81523.59 | 100415.36 |
| Q4 | 98470 | 96001.69 | 89763.57 | 102239.81 | 86461.31 | 105542.07 |
| 2014 Q1 | 85584 | 83314.31 | 76207.97 | 90420.66 | 72446.09 | 94182.54 |

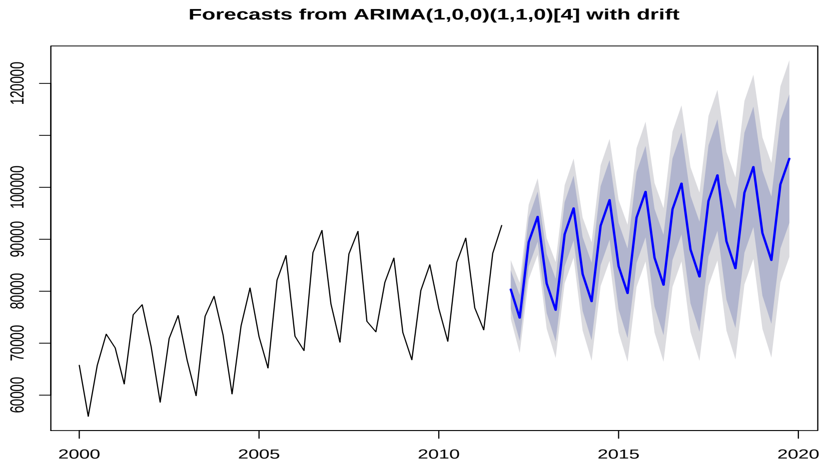


**Fig. 8. Forecasts from SARIMA**$(1, 1, 1)(0, 1, 0)_4$

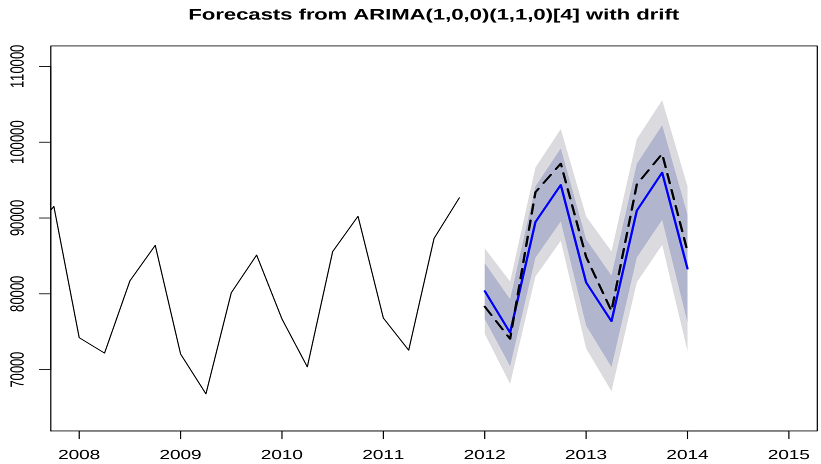


**Fig. 9. Plot to compare actual and forecast values**

# 4 Conclusion

The main objective of this study was to develop the best model that describes the quarterly agricultural gross domestic product of the Kenyan economy. Box-Jenkins modeling technique was applied for analysis. Seasonal and regular differencing were each done once to remove seasonality and trend respectively. ACF and PACF plots for the stationary series were used to identify the order of AR, MA, SAR and SMA terms. Based on AIC, SARIMA$(1, 1, 1)(0, 1, 0)_4$ model seemed to be the suitable model. Using the 'auto.arima' function in R software, SARIMA$(1, 0, 0)(1, 1, 0)_4$

emerged to be another possible model. The two were then compared based on AIC and MAE. From the analysis, SARIMA$(1,0,0)(1,1,0)_4$ model was identified to be the best model with the minimum value of AIC and MAE, hence fits to the quarterly gross domestic product data from 2000 to 2014 quarter 1. The residuals of the model were found to be white noise. The SARIMA$(1,0,0)(1,1,0)_4$ model predicted an increasing trend in the quarterly agricultural gross domestic product of Kenyan economy with a drop from quarter 1 to quarter 2 for every year followed by increase in quarter 3 and quarter 4 of the same year. From equation (10), we conclude that the Kenyan agricultural gross domestic product is based on the nine past agricultural gross domestic product values and the random component. Also, the policy makers have to come up with strategies which would improve the performance of the sector in quarter 2 of a year.

## Acknowledgement

I acknowledge the Kenya National Bureau of Statistics for making the data on quarterly agricultural gross domestic product available on their library and on their web where the data was accessed.

## Competing Interests

Authors have declared that no competing interests exist.

# References

[1] Government of Kenya (2009-2020). Agricultural Sector Development Strategy (ASDS).

[2] Ning W, Kuan-jiang B, Zhifa-fa Y. Analysis and forecast of Shaanxi GDP based on the ARIMA model. Asian Agricultural Research. 2010;2(1):34–41.

[3] New Partnership for Africa's Development (NEPAD). Comprehensive Africa Agriculture Development Programme; 2003.

[4] Enu P. Analysis of the agricultural sector of Ghana and its economic impact on economic growth. Academic Research International. 2014;5(4):267277.

[5] Rahman NMF. Forecasting of Boro rice production in Bangladesh: An ARIMA approach. J. Bangladesh Agril. Univ. 2010;8(1):103-112.

[6] Usman M. Contribution of agriculture sector in the growth rate of Pakistan. Journal of Global Economics. 2016;4(184). 6.

[7] Sayedul A, Mina MH. Time series modeling of the contribution of agriculture to GDP of Bangladesh. European Journal of Business and Management. 2012;4(5): 111122.

[8] Udah SC, Nwachukwu IN, Nwosu AC, Mbanosar JA, Akpan SB. Analysis of contribution of various agricultural subsectors to growth in Nigeria agricultural sector. International Journal of Agriculture, Forestry and Fisheries. 2015;3(3):80–86.

[9] Brockwell JP, Davis AR. Introduction to time series and forecasting. Springer-Verlag New York. 2002;169–174.

[10] Hyndman JR. Time series components; 2017.
Available:www.otexts.org/fpp/6/1

[11] Box GEP, Jenkins G. Time series analysis, forecasting and control. Holden-Day, San Francisco; 1970.

[12] Madrikadis S, Wheelright SC, Hyndman RJ. Forecasting: Methods and applications. New York: Wiley and Sonsq; 1998.

[13] Choge M, Nyongesa K, Mulati O, Makokha L, Tireito F. Time series model of rainfall pattern of Uasin Gishu County. IOSR Journal of Mathematics (IOSR-JM). 2016;11(5):77–84.

[14] Box GEP, Jenkins GM, Reinsel GC. Time Series analysis, forecasting and control. Prentice-Hall, Inc., USA; 1994.

[15] Mwanga D, Ong'ala J, Orwa G. Modeling sugarcane yields in the Kenya sugar industry: A SARIMA model forecasting approach. International Journal of Statistics and Applications. 2017;7(6):280–288.

[16] Otieno G, Mung'atu J, Orwa G. Time series modeling of tourist accomodation demands in Kenya. Mathematics Theory and Modeling.2014;4(10):106–117.

[17] Kibunja WE, Kihoro MJ, Orwa OG, Yodah OW. Forecasting precipitation using SARIMA model: A case study of Mt. Kenya region. Mathematical Theory and Modeling. 2014;4(11):50–58.

[18] Ong'ala JO, Mwanga DM. Application of time series model for predicting future adoption of sugarcane variety: KEN 83-737. Scholars Journal of Physics, Mathematics and Statistics. 2015;2:196–204.

[19] Musundi SW, M'mukiira PM, Mungai F. Modeling and forecasting Kenyan GDP using Autoregressive Integrated Moving Average (ARIMA) models. Science Journal of Applied Mathematics and Statistics. 2016;4(2):64–73.

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