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JOURNAL OF AGRICULTURAL PRODUCTION

ISSN: 2757-6620

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RESEARCH ARTICLE

Modeling and Forecasting Uganda's Beef and Cattle Milk Production using the Box-Jenkins Methodology

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ARTICLE INFO

Article History
Received: 31.10.2022
Accepted: 16.03.2023
First Published: 16.05.2023

Keywords
ARIMA
Beef production
Box-Jenkins
Dairy production
Forecasting
Uganda

ABSTRACT

Beef and cattle milk production play a significant role in reducing hunger, malnutrition, and rural poverty, improving rural livelihoods, creating employment opportunities, and supporting the overall development of Uganda's economy. This study was conducted to find a suitable ARIMA model for forecasting Uganda's beef and cattle milk production using annual time series data from 1961 to 2020, extracted from the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT). Following patterns of the Autocorrelation Function and Partial Autocorrelation Function plots of the differenced series, 4 tentative ARIMA models were identified for milk production, i.e., ARIMA (0,1,0), ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1). While 3 tentative ARIMA models were identified for beef production, i.e., ARIMA (1,1,1), ARIMA (1,1,0), and ARIMA (0,1,1). ARIMA (0,1,0) model was selected to be the most suitable for forecasting cattle milk production because it had the smallest MAPE and Normalized BIC values. On the other hand, ARIMA (1,1,0) was selected to be the best model for forecasting beef production because it had the smallest normalized BIC value and a significant coefficient of the autoregressive component. Forecasts show that milk production will increase at an annual average rate of 1.63%, while beef production will increase at an annual average rate of 0.39% in the five-year forecast period (2021-2025). These findings are important in designing strategies to improve the beef and dairy livestock sub-sectors in Uganda.

Please cite this paper as follows:

Waiswa, D. (2023). Modeling and forecasting Uganda's beef and cattle milk production using the Box-Jenkins methodology. *Journal of Agricultural Production*, *4*(1), 16-29. https://doi.org/10.56430/japro.1197299

1. Introduction

The livestock subsector contributes about 3.5% of Uganda's national Gross Domestic Product (GDP) and 15.01% of the agricultural GDP (UBOS, 2022). Uganda's livestock sector consists of cattle, goats, pigs, sheep, poultry, rabbits, beekeeping, and other animals. Among these, cattle are the most important livestock species, with products that contribute approximately 73% of the gross value of all livestock output, majorly beef and milk (Behnke & Nakirya, 2012; Waiswa et al., 2021). The total national herd consists of 15.5 million heads of cattle as of 2020, representing a 2.7% increase from 15.09 million heads in 2019 (FAO, 2022). According to statistics provided by the United Nations Food and Agriculture Organization (FAO), there has been a 3.63% annual average reduction in beef production in Uganda from 2015 to 2020. This has been attributed to the decrease in the number of animals slaughtered, which has decreased at an annual average rate of 3.09% (FAO, 2022).

Beef production in Uganda stood at 163,889 tons in 2020 (FAO, 2022), produced predominantly by indigenous breeds that make up 93.5% of the total national herd (Waiswa et al., 2021). Among these breeds are the East African short-horned zebu and the long-horned Ankole cattle, which are mainly kept under an extensive management system. The exotic tropical

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beef breeds constitute 0.9% of the total cattle population, most notably the Boran (UIA, 2016; Waiswa et al., 2021). The greatest percentage of Uganda's beef is obtained from culled animals (UIA, 2016). Compared to other meat types, beef is the most widely consumed since it is not affected by cultural or religious restrictions. For example, annual per capita consumption of beef stands at 6 kg compared to 3.2 kg, 0.9 kg, and 0.3 kg for pork, goat meat, and mutton, respectively (Agriterra, 2012; Waiswa et al., 2021).

Milk production on the other hand stood at 2.04 million tons in 2018 (Waiswa et al., 2021; FAO, 2022; Waiswa & Günlü, 2022), 51% of this was produced from exotic dairy breeds and their crosses (UBOS, 2022) which make up 5.6% of the total cattle population (Waiswa et al., 2021). The dairy sub-sector grows at an annual average rate of 7-10% (Waiswa et al., 2021). The industry has significant potential to reduce hunger, malnutrition, and rural poverty, improve rural livelihoods, promote food security and nutrition, create employment opportunities, promote gender equality, and support the overall development of Uganda's economy (Waiswa & Akullo, 2021; Waiswa et al., 2021; Waiswa & Günlü, 2022). Dairy exports contribute to 89% of the total livestock products' exports, and only 7% of the total agricultural exports as of 2021 (DDA, 2021). Additionally, the dairy industry is among Uganda's largest foreign exchange-earners. Dairy exports stood at US$ 139.5 million in 2019, while imports stood at US$ 5.19 million in the same year (DDA, 2020). The higher level of exports compared to imports is an indication of the industry's significant growth levels. The increase in Uganda's dairy export value is attributed to improved compliance of Uganda's dairy products to regional and international market standards, increased adoption of dairy cattle farming as a business by the private sector, and the annual increase in dairy processing capacities (DDA, 2020).

Considering the significant roles played by both sectors in Uganda, this study employs the Box-Jenkins methodology to determine the most appropriate Autoregressive Integrated Moving Average (ARIMA) models for the 1961 to 2020 time series of Uganda's beef and cattle milk production, and make five-year (2021-2025) forecasts with appropriate prediction intervals. Forecasting is important in different fields to enhance short and long-term planning. The Box-Jenkins methodology is one of the widely used forecasting methodologies and has been reported to provide good forecasts (Sánchez-López et al., 2015). This approach has been widely used in several studies to forecast several parameters within the agricultural sector such as production, yield, demand and consumption, and trade (prices, imports, and exports) of agricultural products. Among the available studies, this approach has been used to forecast the production and yield of animal products such as milk (Kaygisiz & Sezgin, 2017; Hassan et al., 2018; Akin et al., 2020; Ganesan et al., 2020; Eştürk, 2021; Taye et al., 2021), beef (Eroğul et al., 2019), and poultry (Sankar, 2014; Hussain et al., 2021).

While comparing with other forecasting methods, the ARIMA model gave the best forecasts for domestic and international beef prices in Indonesia (Putri et al., 2019), and wheat production in Pakistan (Masood et al., 2018), compared to the Linear, Quadratic, Exponential, S-Curve, Double Exponential Smoothing, and Single exponential smoothing models. The ARIMA method was also the most appropriate for forecasting the amount of beef and goat meat in Türkiye (Muhammed & Zengin, 2020). In all these studies, models with the lowest Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE) values were considered to be the best fit in forecasting the given variables.

This paper is organized as follows: Section 1 was an introduction to the subject and provided an overview of the available literature on the subject. Section 2 describes the data and econometric methodology; section 3 presents the results and discussion while section 4 provides the conclusion of the study.

2. Materials and Methods

2.1. Econometric Methodology

Time series data of beef and cattle milk production for 60 years, covering the period from 1961 to 2020 was used in this study. The data was extracted from the FAOSTAT website (FAO, 2022). Stationarity of the data set was tested using the Augmented Dickey-Fuller (ADF) unit root test in EViews version 10 while the rest of the analyses and forecasts were conducted in SPSS statistical program version 26.0. Beef and cattle milk production for the period from 2021 to 2025 was forecast using the Box-Jenkins methodology (ARIMA models).

The Box-Jenkins methodology was first introduced by Box and Jenkins in 1976 (Asteriou & Hall, 2007; Suleman & Sarpong, 2012; Rahman et al., 2016). The general ARIMA model is denoted as ARIMA (p, d, q), where p is the number of lags of the dependent variable (the AR terms), d is the number of differences to be taken to make the series stationary, and q is the number of lagged terms of the error term (the MA terms) (Asteriou & Hall, 2007). The AR(p) model is represented as;

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + u_t \quad (1)$$

The MA(q) model is represented as;

$$Y_t = u_t + \sum_{j=1}^{q} \theta_j u_{t-j} \quad (2)$$

A combination of the AR(p) and the MA(q) models form the Autoregressive Moving Average ARMA (p, q) models which are represented as;

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + u_t + \sum_{j=1}^{q} \theta_j u_{t-j} \quad (3)$$

Where Y_t is the dependent variable at time t, Y_{t-i} is the response variable at time lags t-i, ϕ, and θ are the coefficients to be estimated, u_{t-j} is the error in previous periods that are incorporated in the response Y_t, u_t is the error term at time t, and $|\phi|$ and $|\theta| < 1$.

ARMA models can only be made on stationary time series i.e., the series exhibit constant mean and variance over time, and the covariance between two values from the series depends only on the length of time separating the two values, and not on the actual times at which the variables are observed (Asteriou & Hall, 2007; Gujarati & Dawn, 2009; Kunst, 2012). Non-stationary series can be transformed to stationary by differencing (Asteriou & Hall, 2007; Gujarati & Dawn, 2009; Kunst, 2012). In this study, the series became stationary after the first difference, which was taken using the formula; $\Delta Y_t = Y_t - Y_{t-1}$, where Y_t is the dependent variable at time t, Δ is the change in Y_t, and Y_{t-1} is the dependent variable at time t-1. Differencing non-stationary series forms ARIMA (p, d, q) models, where "d" is the number of differences it takes to make the series stationary. The Box-Jenkins methodology consists of three stages aimed at selecting an appropriate ARIMA model for forecasting purposes. These are; identification, estimation, and diagnostic checking (Asteriou & Hall, 2007).

Identification: At this stage, the time plots of the series autocorrelation function, and partial autocorrelation function are examined to check for stationarity of the data, and find out the appropriate values of p, d, and q (Asteriou & Hall, 2007; Gujarati & Dawn, 2009). As shown in Figure 1 and 3, and the correlograms presented in Figure 5, 6, 9, and 10, the original series were non-stationary. Examination of the correlograms was supplemented by the ADF unit root test to test for stationarity of the series as shown in Table 1. The data was then differenced once to make it stationary. The autocorrelation function (ACF), and partial autocorrelation function (PACF) of the differenced series were plotted again to examine stationarity. As shown in Figure 2, 4, 7, 8, 11, and 12, the series were stationary after the first differencing. Therefore, the "d" value was determined as 1. After achieving stationarity, the p and q orders of the ARlMA models were identified using the autocorrelation function, and partial autocorrelation plots. Following Gujarati and Dawn (2009)'s recommendation on the choice of lag length, a third of the time series (20 lags) was used as the lag length while calculating ACFs and PACFs.

Estimation: Each of the identified ARIMA models was estimated and the various coefficients were examined. The estimated ARIMA models were compared in terms of significant coefficients of the ARMA parameters, the Stationary R-squared, Normalized Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE) values. Models with the lowest BIC, RMSE, MAE, MPE, and MAPE values, while those with the highest Stationary R^2 value were considered to be the most appropriate, and were therefore used for forecasting beef and cattle milk production for the 2021-2025 period. These parameters are expressed as shown below (Oni & Akanle, 2018; Celik, 2019):

$$\text{RMSE} = \sqrt{\frac{\sum e_t^2}{n}} \tag{4}$$

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |e_t| \tag{5}$$

$$\text{MPE} = \frac{1}{n}\sum_{t=1}^{n} \frac{e_i}{X_i} \times 100 \tag{6}$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{e_t}{X_t}\right| \times 100 \tag{7}$$

Where e_t is the estimation error at time t (the actual value at time t minus the estimated value at time t), and n is the number of the estimated periods. When MAPE < 10, the forecasting model has a high accuracy, $10 \leq$ MAPE ≤ 20, the forecasting model has a good accuracy, $20 \leq$ MAPE ≤ 50, the forecasting model has a reasonable accuracy, and MAPE > 50, the forecasting model is unreliable (Celik, 2019).

$$\text{Stationary R-Squared} = 1 - \frac{\sum_t \left(Y_t - \hat{Y}_t\right)^2}{\sum_t (\Delta Y_t - \overline{\Delta Y})^2} \tag{8}$$

Where, ΔY_t is the differenced series.

$$\text{BIC} = \ln\left(\hat{\sigma}_e^2\right) + k\ln(n)/n \tag{9}$$

Where, $\hat{\sigma}_e^2$ is the error variance.

Diagnostic checking: At this stage, the goodness of fit of the model is examined by plotting the residuals and looking out for outliers and evidence of periods in which the model does not fit the data well (Asteriou & Hall, 2007). The Ljung-Box (LB) Q-statistic, which tests for autocorrelations of the residuals was also used.

3. Results and Discussion

According to Figure 1 and 3, there is a generally increasing trend in the original series of Uganda's beef and cattle milk production over the years. This is an indication of the non-stationarity of the series. In addition to Figure 1 and 3, the ADF unit root test was performed to test for the stationarity of the data, and the results are presented in Table 1. The null hypothesis (H_0) was that the series had a unit root, i.e., they were non-stationary, while the alternative hypothesis (H_1) was that the series did not have a unit root, i.e., they were stationary. The ADF test was conducted following Hill et al. (2018). Because the original series appear to be fluctuating around a linear trend as can be observed in Figure 1 and 3, the test equation with the intercept term and trend was used to test for stationarity. In addition, because the differenced series fluctuate around a non-zero sample average and show no trend as can be observed in Figure 2 and 4, the test equation with only the intercept term and no trend was used to test for stationarity.

According to the test results, before differencing, the absolute values of the ADF test statistic for both beef and milk production are smaller than the test critical values at the 5% level, with probabilities greater than 0.05. Therefore, H_0 is accepted, which means that the series (beef and cattle milk production series) have a unit root. In contrast, after the first difference, the absolute values of the ADF test statistic are larger than the test critical values at the 5% level, with probabilities less than 0.05. Therefore, H_0 is rejected, which means that the series did not have a unit root after taking their first difference. Differenced values are also shown in Figure 2 and 4. An important feature to note in these figures is the absence of any sustained increase or decline in the level of the series over the observation period; in other words, they fluctuate around a constant mean level and have no trend-like behavior, a characteristic of stationary series.

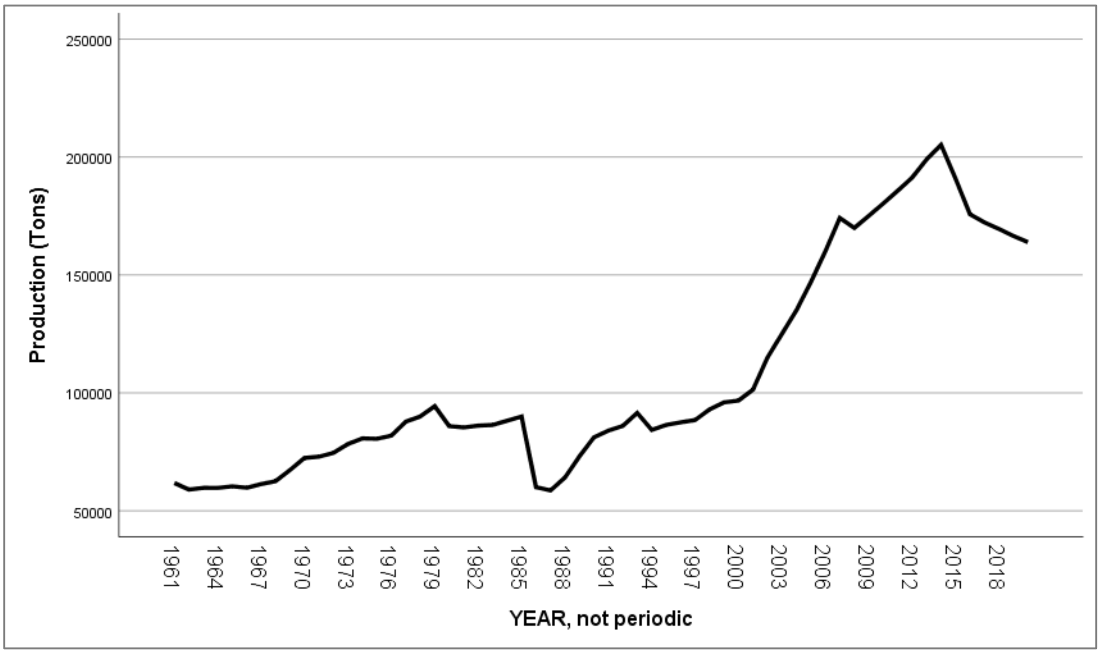

Figure 1. The trend of original beef production series from 1961 to 2020.

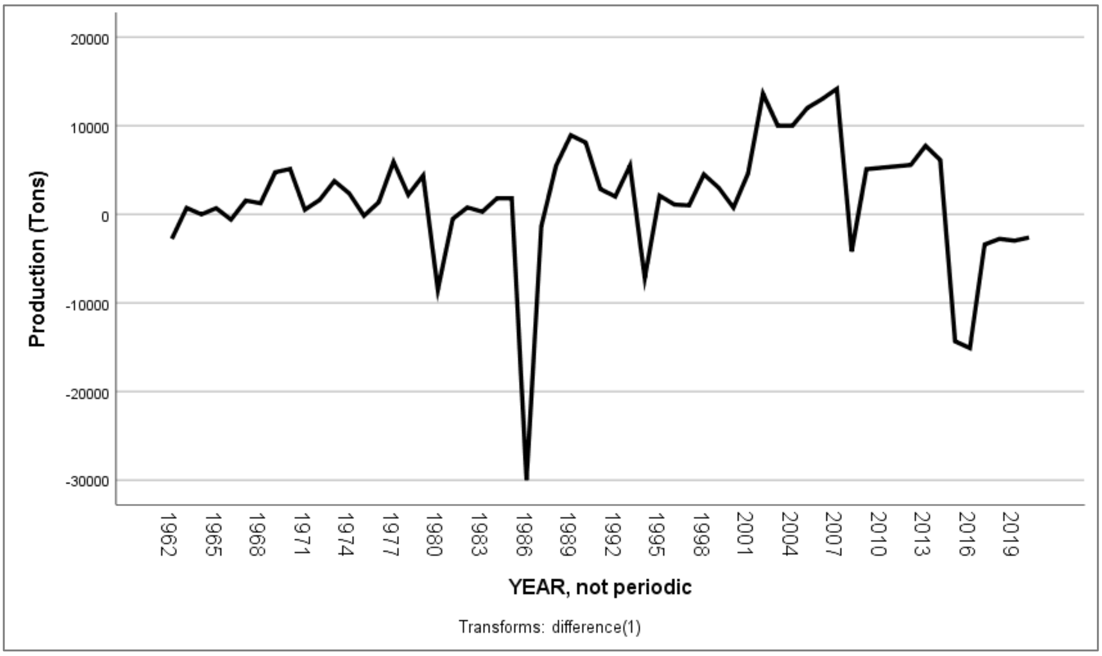

Figure 2. Differenced beef production series from 1961 to 2020.

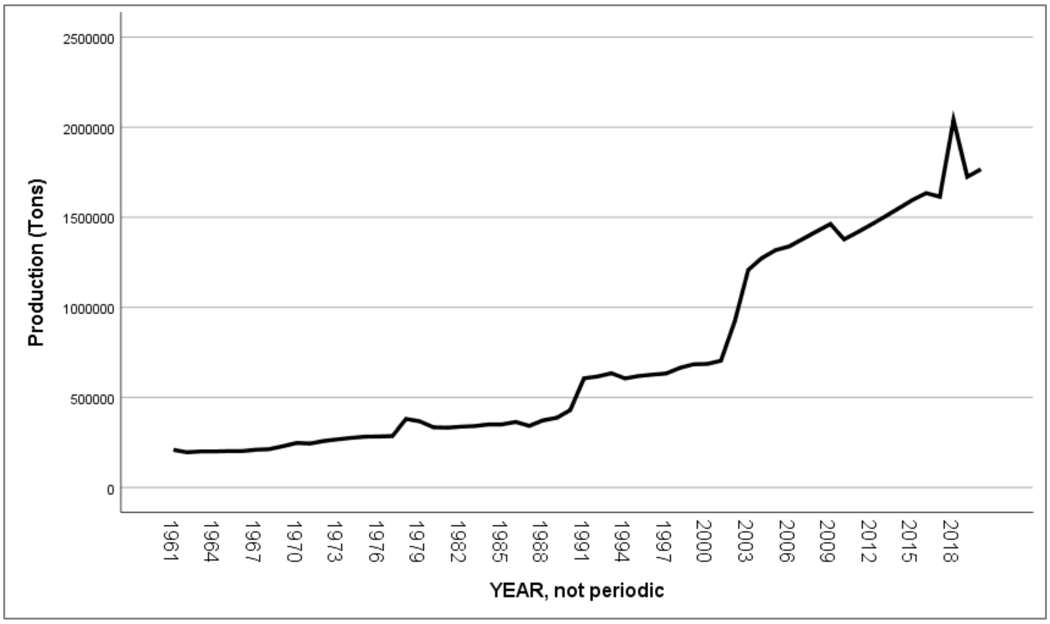

Figure 3. The trend of original milk production series from 1961 to 2020.

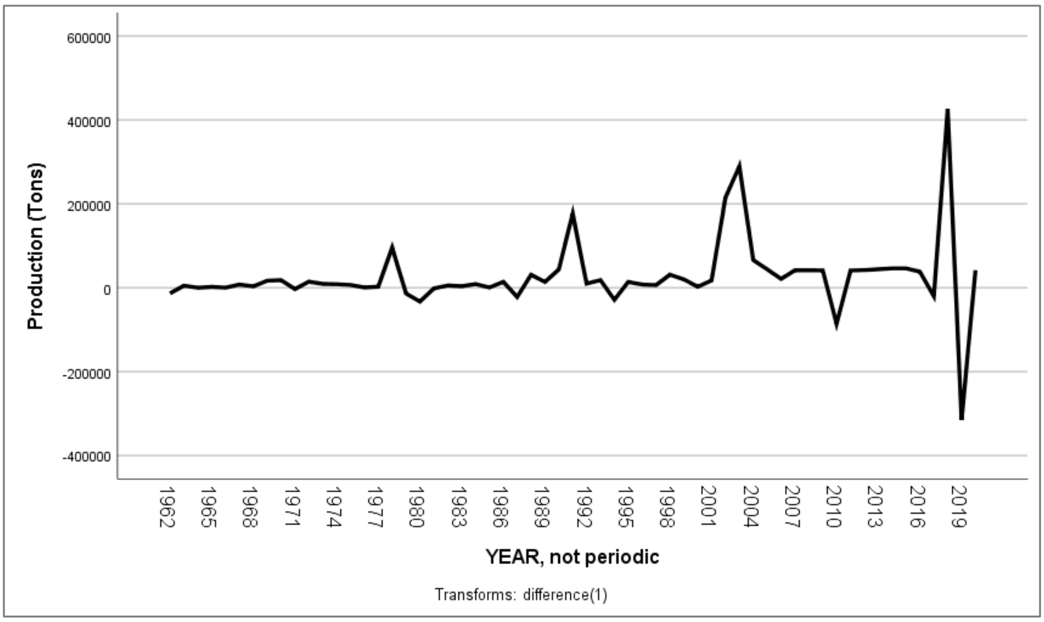

Figure 4. Differenced milk production series from 1961 to 2020.

Table 1. ADF unit root test results for beef and cattle milk production.

			Before differencing		**After first difference**	
Exogenous variable in test equation			Trend and Intercept		Intercept	
			t-Statistic	**Prob.**	**t-Statistic**	**Prob.**
Beef Production (Tons)	ADF test statistic		-1.7909	0.6964	-5.1270***	0.0001
	Test critical values:	1% level	-4.1243		-3.5482	
		5% level	-3.4892		-2.9126	
		10% level	-3.1731		-2.5940	
Cattle milk Production (Tons)	ADF test statistic		-1.988	0.5960	-9.225***	0.0000
	Test critical values:	1% level	-4.121		-3.548	
		5% level	-3.488		-2.913	
		10% level	-3.172		-2.594	

*** denotes rejection of the null hypothesis of the presence of unit root at the 1% level of significance.

Correlograms of the original series as shown in Figure 5, 6, 9, and 10 also show non-stationarity in the data. The Autocorrelation Function (ACF) plots show significant autocorrelations that are outside the 95% confidence interval. From lag 1 up to lag 11 for beef production and lag 14 for milk production, the autocorrelations are significant and their decline is very gradual to zero. While for Partial Autocorrelation Function (PACF) plots, only the first lag is significant for both beef and milk production series while the rest are within the standard error bound. ACF and PACF plots of the differenced series of beef production (Figure 7 and 8) show that only autocorrelations of the first lag are outside the standard error bound, and therefore significant, while the rest of the lags are within the standard error bounds. On the other hand, the ACF and PACF plots of the differenced series of milk production in Figure 11 and 12 show that autocorrelations of all lags lie within the 95% confidence interval.

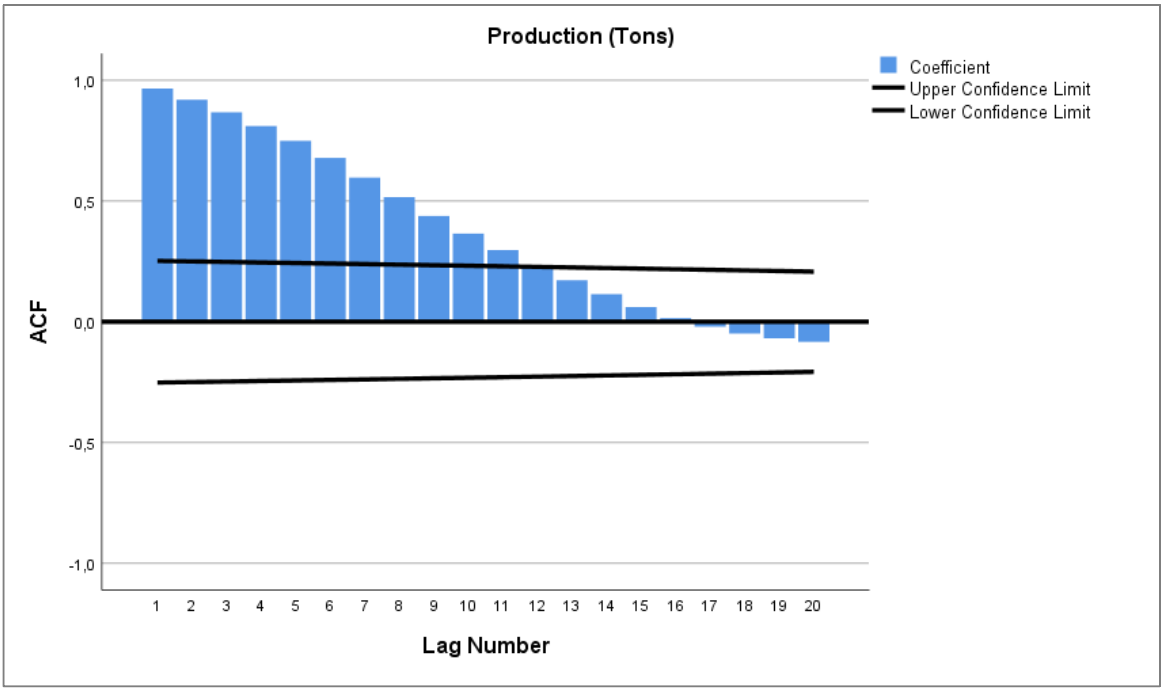

Figure 5. A plot of ACFs of the original beef production series.

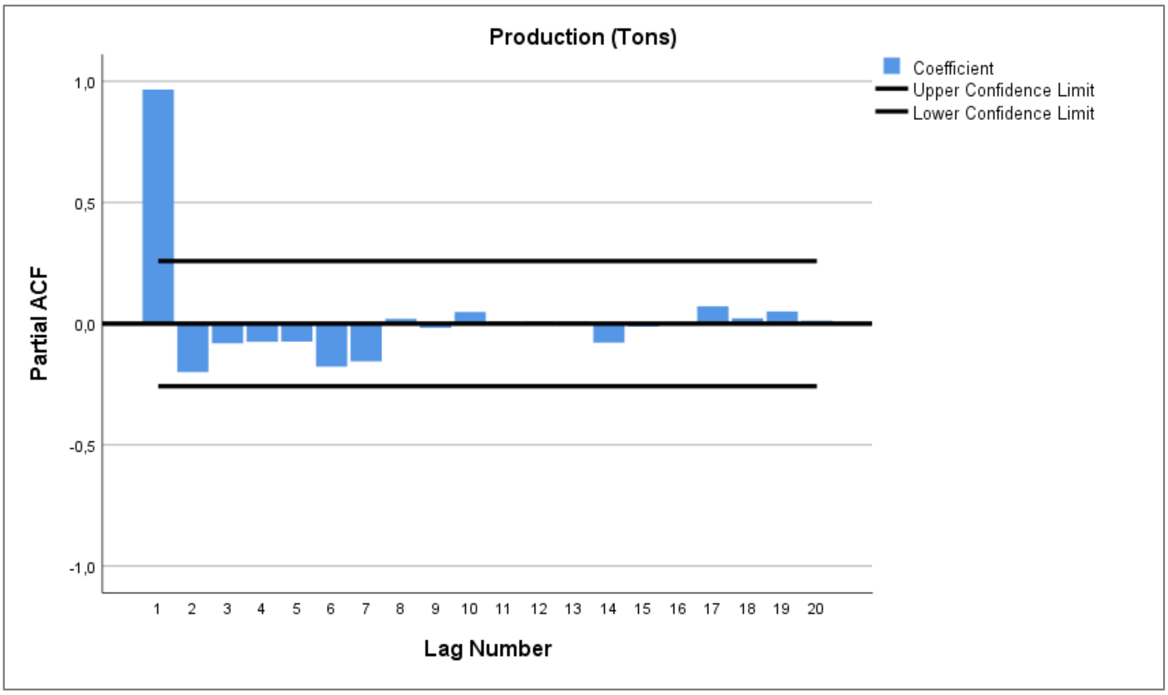

Figure 6. A plot of PACFs of the original beef production series.

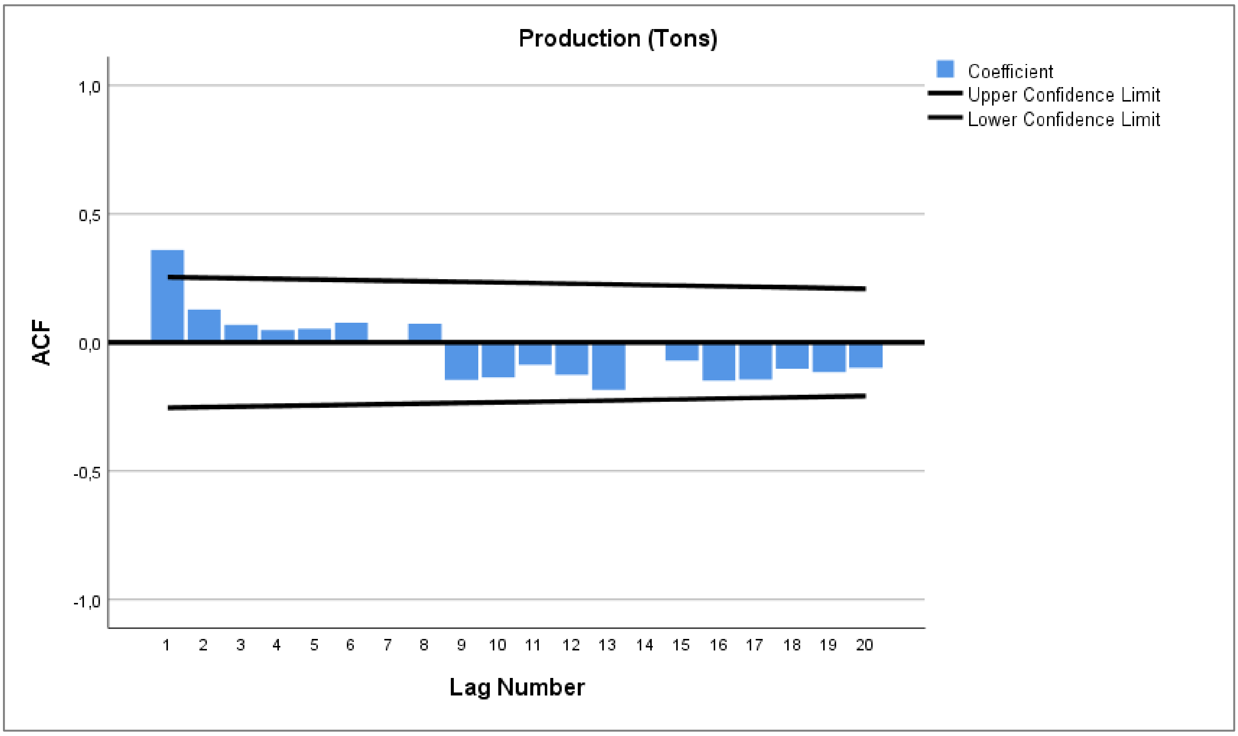

Figure 7. A plot of ACFs of the differenced beef production series.

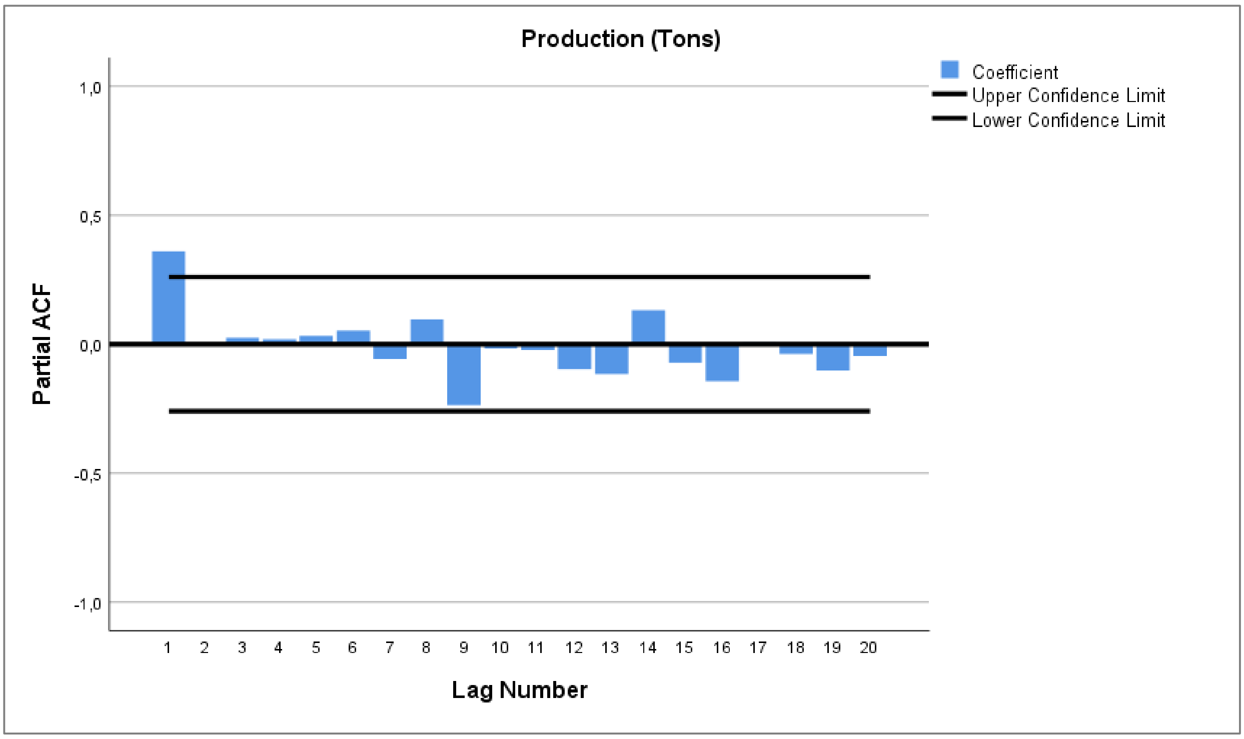

Figure 8. A plot of PACFs of the differenced beef production series.

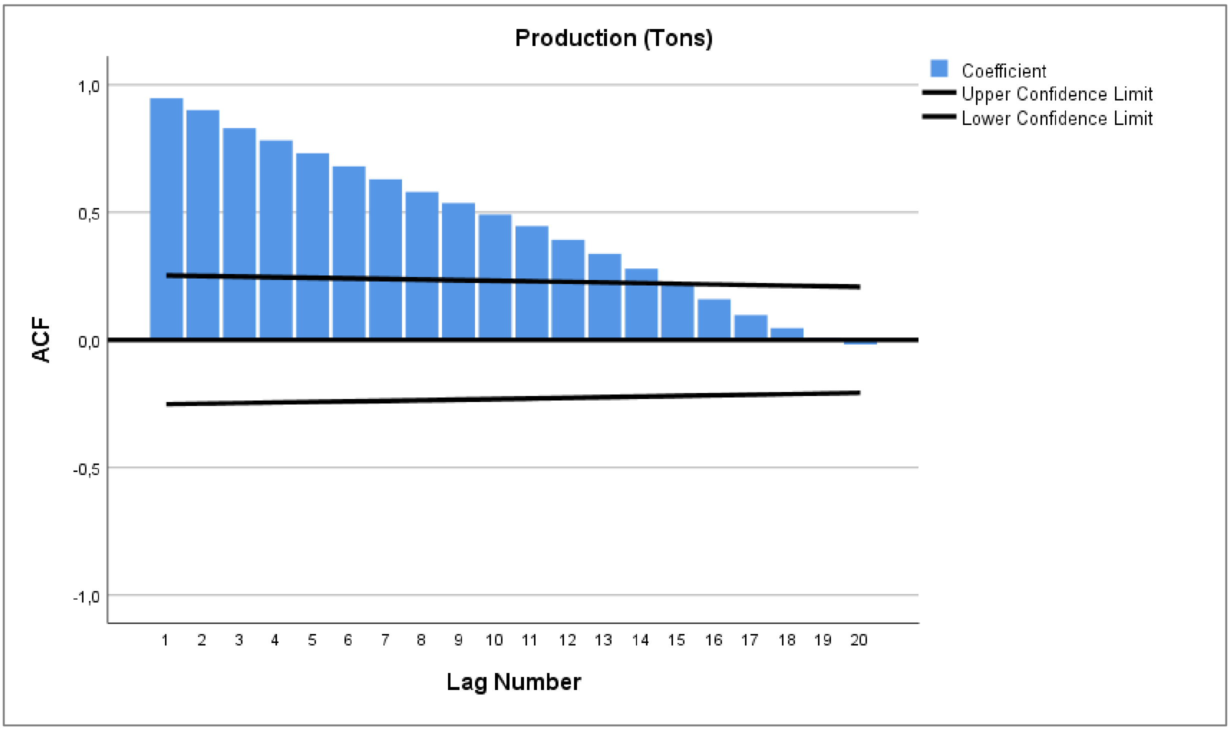

Figure 9. A plot of ACFs of the original milk production series.

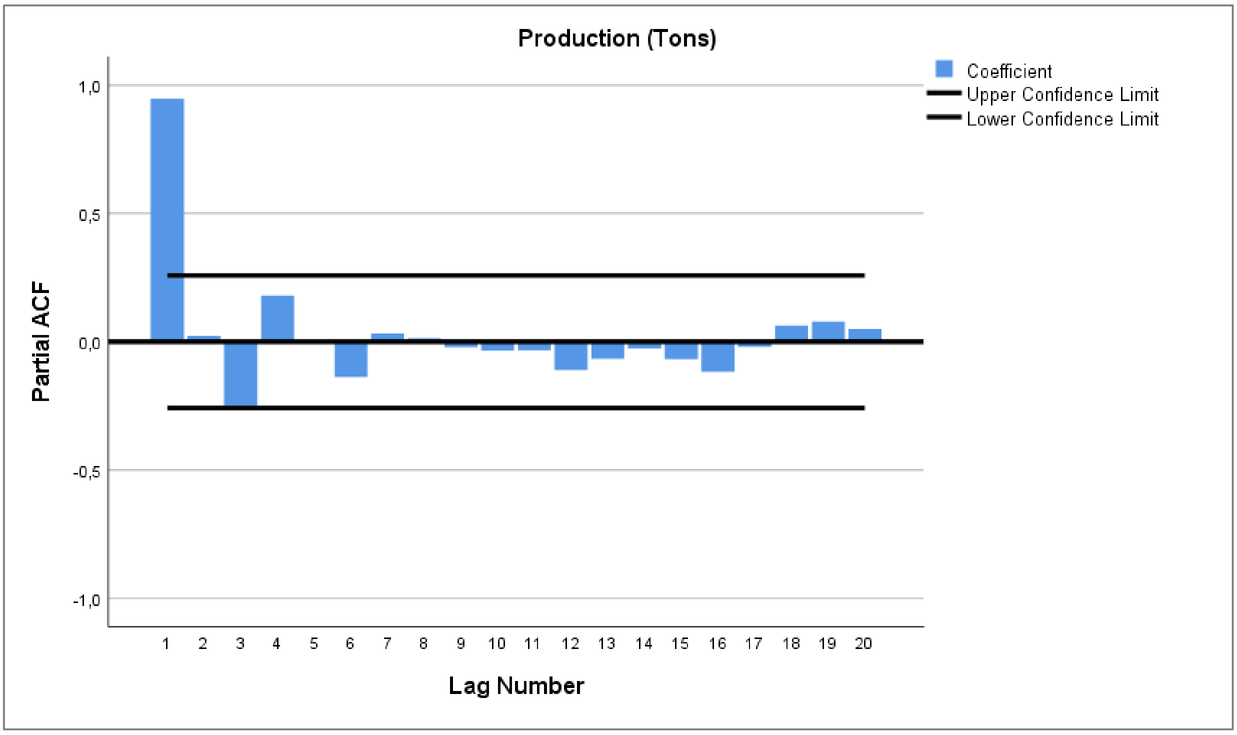

Figure 10. A plot of PACFs of the original milk production series.

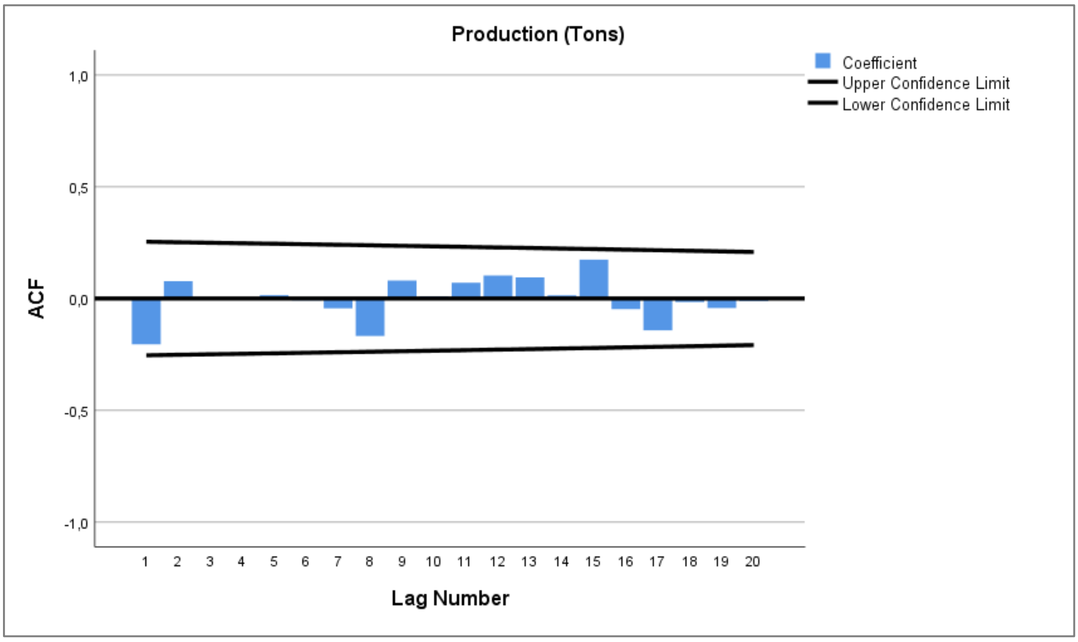

Figure 11. A plot of ACFs of the differenced milk production series.

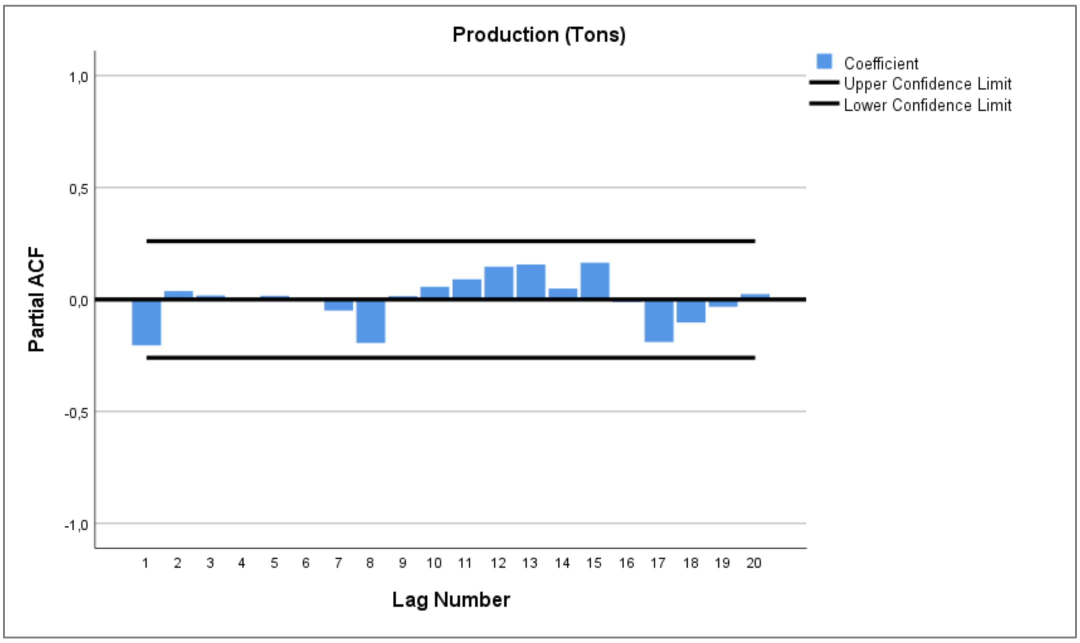

Figure 12. A plot of PACFs of the differenced milk production series.

Following the patterns of the ACF and PACF plots of the differenced series, 3 tentative ARIMA models were identified for beef production, i.e., ARIMA (1,1,1), ARIMA (1,1,0), and ARIMA (0,1,1). On the other hand, 4 tentative ARIMA models were identified for milk production, i.e., ARIMA (0,1,0), ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1). These models were estimated and fit statistic results are presented in Table 2.

According to the results presented in Table 2., among the ARIMA models for milk production, ARIMA (1,1,1) had the largest stationary R^2, ARIMA (1,1,0) had the smallest RMSE and MaxAE values, while ARIMA (0,1,0) had the smallest MAPE, MaxAPE, MAE, and Normalized BIC values. The ARIMA (0,1,0) model having the smallest MAPE, and Normalized BIC value, was selected to be the most appropriate model for forecasting Uganda's milk production. In comparison with other studies that have been conducted using the same methodology to forecast milk production, this study's finding is different from the results of the available studies in the literature. Among the available studies, Eştürk (2021) estimated milk production in Türkiye's Ardahan province and concluded that ARIMA (0,0,1) was the most suitable model. While comparing Artificial Neural Networks and Box-Jenkins models to forecast goat milk production in Türkiye, the results of Kaygisiz and Sezgin (2017)'s study revealed that ARMA (2,1) model was the most appropriate model for forecasting goat's milk production among the identified ARIMA models. Hassan et al. (2018) also used the same methodology to forecast milk production in Sudan's Khartoum state and concluded that ARIMA (1,0,0) model was the most appropriate. While Ganesan et al. (2020) revealed that ARIMA (1,1,0) was the appropriate model for estimating milk production in India. It was also concluded that ARIMA (1,2,1) was the model suitable for forecasting cow milk production at Andassa dairy farm, West Gojam Zone, Amhara Region in Ethiopia (Taye et al., 2021).

Table 2. Tentative ARIMA models for beef and cattle milk production.

Fit Statistic		**Cattle Milk Production (Tons)**				**Beef Production (Tons)**		
		ARIMA (0,1,0)	ARIMA (1,1,0)	ARIMA (0,1,1)	ARIMA (1,1,1)	ARIMA (1,1,1)	ARIMA (1,1,0)	ARIMA (0,1,1)
Stationary R-squared		-2.22E-16	0.042	0.038	0.044	0.130	0.130	0.117
R-squared		0.974	0.975	0.975	0.975	0.979	0.979	0.979
RMSE		88308.81	87194.017	87386.524	87881.331	6681.213	6622.366	6670.689
MAPE		7.11	7.888	7.95	7.667	4.195	4.196	4.198
MaxAPE		24.771	25.323	25.158	25.48	52.838	52.838	52.800
MAE		44509.952	47374.031	47300.937	46732.296	4059.830	4061.253	4146.279
MaxAE		399602.78	390143.81	391364	390548.91	31702.580	31702.859	31680.018
Normalized BIC		22.846	22.89	22.894	22.975	17.821	17.735	17.749
Ljung-Box Q(18)	Statistics	11.909	12.856	12.606	12.702	10.169	10.191	12.175
	DF	18	17	17	16	16	17	17
	Sig.	0.852	0.746	0.762	0.694	0.858	0.895	0.789

Among ARIMA models for beef production, all the identified models had very slight differences in the parameters used for estimation. ARIMA (1,1,1) and ARIMA (1,1,0) had the same stationary R^2, R^2, and MaxAPE values. ARIMA (1,1,1) had the smallest MAPE and MAE values, ARIMA (1,1,0) had the smallest RMSE and normalized BIC values, while ARIMA (0,1,1) had the smallest MaxAPE and MaxAE values. Based on the normalized BIC values, ARIMA (1,1,0) is the best model for forecasting Uganda's beef production because it has the lowest normalized BIC value among the identified ARIMA models. In addition to having the smallest normalized BIC value, this model also had a statistically significant coefficient of the autoregressive component moreover at the 1% level of significance (see Table 3) as recommended in Mahapatra and Satapathy (2019)'s study. All components of the ARIMA (1,1,1) model were not statistically significant as can be observed in Table 3.

It can also be noted that all the identified ARIMA models for both beef and milk production analyzed in this study have a high accuracy in forecasting Uganda's beef and milk production because they have MAPE values of less than 10 as put forward in Celik (2019) and Hassan et al. (2018)'s studies.

Table 3. Parameters of the tentative models for beef and cattle milk production.

	Models	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Beef Production (Tons)	ARIMA (1,1,0)	C	1648.685	1329.957	1.240	0.220
		AR(1)	0.358***	0.124	2.891	0.005
	ARIMA (1,1,1)	C	1647.927	1345.167	1.225	0.226
		AR(1)	0.364	0.349	1.041	0.302
		MA(1)	0.007	0.375	0.018	0.986
	ARIMA (0,1,1)	C	1689.093	1147.509	1.472	0.147
		MA(1)	-0.327**	0.126	-2.605	0.012
Cattle Milk Production (Tons)	ARIMA (0,1,0)	C	26397.220**	11496.828	2.296	0.025
	ARIMA (1,1,0)	C	26468.834***	9470.224	2.795	0.007
		AR(1)	-0.202	0.130	-1.558	0.125
	ARIMA (0,1,1)	C	26644.232***	9336.521	2.854	0.006
		MA(1)	0.183	0.131	1.392	0.169
	ARIMA (1,1,1)	C	26193.357**	9968.750	2.628	0.011
		AR(1)	-0.440	0.840	-0.524	0.603
		MA(1)	-0.248	0.891	-0.278	0.782

** and *** denote significance at the 5% and 1% levels of significance, respectively.

Among the diagnostic tests, plots of residuals of ACF and PACF of ARIMA (0,1,0) and ARIMA (1,1,0) for milk and beef production, respectively as shown in Figure 13 and 14 show that all autocorrelations lie within the 95% confidence interval, all lags are not significant. This implies that all information has been captured by both models. Additionally, the null hypothesis of no serial correlation is accepted in the Ljung-Box Q test for both models as shown in Table 2 ($p>0.05$). This implies that the data are independently distributed.

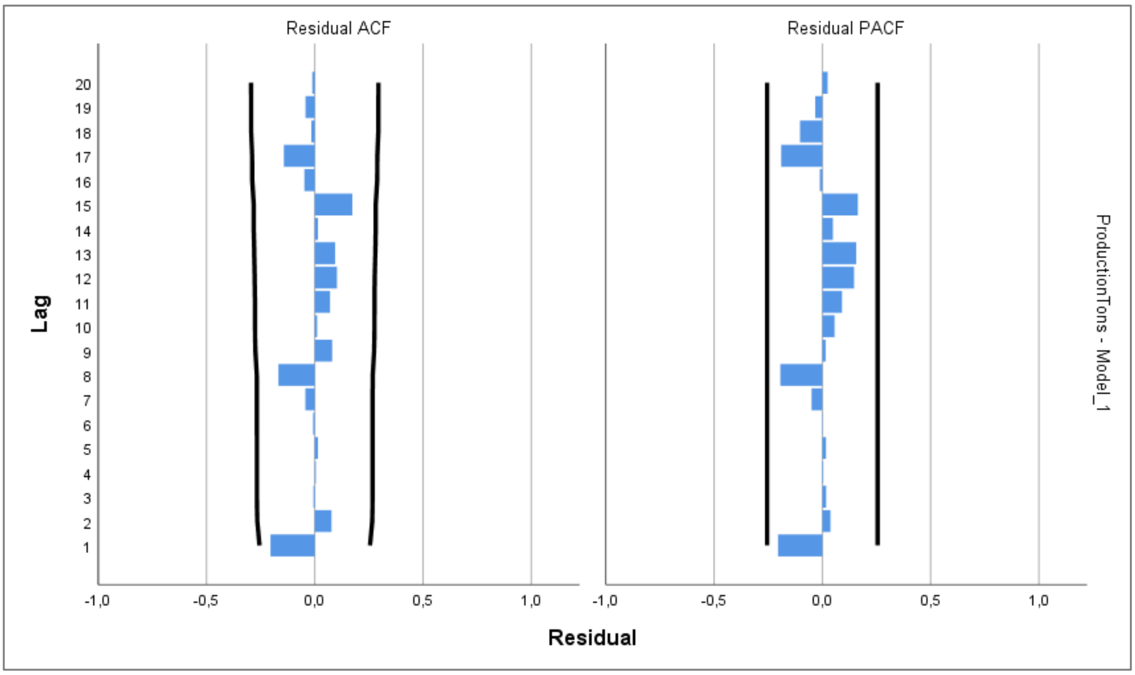

Figure 13. ACF and PACF plots of residuals of ARIMA (0,1,0) for milk production.

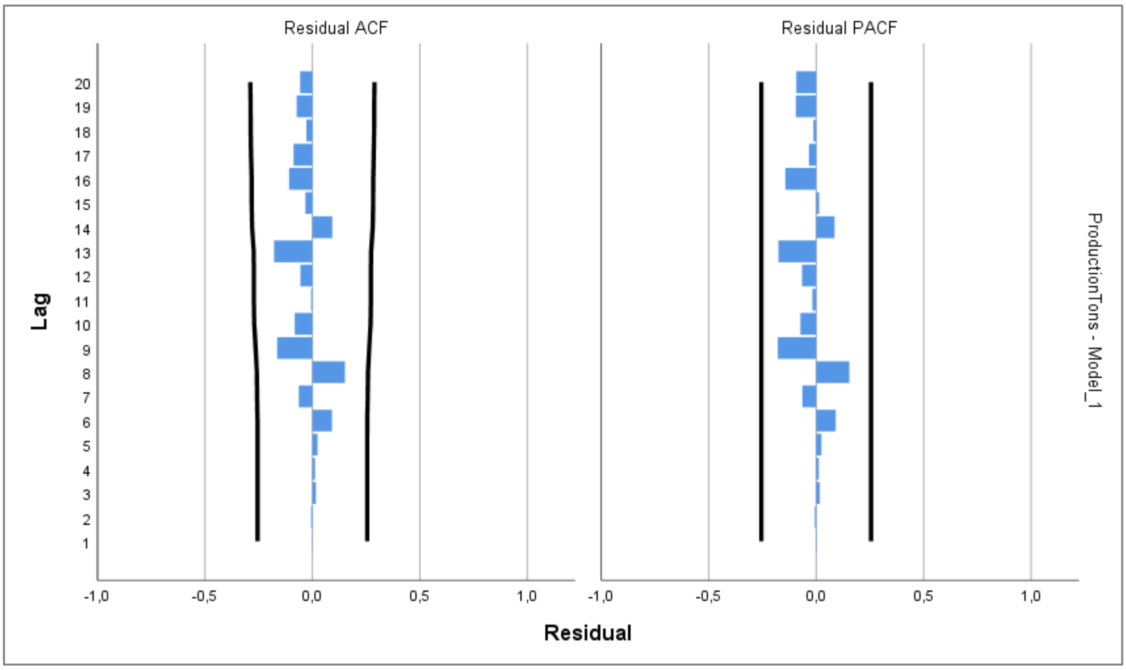

Figure 14. ACF and PACF plots of residuals of ARIMA (1,1,0) for beef production.

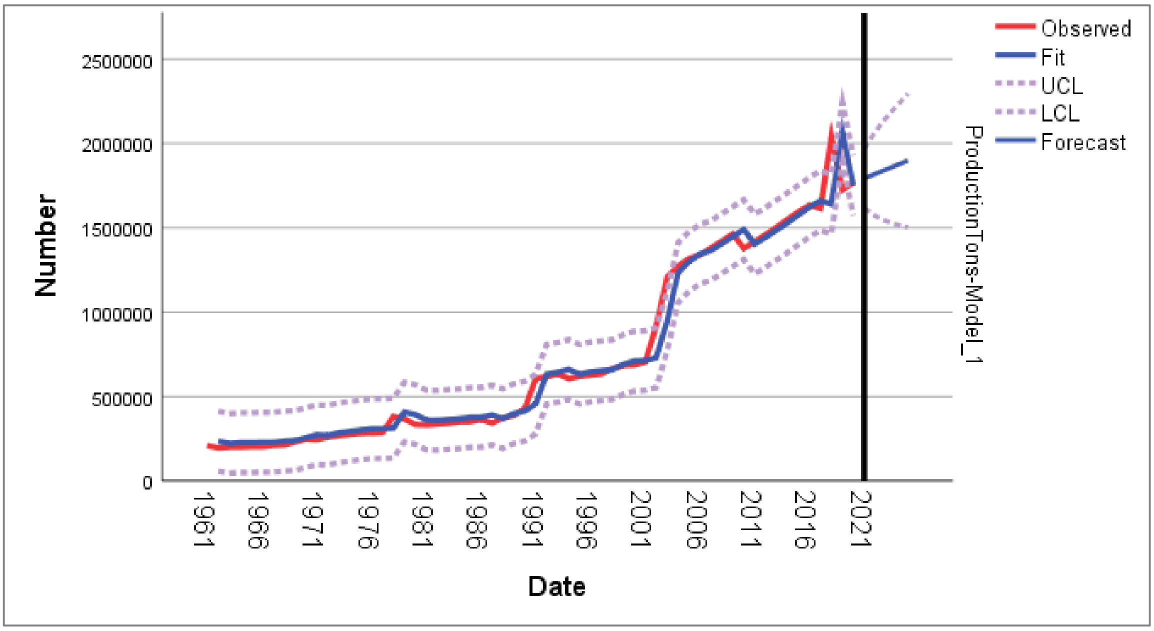

Figure 15. A plot of the observed, fit, and forecast values of ARIMA (0,1,0) for milk production.

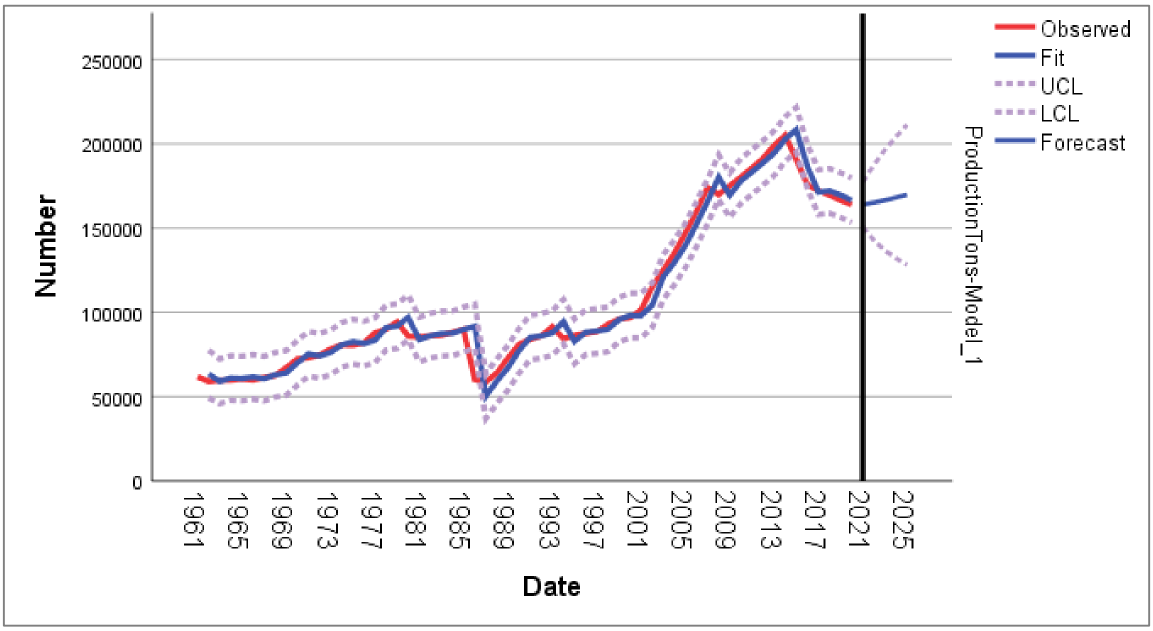

Figure 16. A plot of the observed, fit, and forecast values of ARIMA (1,1,0) for beef production.

Forecasts of both ARIMA (0,1,0) and ARIMA (1,1,0) for milk and beef production are presented in Figure 15 and 16. Additionally, Table 4. presents actual values, estimated values, and forecasts of both models from 2021 to 2025. According to these results, ARIMA (0,1,0) forecasts show that milk production will increase at an annual average rate of 1.629% between 2021 and 2025 making 1.898 million tons in 2025. On the other hand, ARIMA (1,1,0) forecasts show that beef production will increase at an annual average rate of 0.393% between 2021 and 2025 making 169,763 tons in 2025. These rates of growth are far below the actual annual average growth rates registered in the sample period i.e., according to the data presented by FAO, beef and cattle milk production in Uganda increased at an annual average rate of 1.92% and 4.09%, respectively in the period between 1961 and 2020. This suggests the need to increase production in the two livestock sub-sectors through increased investment to exploit the benefits of the increasing demand for beef and cattle milk both domestically and regionally. The current beef production levels can only meet half the domestic and regional beef demand (UIA, 2016). This together with the fact that Uganda's beef is highly preferable owing to its yellow fat that does not contain cholesterol mainly because the cows are grazed on natural pastures (UIA, 2016), present a high potential of the beef sector for the domestic and export market. One of the ways to take advantage of such potential is by increasing production through large-scale commercial farming.

Table 4. Actual and predicted values of ARIMA (0,1,0) for milk production and ARIMA (1,1,0) for beef production.

Year	Milk Production (Tons) (ARIMA (0,1,0))				Beef Production (Tons) (ARIMA (1,1,0))			
	Actual	Predicted	LCL	UCL	Actual	Predicted	LCL	UCL
2015	1596000	1576397	1399628	1753167	190785	208372	195118	221626
2016	1634000	1622397	1445628	1799167	175684	186710	173455	199964
2017	1614000	1660397	1483628	1837167	172275	171336	158082	184590
2018	2040000	1640397	1463628	1817167	169496	172113	158859	185367
2019	1724655	2066397	1889628	2243167	166515	169559	156305	182814
2020	1766386	1751052	1574283	1927822	163889	166506	153252	179761
2021		1792783	1616014	1969553		164007	150753	177262
2022		1819180	1569191	2069170		165108	142755	187461
2023		1845578	1539404	2151751		166561	136766	196355
2024		1871975	1518436	2225513		168139	132082	204196
2025		1898372	1503104	2293640		169763	128273	211252

4. Conclusion

Considering the importance of forecasting in short and long-term planning, this study employs the Box-Jenkins methodology to determine the most appropriate ARIMA models for the 1961 to 2020 time series of Uganda's beef and cattle milk production. The study further makes five-year (2021-2025) forecasts of Uganda's beef and cattle milk production with appropriate prediction intervals. Following patterns of the Autocorrelation Function and Partial Autocorrelation Function plots of the differenced data, 4 tentative ARIMA models were identified for milk production, i.e., ARIMA (0,1,0), ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1) for milk production. While 3 tentative ARIMA models were identified for beef production, i.e., ARIMA (1,1,1), ARIMA (1,1,0), and ARIMA (0,1,1). ARIMA (0,1,0) model was selected to be the most suitable for forecasting cattle milk production because it had the smallest MAPE and Normalized BIC values. Although results revealed very slight differences in the parameters used for estimation in all identified models, ARIMA (1,1,0) was selected to be the best model for forecasting Uganda's beef production because it had the smallest normalized BIC value and a significant coefficient of the autoregressive component at the 1% level of significance. Forecasts using the selected ARIMA models show that milk production will increase at an annual average rate of 1.63%, while beef production will increase at an annual average rate of 0.39% in the 2021-2025 forecast period.

Conflict of Interest

The author declares that he has no conflict of interest.

References

Agriterra. (2012). *Identification of livestock investment opportunities in Uganda*. Retrieved Apr 23, 2022, from https://www.agriterra.org/assets/uploads/15820/Livestock%20market%20study.pdf

Akin, A. C., Tekindal, M. A., Arikan, M. S., & Çevrimli, M. B. (2020). Modelling of the milk supplied to the industry in Turkey through Box-Jenkins and Winters' Exponential Smoothing methods. *Veteriner Hekimler Derneği Dergisi, 91*(1), 49-60. https://doi.org/10.33188/vetheder.643824

Asteriou, D., & Hall, S. G. (2007). *Applied econometrics*. Macmillan International Higher Education.

Behnke, R., & Nakirya, M. (2012). *The contribution of livestock to the Ugandan economy*. Retrieved Apr 23, 2022, from https://core.ac.uk/download/pdf/132642444.pdf

Celik, S. (2019). Modeling and estimation of potato production in Turkey with time series analysis. *International Journal of Trend in Research Development, 6*(5), 111-116.

DDA. (2020). *Dairy Development Authority annual performance report FY 2019/20*. Retrieved Apr 23, 2022, from https://dda.go.ug/assets/files/ANNUAL-PERFORMANCEREPORTFY2019-20.pdf

DDA. (2021). *Dairy Development Authority annual report FY 2020/2021*. Retrieved May 1, 2022, from https://dda.go.ug/assets/files/DDA-annulareport20-21.pdf

Eroğul, N. A., Bozoğlu, M., Topuz, B. K., & Başer, U. (2019). Forecasting the amount of beef production in Turkey. *Tarım Ekonomisi Araştırmaları Dergisi, 5*(2), 101-107.

Eştürk, Ö. (2021). Estimating milk production in Ardahan Province with ARIMA (Box-Jenkins) model. *Journal of Applied Sciences of Mehmet Akif Ersoy University, 5*(2), 271-281. https://doi.org/10.31200/makuubd.972489

FAO. (2022). *Food and Agriculture Organization of the United Nations data (FAOSTAT)*. Retrieved Apr 28, 2022, from http://www.fao.org/faostat/en/#data

Ganesan, M., Xavier, G., & Gupta, V. P. (2020). Forecasting of milk production in India by using time series auto regressive moving average model. *Shodh Sanchar Bulletin, 10*(38), 170-180.

Gujarati, D. N., & Dawn, C. P. (2009). *Basic econometrics*. McGrawHill Press.

Hassan, S. A., Abdelaziz, H. H., Ibrahim, A. H., & Musa, K. S. M. (2018). Milk production -forecasting in Khartoum State, Sudan. *Journal of Agriculture and Research, 4*(12), 6-13.

Hill, R. C., Griffiths, W. E., & Lim, G. C. (2018). *Principles of econometrics*. John Wiley & Sons.

Hussain, J. N., Alsukmany, A. M., & Mohammed, L. A. (2021). Modelling and forecasting of poultry production in Al-Hilla District in Iraq. *PalArch's Journal of Archaeology of Egypt/Egyptology*, *18*(4), 633-642.

Kaygisiz, F., & Sezgin, F. H. (2017). Forecasting goat milk production in Turkey using Artificial Neural Networks and Box-Jenkins models. *Animal Review, 4*(3), 45-52. https://doi.org/10.18488/journal.ar.2017.43.45.52

Kunst, R. M. (2012). *Econometric forecasting*. Institute for Advanced Studies Vienna University of Vienna.

Mahapatra, S., & Satapathy, A. (2019). An application of box-jenkins methodology for forecasting of green gram productivity in Odisha. *Journal of Pharmacognosy and Phytochemistry*, *8*(3), 4383-4387.

Masood, M. A., Raza, I., & Abid, S. (2018). Forecasting wheat production using time series models in Pakistan. *Asian Journal of Agriculture Rural Development, 8*(2), 172-177. https://doi.org/10.18488/journal.1005/2018.8.2/1005.2.172.177

Muhammed, O., & Zengin, Y. (2020). A comparative forecasting approach to forecast animal production: A case of Turkey. *Lalahan Hayvancılık Araştırma Enstitüsü Dergisi, 60*(1), 24-31.

Oni, O., & Akanle, Y. (2018). Comparison of exponential smoothing models for forecasting cassava production. *International Journal of Scientific Research in Mathematical and Statistical Sciences*, *5*(3), 65-68. https://doi.org/10.26438/ijsrmss/v5i3.6568

Putri, R. T., Sukiyono, K., & Sumartono, E. (2019). Estimation of Indonesian Beef Price Forecasting Model. *AGRITROPICA : Journal of Agricultural Sciences, 2*(1), 46-56. https://doi.org/10.31186/j.agritropica.2.1.46-55

Rahman, N. M. F., Hasan, M. M., Hossain, M. I., Baten, M., Hosen, S., Ali, M., & Kabir, M. (2016). Forecasting aus rice area and production in Bangladesh using Box-Jenkins approach. *Bangladesh Rice Journal, 20*(1), 1-10.

Sánchez-López, E., Pérez-Linares, C., Figueroa-Saavedra, F., & Barreras-Serrano, A. (2015). A short term forecast for Mexican imports of United States beef using a univariate time series model. *The Journal of Animal and Plant Sciences, 25*(5), 1283-1289.

Sankar, T. J. (2014). Design of a stochastic forecasting model for egg production. *International Journal of Innovative Science, Engineering, and Technology*, *1*(6), 319-325.

Suleman, N., & Sarpong, S. (2012). Forecasting milled rice production in Ghana using Box-Jenkins approach. *International Journal of Agricultural Management and Development, 2*(2), 79-84.

Taye, B. A., Alene, A. A., Nega, A. K., & Yirsaw, B. G. (2021). Time series analysis of cow milk production at Andassa dairy farm, west Gojam zone, Amhara region, Ethiopia. *Modeling Earth Systems and Environment, 7*(1), 181-189. https://doi.org/10.1007/s40808-020-00946-z

UBOS. (2022). *Uganda Bureau of Statistics, explore statistics*. Retrieved Apr 25, 2022, from https://www.ubos.org/explore-statistics/30/

UIA. (2016). *Uganda Investment Authority, agriculture (Beef)*. Retrieved Apr 28, 2022, from https://www.ugandainvest.go.ug/wp-content/uploads/2016/02/AGRICULTURE-Beef.pdf

Waiswa, D., & Akullo, J. (2021). Implications of gender discrimination for household food security among small holder dairy farmers in Nakaloke, Mbale District, Uganda. *Research Journal of Agriculture and Forestry Sciences*, *9*(2), 1-11.

Waiswa, D., & Günlü, A. (2022). Economic analysis of dairy production in Uganda, a case study on the performance of dairy cattle enterprises in Southwestern Uganda. *Asian Journal of Agriculture*, *6*(2), 61-67. https://doi.org/10.13057/asianjagric/g060202

Waiswa, D., Günlü, A., & Mat, B. (2021). Development opportunities for livestock and dairy cattle production in Uganda: A review. *Research Journal of Agriculture and Forestry Sciences, 9(1)*, 18-24.