



## **Time Series Modelling of The Volume of Overland Timber Export in The Bolgatanga Municipality**

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### **Authors' contributions**

*This work was carried out in collaboration among all authors. JAA designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. HMK took part in designing the study, performing the statistical analysis, managing literature searches and also managing the analyses of the study. SKB took part in designing the study, managing literature searches and in writing the first draft. All authors read and approved the final manuscript.*

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## **ABSTRACT**

**Aims/ Objectives:** This research was carried out with the intention of using time series to model the volume of overland timber exported within Bolgatanga municipality  
**Place and Duration of Study:** Study of the time series was based on a historical data of the volume of timber exported for twenty consecutive years, from 1999 to 2019 within Bolgatanga municipality.  
**Methodology:** The three-stage iterative modeling approach for Box Jenkins was used to match an ARIMA model and to forecast both the amount of timber export and the confiscated lumber. ARIMA method incorporates a cycle of autoregressive and a moving average. The three-stage iterative modeling technique of Box Jenkins which were used are model recognition, parameter estimation and/or diagnostic checks were also made.

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**Results:** From the preliminary investigation, the study showed that the amount of timber exported in municipality is skewed to the right, suggesting that much of the amount of timber exported is below the average. This, together with the high volatility in the volume of timber exported, indicates that the amount of timber exported within the municipalities during the twenty-year period was low. The plots from the trends also showed robust variations in the volume of timber exported indicating that timber exporters do not have better grips with the concepts and applications of export technology, hence the erratic nature of the volume of timber exported over the period. The quadratic pattern and the ARIMA (1,1,1) model best represented the amount of timber exported. The analysis further indicated that there will be a further decrease in the amount of timber export from the five years projection into the future. Over the last two decades the Bayesian approach to VAR has gained ground. For a future report, this estimation method will be followed to examine the "long-run equilibrium relationships" between timber export volumes and climate change.

**Conclusion:** The quadratic pattern and the ARIMA (1,1,1) model best represented the amount of timber exported. There will be a further decrease in the amount of timber export from the five years projection into the future.

*Keywords: Autocorrelation function; partial autocorrelation function; stationary; parameter estimation; parsimonious model; differencing; time Series analysis; linear trend; quadratic trend; timber; analysis of variance; ARIMA.*

**2010 Mathematics Subject Classification:** 37M10, 62M10.

## 1 INTRODUCTION

The Ghana Forestry Commission consists of three (3) major divisions: the Wildlife Division (WD) dedicated to the protection and management of Ghana's wildlife, the Forest Services Division (FSD) dedicated to the protection and management of Ghana's forest and the Timber Industry Development Division (TIDD) dedicated to the provision of specialized services. TIDD is responsible for defining the standards, designing and monitoring the implementation of appropriate timber trading activities, the custody chain, quality and quality control, and settling of grievances and conflicts resulting from the execution contract [1]. It has several offices across the country including Bolgatanga Area Office.

The Bolgatanga Area office offers timber management services in the Savannah, Western, North Central, Upper Central, and Upper West areas in Ghana. This office is responsible for monitoring timber inflows and outflows through the country's northern boundaries from the Savannah, Northern, Northeastern, Upper East and Upper West regions of Ghana to Europe, Asia and other parts of the world, and vice versa. Hamile and Tumu border points in the Upper West region, Paga, Namoo, Kulungugu, Widana

and Mognori border points in the Upper East region are the main border points at the country's north. Nevertheless the most commonly used routes are border points Paga and Tumu due to the poor nature of roads towards the other border points.

Ghana's total land area is approximately 23.85 million hectares (ha) [2] with forest occupying approximately one third of the total area of Ghana. Commercial forestry is concentrated in the southern parts of Ghana [3] and the timber industry plays a significant role in Ghana's socio-economic growth through the export of timber products [4]. Its contribution to the Gross Domestic Product (GDP) increased from 2.5 per cent in 1991 to 8 per cent in 1997, but the GDP dropped to 4 per cent in 2009 due to a decline in forest resources [5]. The sector is not without challenges. It is pointed out in [6] that sawn wood and plywood will face some competition in the international market which will have revenue and tax policy implications for Ghanas forestry sector.

Prior to 1990, Ghana's chainsaw operations were legal, with virtually no restrictions posing a sustainability issue that led to a full ban by 1998. A decade after the chainsaw ban, no drastic crackdown was imposed on the activity. On the contrary, chainsaw operators were on

the rise, flooding cheap timber in both local and foreign markets [2]. The prevalence of criminal activities puts pressure on legitimate operators and decreases their opportunities to abide by the rule of law [7]. Illegal deforestation is seen as posing major barriers to achieving sustainable forest management in the tropics. The amount of illicit timber shipped through Ghana's northern borders alone is about 250,000  $m^3$  per year. There have been substantial changes in the global policy climate recently and these developments have had important effects on how tropical forests in Ghana are handled. A model that was produced in [8], is said to be useful in the optimisation calculations of forest planning.

In line with global thinking on protection of forests, the Forestry Commission is active in ensuring that only legal timber is sold on both export and local markets. But are forestry companies that are involved in legitimate forestry operations being forced to leave the legal loggers' team and join the illegal ones? There have been numerous reports carried out on the number of legal timber companies and the amount of legal timber exported and that of illegal timber confiscated over the years. In addition, some studies have been carried out on the time series behaviour on timber exports in Ghana, but there is still no data on the time series behaviour of overland timber exports and their forecast for the Timber Industry Development Division's Bolgatanga Regional office.

## 2 RESEARCH METHODS

The volumes of the exported timber, measured in cubic metres, were taken from 252 monthly observations. Secondary data was sourced from the Timber Industry Development Division Office in Bolgatanga. The three-stage iterative modelling approach which are explicitly outlined in [9] was used to match an ARIMA model and to forecast both the amount of timber export and the confiscated lumber. This method is made up of model recognition, parameter estimation and/or diagnostic checks, [10]. ARIMA method incorporates a cycle of autoregressive and a moving average. An autoregressive model

makes use of statistical properties of a variable's past behavior to forecast its future behaviour, [11]. [12], another work on time series, reminds us, through an empirical study on forecasting accuracy, that there is no best method that can perform well for any given forecasting situation.

It is worth acknowledging that there have been numerous applications of the autoregressive integrated moving average (ARIMA) on data in several disciplines. [13] estimates and makes some forecast of export demand for moulding and chipboard in Malaysia using univariate time series models like the Holt-Winters Seasonal and the seasonal ARIMA models. [14], conducted a study of earnings but subsequently in [15], ARIMA time series models was also applied to quarterly earnings data of common stockholders for a sample of ninety-four large firms listed on the New York Stock Exchange. The various methods employed in this work are briefly looked at in the following subsections. Minitab and Eviews softwares were employed in analysing the data.

### 2.1 The Trend Models

Trend analysis fits a general trend model, that is, the linear, quadratic or exponential growth models to the time series data. This procedure is often used to fit trend when there is no seasonal component to the series. The trend most accurate to describe the series will be determined using the measures of accuracy, MAPE, MAD and MSD. The model with the minimum measure of accuracy is what best describes the series.

The Linear Trend Model is estimated using the Ordinary Least Square estimation given as

$$y_t = \beta_0 + \beta_1 t + e_t \quad (2.1)$$

Where  $y_t$  is the projected value of the  $y$  variable for a selected value of  $t$ ,  $\beta_0$  is the constant intercept and  $\beta_1$  represents the average change from one period to the next.

The Quadratic Trend Model which accounts for a simple curve is of the form

$$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + e_t \quad (2.2)$$

where the variables have the same designations as given in equation 2.1 above.

Similarly, The Exponential Growth Trend Model accounts for exponential growth or decay. it is given as

$$y_t = \beta_0 \times \beta_1^t \times e_t \quad (2.3)$$

## 2.2 Measures of Model Adequacy

Three measures of accuracy of the fitted model is done by computing Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD) for each of the simple forecasting and smoothing methods. For all three measures, the smaller the value, the better the fit of the model. We use these statistics to compare the fits of the different methods. The MAPE measures the accuracy of fitted time series values, specifically in trend estimation. It usually expresses accuracy as a percentage and is given as

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \quad (2.4)$$

Where  $A_t$  is the actual value,  $F_t$  equals the fitted value, and  $n$  equals the number of observations.

The MAD expresses accuracy in the same units as the data, which helps conceptualise the amount of error. The mean deviation is a measure of how much the fitted value of the data is likely to differ from the actual value. The absolute value is used to avoid deviation with opposite sides cancelling each other out. Its mathematical form is

$$MAD = 1/n \sum_{t=1}^n |A_t - F_t| \quad (2.5)$$

MSD measures the square forecast error, error variance and also recognise that longest errors are disproportionately more expensive than small errors. It is expressed as

$$MSD = 1/n \sum_{t=1}^n |A_t - F_t|^2 \quad (2.6)$$

## 2.3 Stationarity

A stationary process has a mean and variance that do not change over time and the process does not have trends. To proceed with the estimation of an ARIMA model, the series

is required to be stationary and to test for stationarity under this study we consider the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test.

The Augmented Dickey-Fuller Test (ADF) tests the hypothesis;

1. H0: the series is not stationary
2. H1: the series is stationary

At 95% significance level, a p-value less than 0.05 means we reject H0 meaning the series is stationary, else it is not stationary.

Kwiatkowski, Phillips, Schmidt and Shin Test (KPSS) test has a reverse hypothesis to the ADF test. The hypothesis tested are

1. H0: the series is stationary
2. H1: the series is not stationary

This means that at 95% significance level, a p-value less than 0.05 means we reject H0 and say the series is not stationary, otherwise it is stationary.

## 2.4 Autoregressive Integrated Moving Average Models (ARIMA)

If a non-stationary time series which has variation in the mean is differenced to remove the variation the resulting time series is known as integrated time series. It is called integrated because the stationary model which is fitted to the differenced data has to be summed or integrated to provide a model for the non-stationary data. All AR (p) models can be represented as ARIMA (p, 0, 0) that is no differencing and no MA (q) part. Also, MA (q) models can be represented as ARIMA (0, 0, q) meaning no differencing and no AR (p) component. The general model is ARIMA (p, d, q) where p is the order of the AR part, d is the degree of differencing and q is the order of the MA. The general ARIMA (p, d, q) model can be expressed using the backward shift operator as

$$\begin{aligned} (1 - \Phi_1 B - \Phi_2 B^2 - \dots - \Phi_p B^p)(1 - B)^d Y_t \\ = (1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q) e_t \end{aligned} \quad (2.7)$$

Where  $(1 - B)^d$  is the non-seasonal differencing filter.

## 2.5 Model Selection Criteria

The following tools (criteria) are used in the selection of best fit model out of suggested models. The model with the minimum of these statistics is selected as the best fit.

1. The Akaike Information Criteria (AIC) uses the maximum likelihood method. In the implementation of the approach, a range of potential ARIMA models are estimated by maximum likelihood methods, and for each, the AIC is calculated with the formula

$$AIC(p, q) = \ln(\sigma_e^2) + r \frac{2}{n} + constant \quad (2.8)$$

where,  $n$  is the number of observations in the historical time series data,  $\sigma_e^2$  is the maximum likelihood estimate of  $\sigma_e^2$ , and  $r = p + q + 1$  denotes the number of parameters estimated in the model. Given two or more competing models the one with the smallest AIC value will be selected.

2. The Schwarz Bayesian Criterion (BIC) like AIC, uses the maximum likelihood method. The BIC imposes a greater penalty for the number of estimated model parameters than does the AIC. The use of minimum BIC for model selection results in a chosen model whose number of parameters is less than that chosen under AIC. It is determined by the equation

$$BIC(p, q) = \ln(\sigma_e^2) + r \frac{\ln(n)}{n} \quad (2.9)$$

3. The AIC is a biased estimator and the bias can be appreciable for large parameters per data ratios. [16] showed that the bias can be approximately eliminated by adding another nonstatic penalty term to the AIC, resulting in the Corrected Akaike Information Criteria (AICc) which is defined by the formula

$$AIC_c = AIC + \frac{2(r + 1)(r + 2)}{(n - r - 2)} \quad (2.10)$$

## 2.6 Model Diagnostics

To ensure that the selected model is the best model that suits the data, the following diagnostics are performed. The Time Plot of the Residuals is one of such diagnostics. For a fit model, it should not show any fixed pattern, trend in the residuals, no outliers and in general case no changing variance across time.

The Residual ACF plot examines the goodness of fit by plotting the ACF of residuals of the fitted model. If most of the sample autocorrelation coefficients of the residuals are within the 5% significance limits in a random pattern, then the model is a good fit.

The Normal Q-Q Plot is a plot of the quantiles of two distributions against each other, or a plot based on estimates of the quantiles. If most of the points are in line and closer to the normal line, then the model is a good fit.

Ljung-Box Q Statistics is a check of the overall model adequacy. The error terms are examined and for the model to be adequate the errors should be random. If the error terms are statistically different from zero, the model is not adequate. The test statistic used is the Ljung-Box statistic, a function of the accumulated sample autocorrelations,  $r_j$  up to any specified time lag  $m$ . As a function of  $m$ , it is determined as

$$Q(m) = n(n + 2) \sum_{j=1}^m \frac{(r_j^2)}{n - j} \quad (2.11)$$

## 3 RESULTS AND DISCUSSION

Results in this study relate to the results of the different statistical methods used in the analysis of collected data. The findings served as the basis for explanation, debate and conclusion to attain the research goal.

### 3.1 Exploratory Analysis

The exploratory data analysis was employed, using mainly the Box-Jenkins methodology, on the amount of timber exported in cubic metres ( $m^3$ ) over the twenty consecutive years. Several projections were made, accompanied by time series plots and a trend analysis, to obtain the descriptive statistics about the amount of timber exported.

**Table 1. Descriptive statistics of the volume of timber exported in cubic metres ( $m^3$ ) over the 20-year period**

Volume of Timber Exported	
Mean	1519.46
Standard Error	54.90
Median	1333.32
Standard Deviation	871.51
Sample Variance	759522.64
Coef of variation	57.36%
Kurtosis	-0.32
Skewness	0.71
Minimum	171.46
Maximum	4212.87
Sum	382904.08
Confidence Level(95%)	108.12

**Table 2. One-way ANOVA: Timber Export versus yearly**

S = 694.8		R-Sq = 41.50%		R-Sq(adj) = 36.44%	
Source	DF	SS	MS	F	P
yearly	20	79125074	3956254	8.20	0.000
Error	231	111515109	482749		
Total	251	190640183			

The minimum volume of monthly timber exported was found to be 171.46 and the highest was 4212.87, while the average volume of monthly timber exported was 1519.46 with a corresponding standard deviation of 871.51, indicating that the results were broadly distributed across the mean. The coefficient of variation was 57.36 points, which indicates a very high variance in the timber exported from the municipality of Bolgatanga. The amount of the timber exported distribution also indicates positive skewness of 0.71 indicating that the majority of the timber exported is distributed to the right of the mean and has a negative kurtosis value of -0.32 indicating that the data are platykurtic, much of the timber exported is at either end of the distribution, therefore flattened as normal peak.

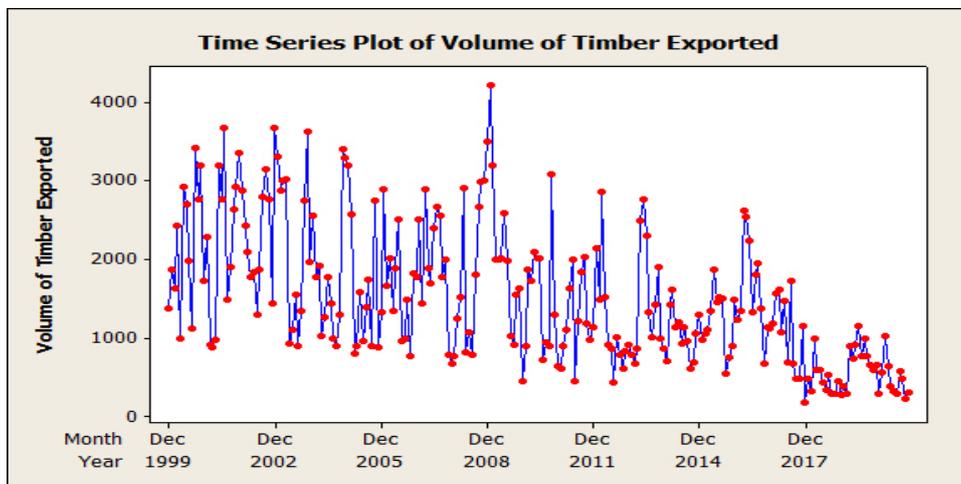
Table 2. indicates that (as shown by the probability value of 0.000) there is a statistically

significant difference in timber exported over the different years. This implies a statistically significant increase or decrease in the amount of timber exported over the period. Which group of years are contributing the difference? Table 3 below displays aspects of the analysis to answer the question.

The Means that don't share a letter are slightly different as indicated in Table 3. It is seen that the amount of timber exported within the municipality in 2017, 2001 and 2002 contributes significantly to these changes. The amount of timber exported seems to be lower in 2017 as compared to 2001 and 2002. It is also observed that the average values for 2001 and 2002 are linked. This means that the amount of timber exported continues to decline over time. This may be as a result of forest depletion.

**Table 3. Grouping information using Tukey method**

yearly	N	Mean	Grouping
2002	12	2337.8	A
2001	12	2302.8	A
2008	12	2214.9	A B
1999	12	2200.6	A B C
2000	12	2112.0	A B C D
2006	12	2030.5	A B C D E
2004	12	1743.0	A B C D E
2003	12	1688.1	A B C D E F
2007	12	1684.4	A B C D E F
2015	12	1640.1	A B C D E F
2005	12	1637.6	A B C D E F
2009	12	1498.8	A B C D E F G
2012	12	1451.2	A B C D E F G H
2011	12	1211.2	B C D E F G H
2010	12	1210.2	B C D E F G H
2014	12	1187.7	C D E F G H
2016	12	1099.9	D E F G H
2013	12	1025.5	E F G H
2018	12	701.4	F G H
2019	12	476.8	G H
2017	12	454.5	H



**Fig. 1. Time series plot of volume of timber exported in bolgatanga**

Fig. 1. shows the trend of volume of timber exported from the time series plot of the data to achieve the study's first objective. The amount of timber exported was plotted on a single graph and the graph showed some non-stationarity in the data as all the series did not fluctuate around a fixed point. There was a show of trend pattern and seasonality was not found in the series and this suggests that the mean and variance was not constant over time and thus the data will have to

be differenced in order to achieve the stationary state. The relative amount of exported timber fluctuation shows relatively high volatility. This figure also revealed high rates of timber exports in December 2017.

### 3.2 Stationarity Tests and The Model

The ADF and KPSS unit root were employed to examine whether the time series data was stationary. When the test was first performed, the trend variable was present. The series was not stationary at the first time at 5% level of significance. In order to achieve stationarity, the data was thus differenced once. From Table 4, both the ADF and KPSS test accepted that the sequence is as stationary as their p-values suggest.

The linear, quadratic, exponential and S-curve models are shown in Fig. 2, 3, 4 and 5 respectively. Round dotted lines represent the actual values of the amount of timber exported in each of the figures, while red lines represent the fitted values based on the different models.

The most suitable model representing the trend in the volume of timber exported is the one with minimal errors, from Table 5. A closed observation of the errors created by the four models, shows that the quadratic model has the minimum MAPE, MAD and MSD, is thus considered to be the best model in describing the trend in the volume of timber exported within the municipality.

Further analysis and tests were carried out on the plots of the Autocorrelation Function (ACF) and those of the Partial Autocorrelation Function (PACF). It is observed that the data tends to be non-stationary with a confidence interval of 95 percent, thus the differencing to achieve stationary state. The ACF and PACF have major spikes shown in Fig. 6 and 7, at lags 1 through lag 8. It means that, after the first discrepancy, there is no rise or non-decrease in both ACF and PACF and this reaffirmed that the sequence is stationary.

The model with the minimum Akaike Information Criteria (AIC), Bayesian Information Criterion

(BIC), and Hannan-Quinn (HQ) is the most appropriate for the volume of timber exported. This means that the ARIMA model (1, 1, 1) has the lowest values as seen in Table 6 and is thus chosen as the best one for forecasting.

Table 7 reveals estimates of the ARIMA(1, 1, 1) Model. The parameters of  $AR_1$  and  $MA_1$  are important with coefficients and p-values of (0.444523, 6.99e-015) and (1.00000, 0.0000) respectively at 5 percent rates. The P-values below 0.05 suggest parameter significance.

### 3.3 Model Diagnosis

The following diagnostics are conducted to ensure that the model selected is the best one suited to the data.

#### 3.3.1 ARCH-LM Test

The ARCH-LM test was used to test for the constant variance assumption. The results for the ARCH-LM test are shown in Table 8. We cannot reject the null hypothesis of no ARCH effects in the residuals because the probability value is 0.0971 and this means that ARCH is not sufficient to be estimated, but rather the ARIMA model offers an adequate representation of the volume of timber exported from the time series data.

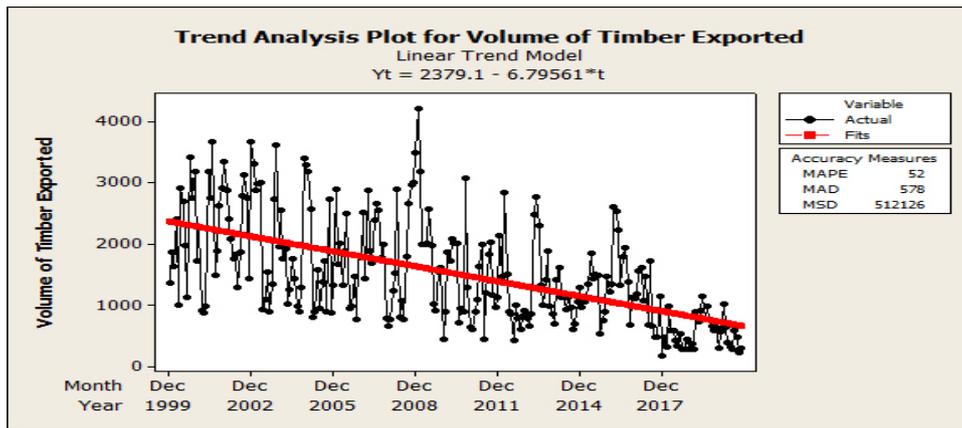
Table 9 displays the LM statistic at lag 10 with the likelihood value. It appears that the likelihood value at lag 10 is not statistically significant suggesting that the model ARIMA(1,1,1) is free from serial correlation. This means that the ARIMA(1,1,1) model is adequate and can be used to forecast the potential conduct of the timber volume exported within the municipality of Bolgatanga.

#### 3.3.2 Residuals Plots

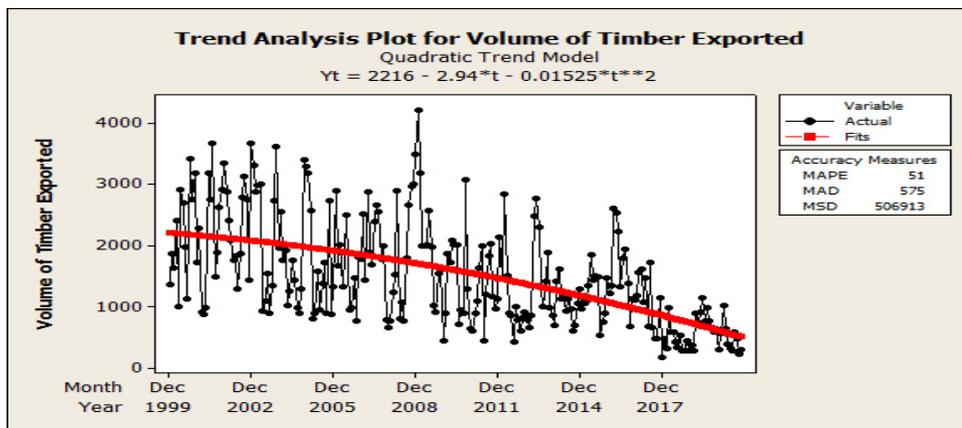
The residual patterns over time around the zero mean as indicated in fig. 8. below show that the residuals are random and independent of each other, thus suggesting that the model is suitable. The ACF and PACF residuals indicate that all the lags fall within the lower and upper bound suggesting that the model is correct.

**Table 4. Stationary test on volume of timber exported**

Test	Statistic	p-value
ADF	-9.2914	0.01
KPSS	0.0226	0.10



**Fig. 2. Linear trend plot of volume of timber exported in bolgatanga**



**Fig. 3. Quadratic trend plot of volume of timber exported in bolgatanga**

### 3.3.3 The Normal Q-Q Plot

The Normal Plot is another diagnostic test on the residuals to determine whether the residuals follow the normal distribution. The standard likelihood plot is used to do this. The standard plots are used to equate a sample's distribution to a theoretical one. If most points are in line and similar to the usual line, then it indicates a good match for the model is. The normal plot shows all points along the normality line in Fig. 9. below, thus the model is deemed correct.

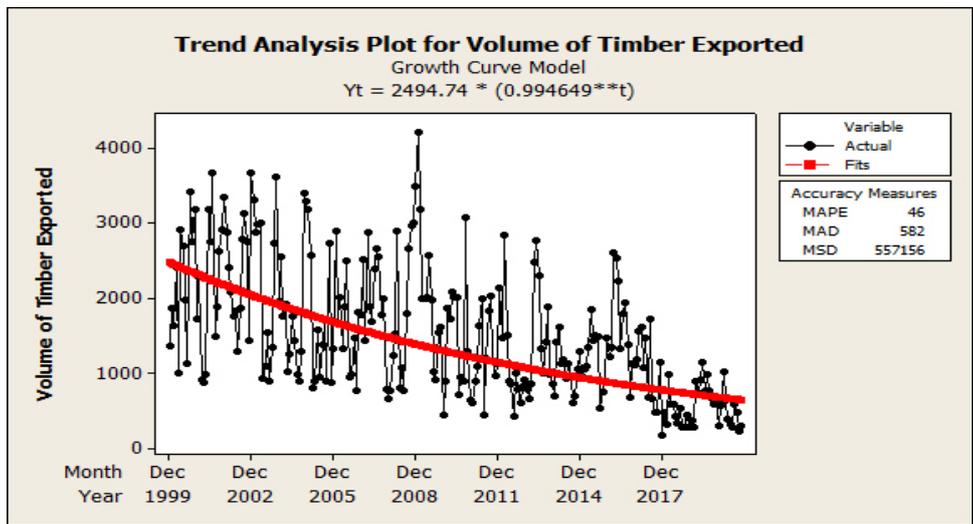


Fig. 4. Exponential trend plot of the volume of timber exported in bolgatanga

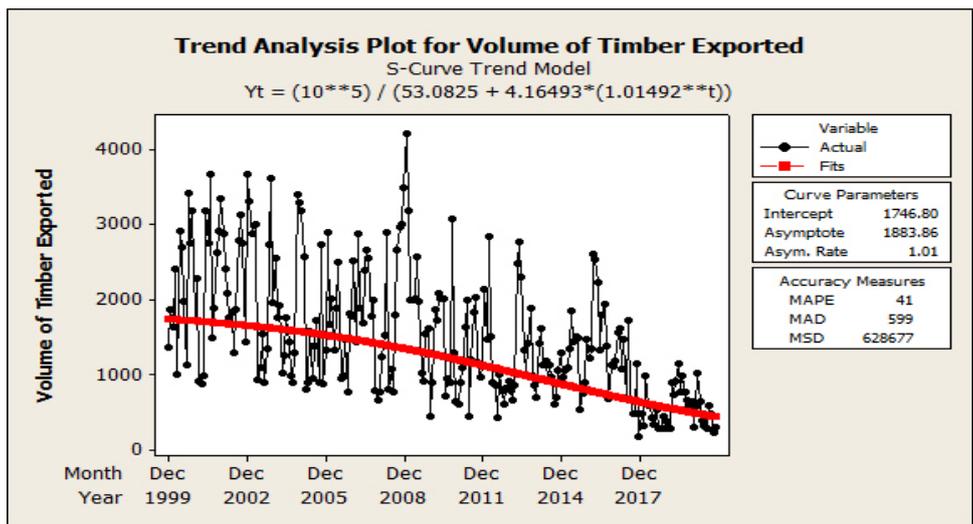


Fig. 5. Curve Trend Plot of the Volume of Timber Exported in Bolgatanga

Table 5. Measures of accuracy

Trend	MAPE	MAD	MSD
Linear	52	578	512126
Quadratic	51	575	506913
Exponential	46	582	557156
S- Curve	41	599	628677

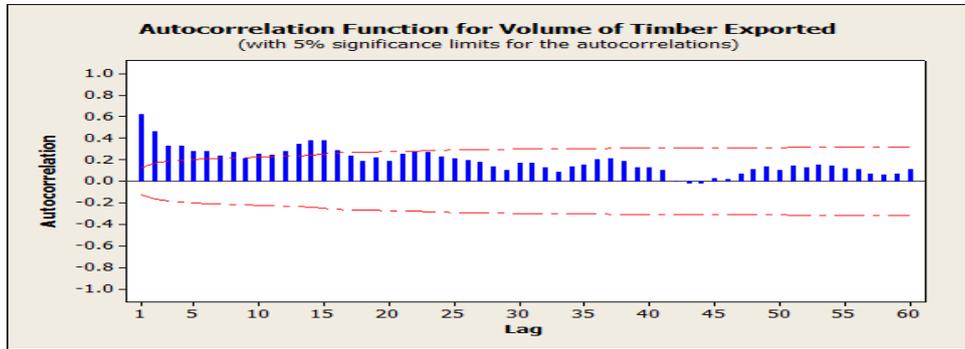


Fig. 6. ACF plot of volume of timber exported in bolgatanga

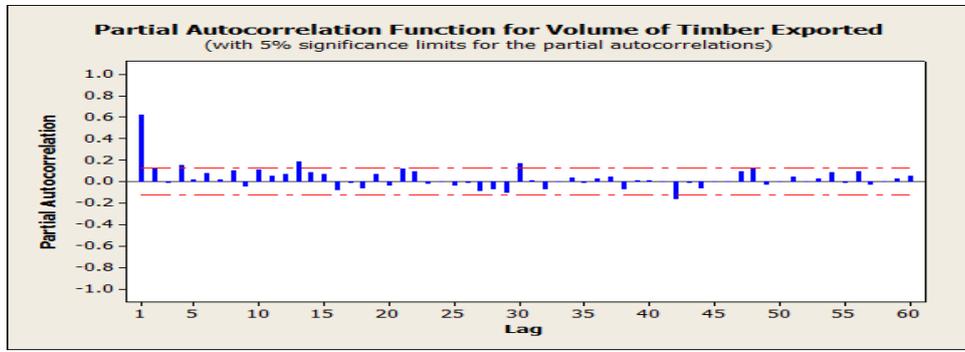


Fig. 7. PACF plot of volume of timber exported in bolgatanga

Table 6. Model identification

Model	AIC	BIC	HQ
ARIMA(0,1,1)	4011.218	4021.794	4015.474
ARIMA(0,1,2)	3984.840	3998.942	3990.515
ARIMA(0,1,3)	3970.513	3988.141	3977.687
ARIMA(0,1,4)	3972.487	3993.639	3980.999
ARIMA(0,1,5)	3982.884	4007.562	3992.815
ARIMA(0,1,6)	3975.838	4004.041	3987.188
ARIMA(0,1,7)	3977.809	4009.538	3990.577
ARIMA(0,1,8)	3977.769	4013.023	3991.956
ARIMA(1,1,1)	3971.999	3986.101	3977.674
ARIMA(1,1,2)	3973.895	3991.522	3980.988
ARIMA(1,1,3)	3972.469	3993.622	3980.982
ARIMA(1,1,4)	3972.519	3997.197	3982.450
ARIMA(1,1,5)	3973.309	4001.513	3984.659
ARIMA(1,1,6)	3975.019	4006.748	3987.787
ARIMA(1,1,7)	3975.523	4010.778	3989.710
ARIMA(1,1,8)	3974.653	4013.433	3990.259

**Table 7. Parameter estimation**

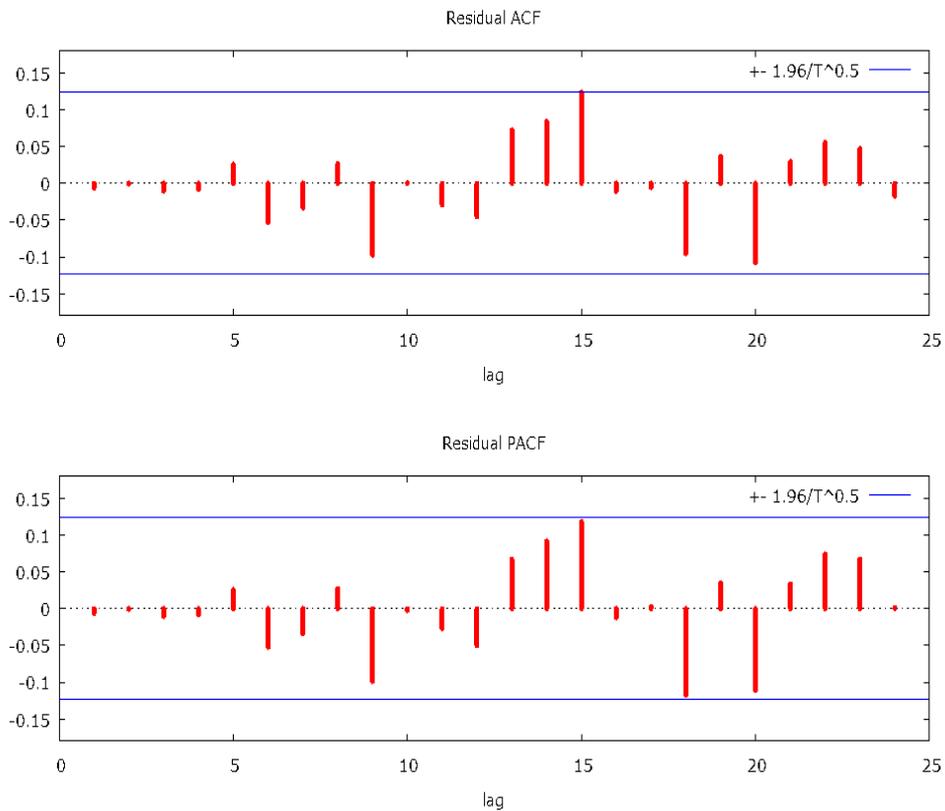
	coefficient	std. error	z	p-value
const	6.7476	0.9952	6.78	1.20e-011 ***
AR <sub>1</sub>	0.4445	0.0571	7.79	6.99e-015 ***
MA <sub>1</sub>	1.0000	0.0115	86.79	0.0000 ***

**Table 8. ARCH-LM test**

F-statistic	2.7613	Prob. F(1,249)	0.0978
Obs*R-squared	2.7529	Prob. Chi-Square(1)	0.0971

**Table 9. Ljung-Box statistic**

LAG	Chi-Square	DF	p-value
10	12.609	10	0.2464



**Fig. 8. Residuals plot of ACF and PACF**

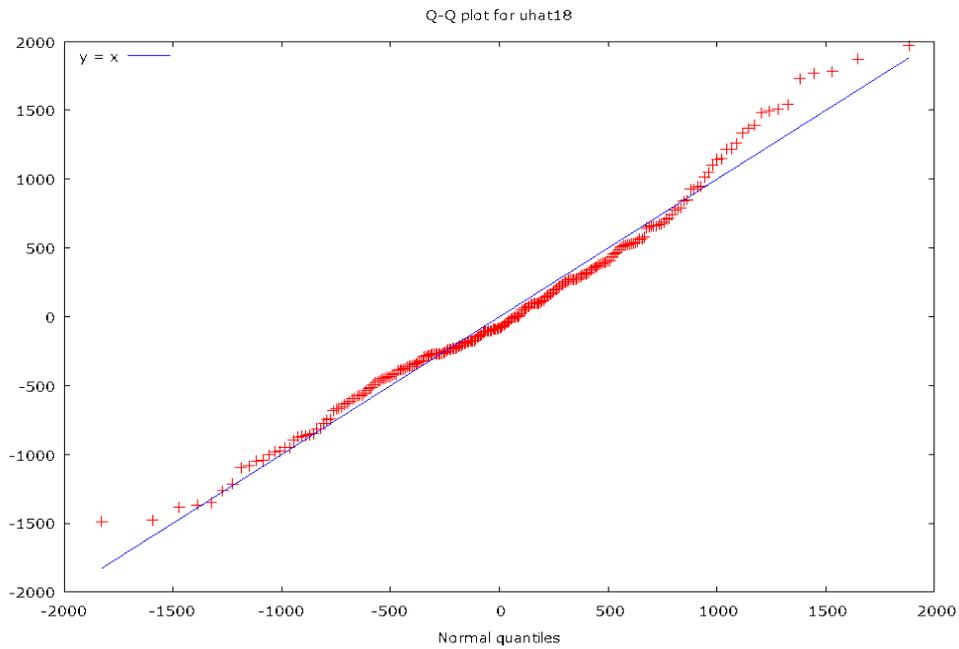


Fig. 9. Normal Q-Q plot

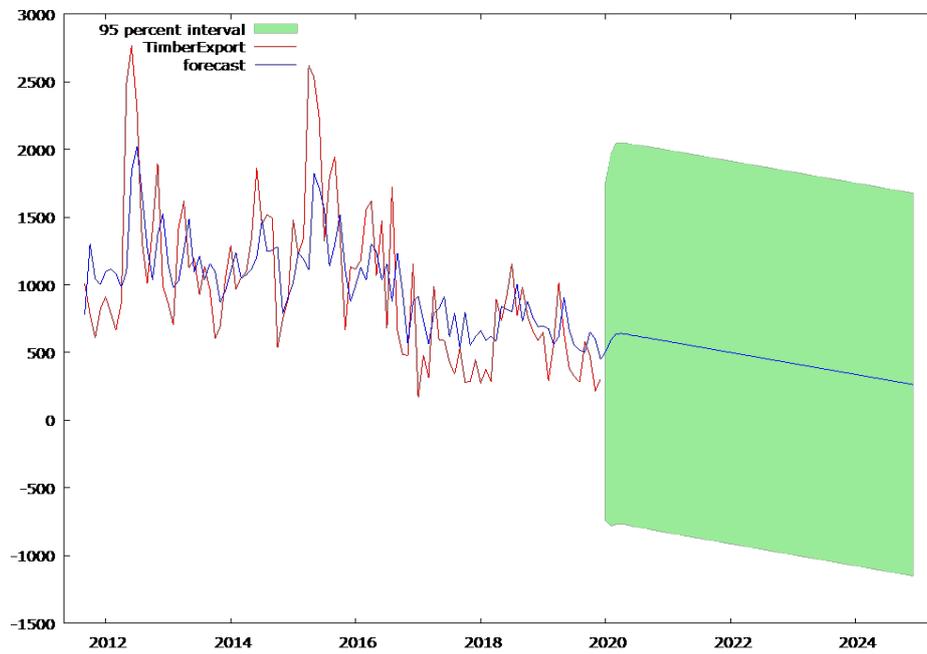


Fig. 10. Five Year forecast of the volume of timber export in bolgatanga

It is projected from Fig. 10. that the amount of timber exports within the municipality is likely to decrease in the coming years and this will happen as a result of no substitution or replanting of new ones when tree are cut down.

## 4 DISCUSSION OF THE FINDINGS

From the descriptive statistics, it is found in Table 1. that the volume of timber is skewed to the right, suggesting that most of the values are concentrated in the left of the mean. This means that most of the volume of timber exported is below the average suggesting poor output of timber. Also, as the peakness displayed a platykurtosis form with a kurtosis coefficient = -0.32, it shows that most scores are distributed to the extreme sides of the curve even showing poor timber exporting technology and also the absence of concrete planting technology.

There was an increase in the amount of timber exported over the years and that happened in the months of December 2001 and 2002. Fig. 2. shows a high and low peak upward and downward pattern suggesting an erratic or unpredictable pattern, with the series showing a generally decreasing trend. Fig. 2. and Fig. 5. explains various sequence trend models and the best trend description for the accuracy measurements in Table 5. is the quadratic trend model with ARIMA (1,1,1) also being selected as the best predictive model.

Although the data was transformed to achieve stationarity, the differencing and the best fit test also indicated that the final model was appropriate for the prediction. The five-year prediction results showed very little decrease in timber volume over time. It further showed that the amount of timber export in the municipality over time is likely to decrease.

## 5 CONCLUSION

The research shows that the overall amount of timber exported within the municipality is low and is likely to decline further. Furthermore, the

result from the ARCH-LM test suggests that the data of the amount of timber exported is not heteroscedastic as the p-values at the different lags (only lag 10 is shown in Table 9.) are greater than 0.05. This means the data are homoscedastic. The ARIMA(1,1,1) model is found to be best in describing and forecasting the time series of the volumes of timber export from the Bolgatanga municipality.

## 6 RECOMMENDATIONS/SUGGESTIONS

Based on the results it is suggested that:

- The policy makers should come up with a policy such that if someone cuts down a tree, he/she will replace it with a new one and this would go a long way to mitigate deforestation within the municipality.
- The authorities should strictly supervise timber dealers to prevent indiscriminate tree felling.
- Over the last two decades the Bayesian approach to Vector Autoregression (VAR) has gained ground. For a future report, this estimation method will be followed to examine the long-run equilibrium relationships between timber export volumes and climate change.

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## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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