Modelling Tea Production in Kenya using the Linear Regression with GARCH error term

Consolata A. Muganda[a], Sewe Stanley[b], Winnie Mokeira Onsongo[c]

[a] Department of Mathematics and Actuarial Science, The Catholic University of Eastern Africa, Kenya.
[b] Department of Mathematics and Actuarial Science, The Catholic University of Eastern African, Kenya.
[c] Department of Statistics and Actuarial Science, University of Ghana, Ghana.

Abstract: Tea is a popular drink globally and contributes to 4% of Kenya's annual GDP. The continued variation in Tea production has prompted numerous research. Some researchers have linked the variation to climatic changes while others to soil fertility dynamics. In the present research, we link the tea production changes to climatic variables. Thus, we attempt to establish the linear regression equation modeling relationship between trends of tea production and climatic variables, namely NDVI, minimum humidity, maximum humidity, rainfall, minimum temperature, maximum temperature, and solar radiation between January 2007 and December 2015. We have also presented the effect of volatility and seasonality of climatic variables on tea production in Kenya. The effect of volatility and seasonality is investigated via the GARCH model, which is used to estimate linear regression error terms for tea production using data from major tea zones in Kenya, namely Embu, Kakamega, Kericho, Kisii, Meru, and Nyeri. The demonstration in the research via the already established GARCH model is based on a combination of garchorder(2,2) and armaorder(1,1) that seasonality affects tea production with climatic variables as independent variables. We compared the analysis results among the data obtained from different major tea zones in Kenya. The results summarized in tables show that in the presence of seasonality larger error term exists than in the absence of seasonality for most tea zones. The AIC and BIC in most of the tables are lower in cases of deseasonalized data. The loglikelihood in most cases is also higher in cases on deseasonalized data. Comparison of deviation between tea production value estimated using data and constructed tea production based on linear regression equation shows that the seasonal data exhibits higher deviation than deseasoned data in most cases. The effect of seasonality on serial correlation is also evident. There exists serial correlation for most cases of deseasoned data compared to when the data has seasonality. A future study may consider estimating linear regression error terms amidst volatility effect on seasonal data for different GARCH models.

Keywords: Tea Production, climatic variables, GARCH error term, seasonality, volatility effect

1. Introduction

Tea is one of the most important popular drinks for 70% of the world population due to its aroma and pharmacological effects such as its ability to suppress tumor cell growth **(Dhekale et al., 2014; Wang et al., 2010)**. Kenya, besides China, India, Sri Lanka, and Indonesia, is one of the principal producers of tea in the world (**Dhekale et al., 2014)**. These countries account for 77% of tea produced in the world and 80% global export **(Dhekale et al., 2014)**. The major tea-producing counties or zones in Kenya are Embu, Kakamega, Kericho, Kisii, Meru, and Nyeri. Kenyan tea sector is the oldest agro-based industry and provides direct and indirect employment to many citizens **(Commision et al., 2008; Hakizimana et al., 2017; Omboi, 2011)**. Tea production in Kenya is a primary foreign exchange earner providing 4% GDP for the Kenyan government **(Muganda et al., 2021; Ochieng et al., 2016)**.

The production of Tea in Kenya has presented fluctuations, following varying climatic conditions **(Omumbo et al., 2011)**. For instance, Kenya produced roughly 43.5 thousand metric tons of tea in June 2021. Thus, the study on trends and production in tea has attracted attention in the research arena in Kenya. A similar trend is observed in the world; for instance, **Ahammed (2012)** analyzed the trends on Bangladesh, India tea using polynomial models. **Bordoloi (2012)** analyzed the global tea production and export in India via linear regression analysis. **Gijo (201)** used ARIMA to forecast tea production in Sri Lanka. **Dutta et al. (2012)** established linear relationship between rainfall and fertilizer for tea production. **Cheserek et al. (2015)** linked tea production in Kenya with different climatic variables. **Okoth (2011)** analyzed tea production with climatic change in Kericho County. **Oddah (2019)** used ARIMA to forecast prices at the Mombasa tea auction center in Kenya. **Mwangi and Wangui (2017)**used ARIMA to forecast the production of cash crops in Kenya. **Sitienei et**

al. (2017)used regression models to predict crop yield response to climate change for the case of Nandi East, sub-county of Nandi county. Finally, **Muganda et al. (2021)** used ARIMA to capture the effects of climatic variables on tea production in Kenya. The literature presented shows that tea production has received great attention. However, there is no literature on the modeling volatility effect of tea production on climatic variables in Kenya. Thus, in this study, an attempt has been made to study the effect of seasonality on linear regression analysis where error term is estimated based on the effect of the volatility of climatic variables via the GARCH model for tea production in Tea zones in Kenya.

The paper is organized as follows: Section 1 introduces the study topic covering brief literature and contribution of the paper. Section 2 outlines contribution of the paper. Section 3 presents review of the proposed work. Section 4 is the experimental setup for attaining the results presented in the study. Section 5 presents model fitting, analysis and results. Section 6 presents discussion of the findings. Section 7 is a conclusion of the study and recommendations.

2.Contribution of the study

The proposed study has four main contribution outlined below.

1. Construct a linear regression model equation for tea production with climatic variables in Kenya.
2. Linear regression error term estimated via GARCH analysis in Kenya.
3. Model volatility effect of tea production with climatic variables in Kenya.
4. Establish the effect of seasonality on linear regression analysis of tea production with climatic variables in Kenya.

3.Proposed Work

Volatility is one of the stylized facts which shows changes in the variables. **Mandelbrot (1963)** noted that volatility specifies that large changes tend to be followed by large changes of either sign and vice-versa. The autoregressive conditional heteroskedasticity (ARCH) model proposed by **Engle (1982)**, and its generalized form, GARCH, have become cornerstone structures for addressing the volatility clustering in time series **(Agbeyegbe, 2022; Junior et al., 2022; Paolella, 2018)**. The subsequent growth extension of modeling has seen many variations of the GARCH idea in many fields other than the dominant financial time series. Volatility is visible in all data spheres, and climatic and crop yields are no exception. A majority of the climatic variables and agricultural yields data are time-series, making them easily modeled via GARCH and ARCH models (**Ramirez and Fadiga, 2003)**. This is because most time-series variables exhibit auto-correlation and dynamic heteroskedasticity **(Bollerslev, 1987; Buguk et al., 2003)**. The variation in tea production may have some patterns due to different climatic variables. Thus, GARCH (p, q) can be an alternative to the time-trend linear regression model. The GARCH, which is an alternative to the ARMA process with $m = \max(p, q)$, where p is the squared disturbance, is critical in modeling systematic changes in crop production. In this application, the GARCH becomes similar to **Just and Pope (1978)** stochastic production function, which allows relationships of inputs with climatic variables analogous to independent variables and tea production comparable to the dependent variable. The traditional time-series trend may explain the variation in tea production. However, heteroskedasticity may lead to model mis-specification due to the omission of variables. The inclusion of NDVI, humidity, temperature and rainfall values may remove heteroskedasticity. Unlike the common theory by statisticians, GARCH model arguably does not consider the trend and seasonality in data **(Zhang et al., 2014)**[28]. If there is a trend or seasonality, the performance of the GARCH model may be affected. Thus, in the paper our focus is to use the GARCH model to estimate error term and hypothetical test for serial correlation. Detrending the data to remove the seasonality may help establish its effect on the linear model. This attempt aims to approximate the seasonality variance without biasing the data.

The GARCH process is designed to allow conditional variance to change over time. The potential sources of heteroskedasticity are the climatic variables. However, to remove seasonality, the proposed work de-trends the data. This is achieved by dividing the data into three components, trend, seasonal, and remainder. The trend data is used to test the presence of seasonality during the estimation of the error term. The raw data is used as the control to test seasonality during the estimation of the error term.

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4.Experimental Setup

The study is focused on the volatility of tea production under climatic variables, namely the Normalized Difference Vegetation Index (NDVI), humidity minimum (H_n), humidity maximum (H_x), rainfall (R), temperature minimum (T_n), temperature maximum (T_x), and solar radiation (S). Based on time-series data for climatic variability and tea production, we investigate the volatility of six Kenya tea zones: Embu, Kakamega, Kericho, Kisii, Meru, and Nyeri. The climatic variables data were obtained from the Kenya Meteorological department for climatic variables and tea production from Kenya Tea Development Authority (KTDA). We divided the data into six main categories based on the tea zones. The data were collected between January 2007 and December 2015. Before this paper, we had established a suitable GARCH model to capture the volatility of tea production under climatic variability. We demonstrated that GARCH(2,2) and ARMA(1,1) models are the most suitable from a total of 54 models selected. We evaluated the models based on AIC, BIC, and LogLikelihood. The goodness of fit is measured using AIC and BIC. LogLikelihood indicates the final value of the loglikelihood after maximization of all model parameters. The rule is, for a better model, the value of AIC and BIC must be lowest **(Kuha, 2004)**.

The basic regression analysis is as follows

$$y_t = \lambda_0 + \lambda_1 x_{t,1} + \lambda_2 x_{t,2} + \epsilon_t : \mathrm{i} = 1, \ldots, \mathrm{n}, \tag{4.1}$$

$$\epsilon_t = \sigma_t Z_t, \tag{4.2}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{2} \alpha_i \epsilon_{t-i} + \sum_{j=1}^{2} \beta_j \sigma_{t-j}, \tag{4.3}$$

where (4.1) is the linear regression analysis equation, (4.2) is the error term equation, and (4.3) is the GARCH analysis equation giving a component of σ in the error term. Z_t is an independent and identically distributed random variable with continuous density such that it has zero mean and variance.

5.Data Analysis and Findings

5.1.Embu

5.1.1.Analysis

A summary for regression analysis for Embu data is presented in Table 1.

Table 1: Summary of linear regression analysis for data with and without seasonality for Embu County

	Estimate	
	Raw	**Deseasonalized**
(Intercept)	-5043081.1	-6755736.9
NDVI	4707766.2	3828966.6
H_n	-645.9	24407.7
H_x	4900.3	27175.7
R	649.0	-1408.5
Tn	28852.5	-7876.1
T_x	45966.8	34262.0
S	22219.5	50342.0

We use Table 1 to construct a linear regression analysis equation for Embu data in the presence of seasonality (5.1) and without seasonality (5.2)

$$y_{Embu} = -5043081.1 + 4707766.2NDVI - 645.9Hn + 4900.3Hx + 649.0R + 28852.5Tn + 45966.8Tx + 22219.5S + \epsilon_e \tag{5.1}$$

$$y_{EmbuDes} = -6755736.9 + 3828966.6NDVI + 24407.7Hn + 27175.7Hx - 1408.5R - 7876.1Tn + 34262Tx + 50342S + \epsilon_e d \tag{5.2}$$

We use GARCH analysis to estimate ϵ_e and $\epsilon_e d$ as based on the following GARCH optimal parameters in Table 2.

Table 2: Summary of Optimal parameter values and test for serial correlation for Embu County data with and without seasonality

Optimal parameter	**Value**	
	Raw	**Deseasonalized**
mu	8.9138e+05	8.5543e+05
ar1	1.9779e-01	9.9691e-01
ma1	3.9417e-01	4.6635e-01
omega	1.2780e+08	1.1863e+07
alpha1	0.0000e+00	5.5675e-01
alpha2		4.0000e-06
beta1	9.9900e-01	4.4224e-01
beta2		0.0000e+00
Weighted Ljung-Box Test on Standardized Residuals		
	p-value	
	Raw	**Deseasonalized**
$Lag[1]$	0.9348	5.702e-03
$Lag[2*(p+q)+(p+q)-1][5]$	0.4742	0.000e+00
$Lag[4*(p+q)+(p+q)-1][9]$	0.5040	4.091e-10

H0 : No serial correlation

Table 2 shows the GARCH analysis output results indicating no evidence of serial correlation based on the $p-values$ obtained among the raw data set. We used the results obtained in the GARCH analysis output with the regression coefficients in Table 1 to get $\epsilon_e = -25952.19$ and $\epsilon_e d = -1603.563$ for seasonal and deseasonal data, respectively. Thus, linear regression equation (4.1) for Embu data in the presence of and without seasonality is given by (5.3) and (5.4), respectively.

$$\begin{aligned} y_{Emburaw} &= -5043081.1 + 4707766.2NDVI - 645.9Hn + 4900.3Hx \\ &+4900.3R + 649.0Tn + 28852.5Tx + 22219.5S - 25952.19 \end{aligned} \tag{5.3}$$

$$\begin{aligned} y_{EmbuDes} &= -5043081.1 + 4707766.2NDVI - 645.9Hn + 4900.3Hx + 4900.3R + \\ &649.0Tn + 28852.5Tx + 45966.8Tx + 22219.5S - 1603.563 \end{aligned} \tag{5.4}$$

We used (5.1) to find the average tea production in Embu between 2007 and 2015 as 866671.4, while the average from the data recorded is 892621.8426. This gives a deviation of (5.5). Similarly, We used (5.2) to find deasesoned average tea production in Embu between 2007 and 2015 as 891853.2, while the average from the data recorded is 895110.1, giving a deviation of (5.6).

$$\begin{aligned} Dev_{EmbuRaw} &= y_{(5.3)} - mean(y) \\ &= 25950.45 \end{aligned} \tag{5.5}$$

$$\begin{aligned} Dev_{EmbuDes} &= y_{(5.3)} - mean(y) \\ &= 3256.92 \end{aligned} \tag{5.6}$$

5.1.2.Summary

The components of Embu data for tea production and climatic variables in terms of seasonality, trend, remainder, and raw data is displayed in **Figure 1**.

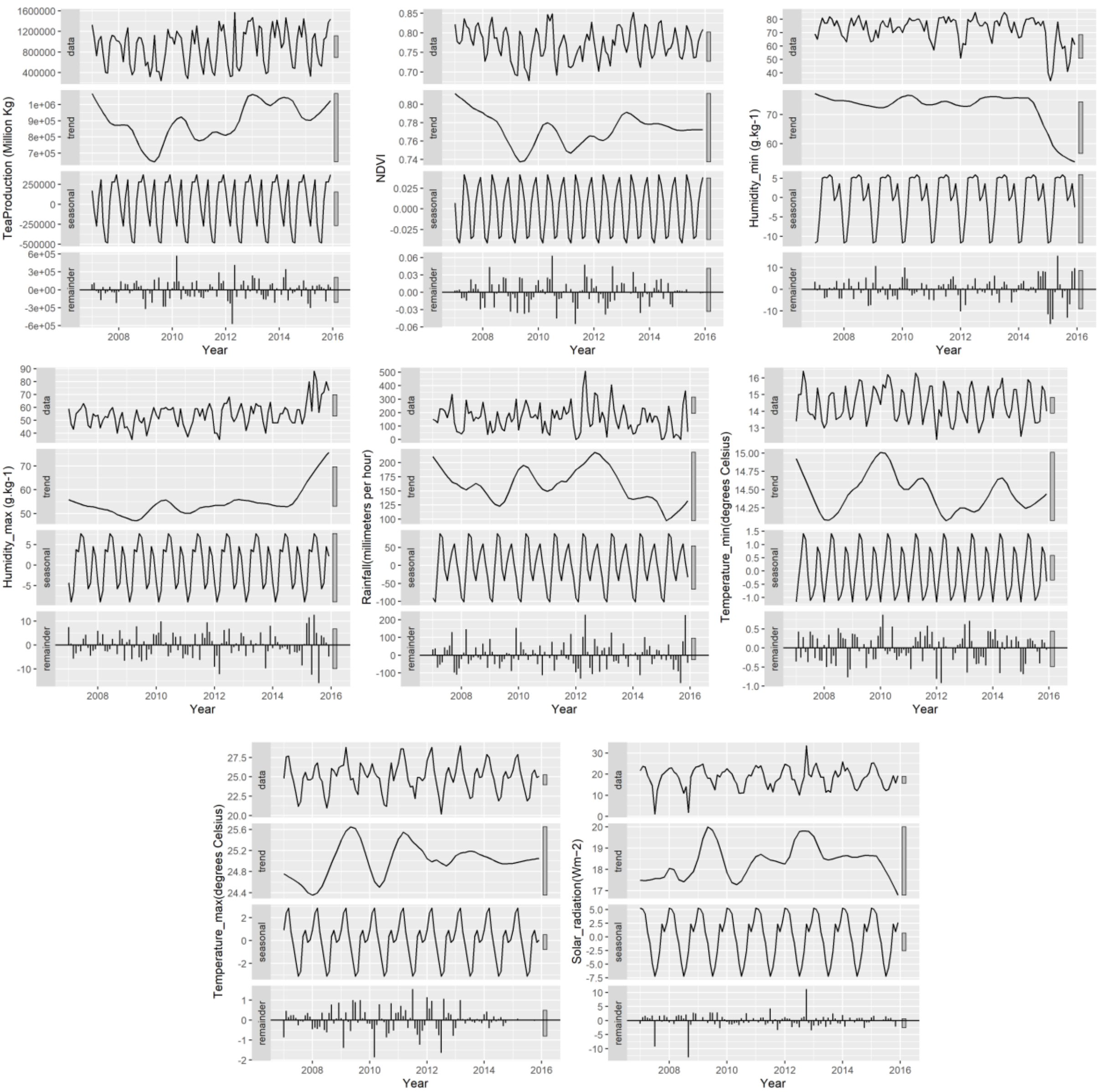

Figure 1: Data components for Tea Production and climatic variables namely NDVI, minimum and maximum humidity, rainfail, minimum and maximum temperature for Embu County . From bottom to top is the remainder, seasonal, trend, and raw data.

We present a summary of results in Table 3. We noted a larger error term in the presence of seasonality compared to that in the absence of seasonality. The table presents AIC, BIC, and Loglikelihood. Lower values of AIC and BIC are desirable. A larger loglikelihood value indicates a better model. Thus, the model without seasonality is better than that with seasonality. Therefore, volatility in seasonality in the Embu data has a more significant effect on the regression analysis of tea production with climatic variables. A further comparison also indicates that the linear regression equation has a larger deviation in the presence of seasonality.

Table 3: Comparison of GARCH analysis between the Raw and Deseasonalized data for Tea Production in Embu County with climatic variables. Y_{est} is Linear regression plus GARCH, and Y_{aver} is Average Tea Production between 2007 and 2015.

Parameter	Raw	Deseasonalized
AIC	28.262	22.309
BIC	28.485	22.532
LogLikelihood	-1517.125	-1195.677
Y_{est}	866671.4	891853.2
Y_{aver}	892621.84	895110.1
Y_{est} -Y_{aver}	-25950.45	3256.92
Error Term	**- 25952.19**	-1603.56

5.2.Kakamega

Similar operations to those presented in Section 5.1 are performed for data from Kakamega to obtained the following results summarized in Table 4

Table 4: Comparison of GARCH analysis between the Raw and Deseasonalized data for Tea Production and Climatic Variables for Kakamega County. Y_{est} is Linear regression plus GARCH, and Y_{aver} is Average Tea Production between 2007 and 2015.

Parameter	Raw	Deseasonalized
AIC	24.545	19.249
BIC	24.769	19.472
LogLikelihood	-1316.456	-1030.421
Y_{est}	256116.8	254466.5
Y_{aver}	253179.9	254408.7
Y_{est} -Y_{aver}	2936.869	-57.81
Error Term	**2936.807**	57.21

We noted a larger error term in the presence of seasonality compared to that in the absence of seasonality. The table presents AIC, BIC, and Loglikelihood. Lower values of AIC and BIC are desirable. A large loglikelihood value indicates that the model without seasonality in data is better than that with seasonality. Thus, volatility in seasonality in the Kakamega data has a more significant effect on the regression analysis of tea production with climatic variables. A further comparison also indicates that the linear regression equation has a larger deviation in the presence of seasonality.

5.3.Kericho

Similar operations to those under section 5.1 are performed for data from Kericho to obtained the following results summarized in Table 5.

Table 5: Comparison of GARCH analysis between the Raw and Deseasonalized data for Tea Production and Climatic Variables for Kericho County. Y_{est} is Linear regression plus GARCH, and Y_{aver} is Average Tea Production between 2007 and 2015.

Parameter	Raw	Deseasonalized
AIC	31.060	28.54
BIC	31.284	28.85
LogLikelihood	-1668.256	-1373.260

Y_{est}	6732370	26616719
Y_{aver}	6101850	6120363
Y_{est} -Y_{aver}	-630519.8	-20496357
Error Term	**-45359.93**	39756.81

We noted a larger error term in the presence of seasonality compared to that in the absence of seasonality. The table presents AIC, BIC, and Loglikelihood. Lower values of AIC and BIC are desirable. A large loglikelihood value indicates that the model without seasonality is better than that with seasonality in data. Thus, volatility in seasonality in the Kericho data has a more significant effect on the regression analysis of tea production with climatic variables. A further comparison also indicates that the linear regression equation has a larger deviation in the presence of seasonality.

5.4.Kisii

We follow a similar procedure under Section 5.1 for data from Kisii to obtained the following results summarized in Table 6

Table 6: Comparison of GARCH analysis between the Raw and Deseasonalized data for Tea Production and Climatic Variables for Kisii County. Y_{est} is Linear regression plus GARCH, and Y_{aver} is Average Tea Production between 2007 and 2015.

Parameter	**Raw**	**Deseasonalized**
AIC	28.638	22.397
BIC	28.862	22.620
LogLikelihood	-1537.46	-1200.416
Y_{est}	427978.5	5326773
Y_{aver}	1957566	1960373
Y_{est} -Y_{aver}	2385544	-3366400
Error Term	**883.7754**	-347.4205

We noted in Table 6 a larger error term (883.7754) in the presence of seasonality compared to that in the absence of seasonality. The table presents AIC, BIC, and Loglikelihood. Lower values of AIC and BIC are desirable. A large loglikelihood value indicates that the model without seasonality is better than that with seasonality in data. Thus, volatility in seasonality in the Kisii data has a more significant effect on the regression analysis of tea production with climatic variables. A further comparison also indicates that the linear regression equation has a larger deviation in the absence of seasonality, unlike in the case of Embu, Kakamega, and Kericho county data.

5.5.Meru

We present a summary of the findings for Meru county data in Table 7 based on the similar procedure from Section 5.1.

Table 7: Comparison of GARCH analysis between the Raw and Deseasonalized data for Tea Production and Climatic Variables for Meru County. Y_{est} is Linear regression plus GARCH, and Y_{aver} is Average Tea Production between 2007 and 2015.

Parameter	**Raw**	**Deseasonalized**
AIC	29.307	23.312
BIC	29.530	23.536

LogLikelihood	-1573.577	-1249.867
Y_{est}	528642.1	5436951
Y_{aver}	1967948	1971867
Y_{est} -Y_{aver}	1439306	-3465084
Error Term	**1430.095**	-76016.2

We noted a larger error term in the absence of seasonality compared to that in the presence of seasonality. This observation is unlike in the case of Embu, Kakamega, and Kisii. The table presents AIC, BIC, and Loglikelihood. Lower values of AIC and BIC are desirable. A large loglikelihood value indicates that the model without seasonality is better than that with seasonality in data. Thus, volatility in seasonality in the Meru data has a more significant effect on the regression analysis of tea production with climatic variables. A further comparison also indicates that the linear regression equation has a larger deviation in the absence of seasonality, contrary to those observed in Embu, Kakamega, and Kericho.

5.6.Nyeri

We present a summary of the findings for Meru county data in Table 8 based on the similar procedure from Section 5.1.

Table 8: Comparison of GARCH analysis between the Raw and Deseasonalized data for Tea Production and Climatic Variables for Nyeri County. Y_{est} is Linear regression plus GARCH, and Y_{aver} is Average Tea Production between 2007 and 2015.

Parameter	**Raw**	**Deseasonalized**
AIC	28.963	23.523
BIC	29.187	23.746
LogLikelihood	-1555.002	-1261.219
Y_{est}	3998252	1627775
Y_{aver}	1592962	1597023
Y_{est} -Y_{aver}	-2405290	-30752.18
Error Term	**70888.27**	-47680.77

We noted a larger error term in the presence of seasonality compared to that in the absence of seasonality. This observation is similar to that of Embu, Kakamega and Kisii. The table presents AIC, BIC, and Loglikelihood. Lower values of AIC and BIC are desirable. A large loglikelihood value indicates that the model without seasonality is better than that with seasonality in data. Thus, volatility in seasonality in the Nyeri data has a more significant effect on the regression analysis of tea production with climatic variables. A further comparison also indicates that the linear regression equation has a larger deviation in the presence of seasonality, which is similar to that observed in Embu, Kakamega, and Kericho

6. Discussion

Tea is a popular drink among 70% of the world population. Kenya is one of the principal producers of tea in the world. The major tea-producing counties or zones in Kenya are Embu, Kakamega, Kericho, Kisii, Meru, and Nyeri. Kenyan tea sector provides direct and indirect employment to many citizens. Tea production in Kenya contributes to 4% GDP. Tea production has witnessed variation in climatic conditions prompting a study on trends on their relationship with climatic variables. This study presents a study attempting to model the volatility of climatic variables on tea production in Kenya. We specifically aimed to establish the effect of the seasonality of tea production and climatic variables on the linear regression equation. The seasonality is investigated via linear regression error term estimated using the GARCH model for tea production for major tea zones in Kenya. Combining GARCH modeling to estimate linear regression error terms helps establish the effect of volatility on the seasonal relationship between climatic variables and tea production.

Volatility shows changes in the variables. Volatility specifies that large changes tend to be followed by large changes of either sign and vice versa. GARCH has been used widely to address the volatility in time series. A majority of the climatic variables and agricultural yields data are time-series, making them easily modeled via GARCH. Thus, in this study, we have used the GARCH model to estimate the error term in a linear regression model. Detrending the data to remove the seasonality may help establish the effect of volatility on the linear regression model. Thus, deseasoning can help us approximate the seasonality variance without biasing the data.

In the proposed study, we focused on the volatility of tea production under NDVI, minimum humidity, maximum humidity, rainfall, minimum temperature, maximum temperature, and solar radiation. This was established for data obtained from six Kenya tea zones: Embu, Kakamega, Kericho, Kisii, Meru, and Nyeri. The data ranges from January 2007 to December 2015. With an already established GARCH model based on a combination of garchorder(2,2) and armaorder(1,1), we have demonstrated that seasonality affects tea production as the dependent variable and climatic variables as independent variables. In order to extend our analysis and suggest a suitable model between seasoned and deseasoned data, we have employed the use of AIC, BIC, and LogLikelihood. AIC and BIC measure the goodness of fit while LogLikelihood indicates the final value of the loglikelihood after maximization of all model parameters. A better model has lower values of AIC and BIC and higher loglikelihood.

The results summarized in Tables 3 - Table 8 have shown that in the presence of seasonality, there exists a larger error term compared to that in the absence of seasonality. The AIC and BIC in most of the Tables are lower in cases of deseasonalized data. The loglikelihood in most cases is also higher in cases on deseasonalized data. Comparison of deviation between tea production value estimated using data and constructed tea production based on linear regression equation shows that the seasonal data exhibits higher deviation than those for deseasoned data in most cases. The effect of seasonality on serial correlation is also evident. For most cases of deseasoned data, there is serial correlation yet for the cases where the data has seasonality; there are no serial correlations.

8.Conclusion

Tea is a popular drink globally and contributes to 4% of Kenya's annual GDP. Tea production has continued to vary, prompting numerous research due to varying climatic variables. Thus, in this research, we tend to establish the linear regression equation modeling relationship between trends of tea production and climatic variables, namely NDVI, minimum humidity, maximum humidity, rainfall, minimum temperature, maximum temperature, and solar radiation between January 2007 and December 2015. We have also presented the effect of volatility and seasonality of climatic variables on tea production in Kenya. The effect of volatility and seasonality is investigated via the GARCH model, which is used to estimate linear regression error terms for tea production using data from major tea zones in Kenya, namely Embu, Kakamega, Kericho, Kisii, Meru, and Nyeri. The demonstration in the research via the already established GARCH model is based on a combination of garchorder(2,2) and armaorder(1,1) that seasonality affects tea production with climatic variables as independent variables. We compared the analysis results among the data obtained from different major tea zones in Kenya. The results summarized in tables show that in the presence of seasonality larger error term exists than in the absence of seasonality for most tea zones. The AIC and BIC in most of the tables are lower in cases of deseasonalized data. The loglikelihood in most cases is also higher in cases on deseasonalized data. Comparison of deviation between tea production value estimated using data and constructed tea production based on linear regression equation shows that the seasonal data exhibits higher deviation than deseasoned data in most cases. The effect of seasonality on serial correlation is also evident. There exists serial correlation for most cases of deseasoned data compared to when the data has seasonality. A future study may consider estimating linear regression error terms amidst volatility effect on seasonal data for different GARCH models.

References

Agbeyegbe, T. D. (2022). Modelingjse stock returns dynamics: Garch versus stochastic volatility.The Journal of Developing Areas, 56(1):175–191.

Ahammed, K. M. (2012). Investment for sustainable development of bangladesh tea industry–an empirical study. In BEA XVIIl Biennial Conference Papers, pages 1–20.

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. The review of economics and statistics, pages 542–547.

Bordoloi, P. K. (2012). Global tea production and export trend with special reference to india. Two and a Bud, 59(2):152–156.

Buguk, C., Hudson, D., and Hanson, T. (2003). Price volatility spillover in agricultural markets:an examination of us catfish markets. Journal of Agricultural and Resource Economics, pages86–99.

Cheserek, B. C., Elbehri, A., and Bore, J. (2015). Analysis of links between climate variablesand tea production in the recent past in kenya. Donnish Journal of Research in EnvironmentalStudies, 2(2):005–017.

Commission, K. H. R. et al. (2008). A comparative study of the tea sector in kenya; a case studyof large-scale teaestates. KHCR.

Dhekale, B., Sahu, P., Vishwajith, K., Mishra, P., and Noman, M. (2014). Modeling and forecastingof teaproduction in west bengal. Journal of Crop and Weed, 10(2):94–103.

Dutta, R., Stein, A., Smaling, E., Bhagat, R., and Hazarika, M. (2012). Modelling and quantifyingtea productivity in northeast india. Two and a Bud, 59(2):56–63.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance ofUnited Kingdom inflation. Econometrica: Journal of the econometric society, pages 987–1007.

Esther, N. M. and Magdaline, N. W. (2017). Arima modeling to forecast pulses production inkenya. Asian Journal of Economics, Business and Accounting, pages 1–8.

Gijo, E. (2011). Demand forecasting of tea by seasonal arima model. International Journal ofBusiness Excellence, 4(1):111–124.

Hakizimana, C., Goldsmith, P., Nunow, A. A., Roba, A. W., and Biashara, J. K. (2017). Land andagricultural commercialisation in meru county, kenya: Evidence from three models. The Journalof Peasant Studies, 44(3):555–573.

Junior, P. O., Tiwari, A. K., Tweneboah, G., and Asafo-Adjei, E. (2022). Gas and garch basedvalue-at-risk modeling of precious metals. Resources Policy, 75:102456.

Just, R. E. and Pope, R. D. (1978). Stochastic specification of production functions and economicimplications.Journal of econometrics, 7(1):67–86.

Kuha, J. (2004). Aic and bic: Comparisons of assumptions and performance. Sociological methods& research, 33(2):188–229.

Mandelbrot, B. (1963). e variation of certain speculative prices,e journal of business, 36 (4), 394-419. OI: http://dx. doi. org/10.1086/294632.

Muganda, C. A., Sewe, S., and Onsongo, W. (2021). Modeling effects of climatic variables on teaproduction in kenya using linear regression model with serially correlated errors. Asian Journalof Probability and Statistics, pages 56–75.

Ochieng, J., Kirimi, L., and Mathenge, M. (2016). Effects of climate variability and change onagricultural production: The case of small-scale farmers in Kenya. NJAS-Wageningen Journal ofLife Sciences, 77:71–78.

Oddah, A. O. (2019). Application of auto-regression integrated Moving average model to forecasttea Prices at Mombasa tea auction center in Kenya. PhD thesis, Maseno University.

Okoth, G. K. (2011). Potential response of Tea production to climate change in Kericho County.PhD thesis, University of Nairobi, Kenya.

Omboi, B. M. (2011). The effect of performance appraisal systems on employees in Kenya teadevelopmentagency: A survey of selected tea factories in Meru county-Kenya. Research Journalof Finance and Accounting.

Omumbo, J. A., Lyon, B., Waweru, S. M., Connor, S. J., and Thomson, M. C. (2011). Raisedtemperatures overthe Kericho Tea estates: revisiting the climate in the east African highland'smalaria debate. Malaria Journal, 10(1):1–16.

Paolella, M. S. (2018). Linear models and time-series analysis: regression, ANOVA, ARMA andGARCH. John Wiley & Sons.

Ramirez, O. A. and Fadiga, M. (2003). Forecasting agricultural commodity prices with asymmetric-error garch models. Journal of Agricultural and Resource Economics, pages 71–85.

Sitienei, B. J., Juma, S. G., and Opere, E. (2017). On the use of regression models to predict teacrop yield responses to climate change: A case of Nandi east, sub-county of Nandicounty, Kenya.Climate, 5(3):54.

Wang, H., Wen, Y., Du, Y., Yan, X., Guo, H., Rycroft, J. A., Boon, N., Kovacs, E. M., and Mela,D. J. (2010). Effects of catechin enriched green tea on body composition. Obesity, 18(4):773–779.

Zhang, Y., Haghani, A., and Zeng, X. (2014). Component garch models to account for seasonalpatterns and uncertainties in travel-time prediction. IEEE Transactions on Intelligent Transportation Systems, 16(2):719–729.