International Journal of Advanced Research and Publications
ISSN: 2456-9992

Model For Minimum And Maximum Temperature Of The Upper East Region Of Ghana

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Abstract: This paper analyzes and use a Vector Autoregressive (VAR) model to jointly forecast minimum and maximum temperature values. The study was carried out using data collected in the Upper East Region of Ghana. It examines the best trend of the temperature data and it illustrates how the VAR (p) model can be fitted to the data based on the Lag selection for the model using the AIC, SIQ and BIC. Particular attention was given to the unit root test of stationary, the Johansen test of co-integration and the Granger causality test to investigate the bilateral causality of the data. Interest is paid to the properties of VAR model, to the estimation of the parameters of the model and to the determination of the number of co-integration vectors. The study was carried on a monthly data from January 1954 to December 2014 and finally the study permits the forecast of three years ahead. The results conclude that the relationship between the minimum and maximum temperature is a bilateral causality since both are co-integrated and granger cause.

Key Words: Climate; Temperature; Upper East Region; Auto Regression; Harmattan

1. Introduction

Climate is commonly thought of as the expected weather conditions at a given location over a definite period of time. Climate can be measured by statistics such as average temperatures, average number of rainy days, and the quantity of rain. Climate change refers to changes in these statistics over years, decades, or even centuries [1]. Climate weather forecasts are made by collecting such data and using understanding of atmospheric processes through meteorology to determine how the atmosphere evolves in the future to make predictions. However, the random and stochastic nature of the atmosphere and incomplete understanding of the processes mean that forecasts become less accurate as the range of the forecast increases. A longstanding literature of academic paper explores the question of forecasting the average daily temperature or the causal impact of temperature on a range of outcomes including health and labor productivity [2]. And yet, few studies have documented the joint study and forecast of daily or monthly minimum and maximum temperature, the causal or correlated relationship and even the effect of the joint forecast on other outcomes. A survey of the literature on weather and climate studies and research suggest that majority is done considering the daily averages of the variable of interest. Time series is basically a measurement of data taken in chronological order from a certain time to another. There are standard and elementary time series models developed for univariate and multi variate time series data. VAR models are a specific case of more general VARMA models. VARMA models for multivariate time series include the VAR structure above along with moving average terms for each variable. More generally yet, these are special cases of VARMAX models that allow for the addition of other predictors that are outside the multivariate set of principal interest. The multivariate time series model used is the Vector Auto regression (VAR) model which is basically a combination of Autoregressive (AR) models that is used to model and forecast temperature data [3]. VAR models were originally developed to provide adequate tools for empirical analysis of economic time series. The recognition that economic time series are non-stationary profoundly altered the technology of econometrics, introducing the concepts and tools associated with integrated-co integrated. Even though the procedures so far have mostly been used in the analysis of economic data, their applicability is by no means restricted to such data [4]. The use of the VAR model was motivated by the aim of jointly studying both the daily minimum and maximum temperature instead of just studying the average. Unlike the univariate models, in VAR model, the strength of associations among different variables across time lags (shifts in time) are indexed with cross-correlations [5] and several possible lags can be used and combine to examine cross-correlations. The VAR model is advantageous because of it simplicity among the multivariate time series models and it can explain past and causal relationships among multiple variables over time, as well as predict future observations [6]. Explanation and prediction of future observations in a time series is dependent upon correctly postulating a VAR model and estimating its parameters [6]. This study will help identify the patterns in environmental temperature with the causal correlation of both variable in the region, bring out a model to predict the future temperature [7] in the region and finally, the study will be an introduction for future research especially in the forecast of heat related diseases such as CSM, malaria etc [8]. The global average surface temperature has increased by about 0.6ºC during the twentieth century [9] and has led to changes in land and water conditions. Climate changes resulting in adverse climatic situations are common in the semi-arid regions of West Africa. The recent mean temperatures in the Upper East region are higher when compared to the rest of Ghana and mean annual rain figures are low when compared to the rest of Ghana. Recent disasters, including floods and droughts in the region are signs of a change in climatic condition [10]. Worldwide, climate change has had implications for freshwater ecosystems, such as changes in water salinity, water nutrient content, sun ray effects and other pollutants and pH balance [11]. Statistically, many methods, techniques and models have been adapted to the study of the variation in the weather and climatic variables.

[12] use complex least square method to derive a complex autoregressive model for forecasting monthly temperature anomalies. The application complex autoregressive model in this work shows that using a complex number to fit a meteorological element field and predicting with the complex autoregressive model is effective in improving the forecast results [7]. [13] applied Mann-Kendall rank correlation and Wald-Wolfowitz serial correlation tests to temperature series in other to determine the trends and abrupt changes in the temperatures and the Gaussian Filtering or Smoothing was used to show the variations and trends graphically. [14] study focuses on detecting theoretical advances while, Daniel uses the extreme value theory to model a bivariate lichenometry model of weather using a simulation. In time-series analysis of total daily mortality and weather data for the city of Beirut, [15] constructed a Poisson Auto Regressive Model (PARM) to assess the effect of an average increase in temperature on yearly mortality. The study demonstrated that heat-related mortality at moderately high temperatures can be a significant public health issue in countries with warm climates. Moreover, at their projected climate change over the next 50 years, heat-related losses are unlikely to be offset by cold-related gains. [16] examined long term data of rainfall and temperature from coastal areas of Queensland Australian. They used ARIMA model, Fourier Analysis (FA) and Linear Regression (LR) to examine autocorrelation and seasonality in the time series data. In their study, they found that temperature data appeared stationary. In his paper, [17] proposed two models for week-ahead forecasting of temperature driven electricity load, which are a time series model and an Artificial Neural Network (ANN) model. For the time series model, Seasonal Autoregressive Integrated Moving Average with exogenous (SARIMAX) variables scheme was proposed. A method called "pre-whitening" was used to determine the lagged effect of temperature on electricity load. Comparison between ANN model and SARIMAX model was conducted to see which one gave a better forecasting performance. The forecast performance was characterized by two statistical estimates, the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The results showed that while the ANN model behaved better in the estimation stage, the performance of the model worsen compared to the SARIMAX model in the forecasting stage [18].

2. Study area

The study was conducted in the Upper East Region of Ghana which is located between latitudes 10º 30′ to 11º 00′ North of the Equator and longitudes 0º to 1º 30′ West of the Greenwich Meridian within the White Volta River Basin, (See Figure1) [19]. The Region has two international boundaries with the Republics of Burkina Faso to the north and Togo to the east. The other boundaries are Northern Region and Upper West Region of Ghana to the south and west respectively [19].

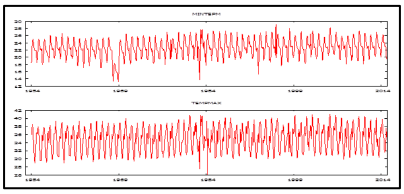

figure 1. *Map of Upper East Region of Ghana showing study districts*

3. Materials and Methods

3.1 Sources of data

A secondary data of the maximum and minimum temperature records of the Upper East Region of Ghana from January 1954 to December 2014 was collected from the Ghana Meteorological Agency (GMA) Accra (Phone: +233 307010019 email: info@meteo.gov.gh or client@meteo.gov.gh). The data was analyzed using R, STATA, SAS, SPSS and Gretel statistical soft wares.

3.2 Data Analysis

3.2.1 Autoregressive Model AR (p)

Autoregressive models are based on the idea that the current value of the series, Y_t, can be explained as a function of p past values, $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$, where p determines the number of steps into the past needed to forecast the current value. An autoregressive model of order p, abbreviated AR (p), is of the form:

$$Y_t = \alpha + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \epsilon_t$$

Where Y_t is stationary, $\phi_i, i = 1, 2, \dots, p$ are constants. Unless otherwise stated, ϵ_t is assumed Gaussian white noise series with mean μ zero and variance σ_ω^2.

3.2.2 Vector Auto regression

Vector Auto Regression model (VAR) model is used to capture the linear interdependencies among observed data. VAR models generalize the autoregressive (AR) model described above by allowing for more than one evolving variable and it is a system in which each variable is expressed as a function of its own lags as well as lags of each of the other variables [20] in other language, each variable is expressed as a linear function of its own past values and past values of all other variables. All variables in a VAR are treated symmetrically; in a structural sense each variable has an equation explaining its evolution based on its own lags and the lags of the other variables in the model [20]. The p^{th} order VAR model VAR (p) of 2 variables is written as:

$$Y_{1,t}=\phi_{1,0}+ \phi_{1,t-1,1}Y_{1,t-1}+\phi_{1,t-1,2}Y_{2,t-1} + \dots+\phi_{1,t-p,1}Y_{1,t-p}+\phi_{1,t-p,2}Y_{2,t-p}+ \epsilon_{1,t}$$
$$Y_{2,t}=\phi_{2,0}+ \phi_{2,t-1,1}Y_{1,t-1}+\phi_{2,t-1,2}Y_{2,t-1} + \dots+\phi_{2,t-p,1}Y_{1,t-p}+\phi_{2,t-p,2}Y_{2,t-p}+ \epsilon_{2,t}$$

In matrix notation: $Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \dots + \Phi_p Y_{t-p} + \epsilon_t$

Where Y_t is a 2 by 1 vector stochastic process $Y_t = \begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix}$,

Φ_0 is a 2 by 1 vector of intercept parameters $\Phi_0 = \begin{bmatrix} \phi_{1,0} \\ \phi_{2,0} \end{bmatrix}$,

Φ_ps are 2 by 2 parameter matrices $\Phi_p = \begin{bmatrix} \phi_{1,t-p,1} & \phi_{1,t-p,2} \\ \phi_{2,t-p,1} & \phi_{2,t-p,2} \end{bmatrix}$, $Y_{t-p} =$

$\begin{bmatrix} Y_{1,t-p} \\ Y_{2,t-p} \end{bmatrix}$ and ϵ_t is a vector white noise process with the additional assumption that $E(\epsilon_t) = 0$. $\epsilon_t = \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}$ $Y_{1,t}$, is the minimum temperature and $Y_{2,t}$ is the maximum temperature.

3.2.3 Unit Root test and Stationary

Stability condition is applied when applying the VAR model to the system, which is defined as a condition where the means and variances are constant and the covariance is not time-dependent but rather lag dependent. There are many tests used to investigate the stationary of the variable [20] but in our study, the Augmented Dickey Fulley (ADF) test is used to test for the stationary of the variables.

The VAR model is stationary if $\det(A(L)) = \det(I_k - \Phi_1 z - \Phi_2 z^2 - \cdots - \Phi_p z^p) = 0$ for z element of C has its p x k roots of the characteristic polynomial outside of the unit circle. The unit circle's equation is $\mu = (I_k - \Phi_1 - \Phi_2 - \Phi_3 - \cdots - \Phi_p)^{-1}\Phi_0$

3.2.4 Causality Test

The Granger Causality test (GCT) was used to test the assumption causality among the variables. The test is measured in terms of the Mean Square Error (MSE).

In the bivariate approach, considering two variables $Y_{1,t}, Y_{2,t}$ and two forecast of $Y_{1,t}$, s periods ahead $\hat{Y}_{1,t}(s) = E(Y_{1,t+s} | (Y_{1,t}, Y_{1,t-1}, Y_{1,t-2}, \dots))$ (1)

and

$\hat{Y}_{1,t}(s) = E(Y_{1,t+s} | (Y_{1,t}, Y_{1,t-1}, Y_{1,t-2}, \dots \quad Y_{2,t}, Y_{2,t-1}, Y_{2,t-2}, \dots))$ (2)

Granger causality exists if $MSE\left(\hat{Y}_{1,t}(s)(1)\right) < MSE\left(\hat{Y}_{1,t}(s)(2)\right)$

In bivariate approach it follows that the test hypothesis are:

H_0: $Y_{1,t}$ *does not granger cause* $Y_{2,t}$

H_1: $Y_{1,t}$ *does granger cause* $Y_{2,t}$

And the test statistic is

$F = \frac{RSS_2 - RSS_1}{RSS_1/(T-2p-1)}$ Where $F \sim \chi^2$

3.2.5 Co-integration Test (Johansen test)

The Johansen test permits more than one co-integrating relationship so is more generally applicable than the Engle Granger test which is based on the Dickey Fuller test for unit root.There are two type of Johansen test, either with the trace or with the eigenvalue.

The null hypothesis for the trace test is the number of co-integration vectors $r = \pi$ and the test statistics for this test is $\lambda_{trace}(r) = -T\sum_{i-r+1}^{n} \ln(1 - \hat{\lambda}_i)$ where $\hat{\lambda}_i$ denotes the estimated values of the characteristic roots obtained from the estimated π, and T is the number of observations.

3.2.6 Model Selection Criteria

We used several model selection criteria to evaluate the model selection. The Aikake's Information Criterion (AIC) value is generally defined using the mathematical equation $AIC = \log(\det(\Sigma_m)) + \frac{2}{n} m\,K^2$, Where $\Sigma_m = \frac{1}{n}\sum_{i=1}^{n} \epsilon_t \epsilon_t'$ is the OLS residual covariance matrix estimator of the VAR model of order m and $m\,K^2$ is the number of VAR parameters in a model with order m. The Bayesian information criterion (BIC) or Schwarz information criterion (also SIC, SBC, SBIC) is a criterion for model selection among a finite set of models; the model with the lowest BIC is preferred. It is based, in part, on the likelihood function and it is closely related to the Akaike information criterion (AIC). The BIC is formally defined as $BIC = \log(\det(\Sigma_m)) + \log(m)\,K^2$,

The Hannan–Quinn information criterion (HQC) is is an alternative criterion for model selection to Akaike information criterion (AIC) and Bayesian information criterion (BIC). It is given as $HQC = \log(\det(\Sigma_m)) + 2m\log(\log(K))$

3.2.7 Mean Absolute Percentage Error (MAPE)

The forecast accuracy level of the model was evaluated mathematically using the mean absolute percentage error which is mathematically defined as $MAPE = \left(\frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - F_t}{Y_t}\right|\right) x\ 100\%$

Where F_t are the forecasted values and Y_t are the actual values. The model is a good one for a value of MAPE less or equal to 10%.

4 Results and discussion

4.1 Preliminary Analysis

In the analysis, the yearly summary statistics of the minimum monthly temperature (Appendix I), the yearly summary statistics of maximum monthly temperature (Appendix II), the monthly summary statistics of the minimum temperature (Appendix III), the monthly summary statistics of the maximum temperature (Appendix IV), the QQ plot of the minimum average temperature (Appendix V) and the QQ plot of the maximum average monthly temperature (Appendix VI) were investigated. The data used for this analysis was the monthly average minimum and maximum temperature calculated from daily observed data from January 01, 1954 to December 31, 2014, thus 720 pairs of observations. The values of the minimum and maximum temperatures were recorded to be 13.25°C, 29.10°C and 26.10°C, 41.10°C respectively. The mean temperatures were 22.60 °C and 35.00 °C respectively (Table 1). With a standard deviation of 2.47 and 2.97 respectively and a skewness of -0.37 and -0.10 respectively, thus the data's distribution portraits the characteristics of a normal distribution.

Table 1: *Summary Statistics of the Maximum and Minimum Monthly Temperature*

Variable	*Mean (°C)*	*Median (°C)*	*Minimum (°C)*	*Maximum (°C)*
MINTEMP	*22.5714*	*22.6000*	*13.2500*	*29.1000*
MAXTEMP	*34.8750*	*35.0000*	*26.1000*	*41.1000*
Variable	*Std. Dev.*	*C.V.*	*Skewness*	*Ex. kurtosis*
MINTEMP	*2.46697*	*0.109296*	*-0.372942*	*0.448843*
MAXTEMP	*2.96987*	*0.0851574*	*-0.101042*	*-0.962200*

A study of the observations shows that the minimum temperature of 13.25 °C occurs in January which corresponds to the Harmattan season while the maximum temperature did occur in March which corresponds to a season of maximum heat in the region. High temperatures of more than 35°C and low temperatures of less than 15°C have both shown adverse effects on mortality and an estimated 7.7% of mortality was attributable to non-optimum temperature [21]. From the analysis temperatures in December and January were low and was associated with high cases of pneumonia and during the months of high temperatures (March and April) cases of meningitis was high. The descriptive statistic of the monthly minimum observation of each year show that in 1954 for example, average minimal temperature was 22.08 °C, the minimal minimum temperature was 18.5 the maximum minimal temperature was 39.8 °C while the sample standard deviation of the maximal temperature in 2014 was 2.17 °CThe time series plot (Figure 2) of both the average minimal temperature and the average maximal temperatures from January 1954 to December 2014 seems to follow a common long-run path prompting the question whether the long-run trend is the same in the two temperatures. The Unit Root tests performed suggest that there is no unit root in the data; which means the data are stationary.

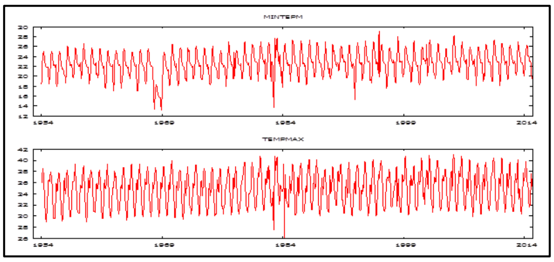

Figure 2: *Time Series Plot of Average Minimum and Maximum Temperature.*

The Augmented Dickey Fulley test statistics of -1.3868 and the KPSS test statistic of 1.1391 been greater than the critical values of -1.95 and 0.574 at 5% level suggest to us that we reject the null hypothesis of the existence of a unit root in the data. Therefore, we can model the data as levels applications, since the early motivations for unit root tests was to help determine whether to use forecasting models in differences or levels in particular applications [22]. From the test also, we conclude that minimum temperature data is stationary. Applying the same test to the maximum temperature, we came to the same conclusion as that of the minimum temperature since the test statistics of the Augmented Dickey Fulley test is -1.1148 and the KPSS test statistic is 1.1606 which are greater than the critical values of -1.95 and 0.463. Tables 2, 3, and 4 summaries the results of the unit root test conducted.

Table 2: *Results of the Unit root test on the minimum temperature*

Test	T statistics	Critical at 5%
ADF	-1.3868	-1.95
KPSS	1.1391	0.574

Table 3: *Results of the Unit root test result on the maximum temperature*

Test	T statistics	Critical at 5%
ADF	-1.1148	-1.95
KPSS	1.1606	0.463

Table 4: *Results of the Johansen Cointegration test*

Test type	Eigen Values	hypothesis	Test statistic	Critical value 5%
Without linear trend and constant	0.28 0.0957	r = 0	590.88	17.95
	1.11 x 10^{-16}	r<=1	237.05	8.18

The Johansen test tests the null hypothesis that there is no co-integration between the time series. That is the rank of the matrix of the variables r=0. From table 5, it can be seen that the test statistic of the test 590.88 which is greater than the critical value of 17.95 at 5% confidence level suggest to us that the null hypothesis of no co-integration should be rejected suggesting other tests of the value of r. Hence testing the value of r = 1, we still reject the hypothesis that r = 1 since the test statistics of 237.05 is considerably greater than the critical value of 8.18 from here, it seems likely that there is more than one co-integration in the series of the data. Table 5 gives the results of the Granger causality test.

Table 5: *Results of the Granger Causality test.*

LAG	*F Statistics of max granger cause min*	*p value of max granger cause min*	*F Statistics of min granger cause max*	*p value of min granger cause max*
1	*56.95*	*1.34 x 10^{-13}*	*108.71528*	*0*
2	*28.65*	*1.06 x 10^{-12}*	*98.05118*	*0*
3	*46.92*	*0*	*75.92159*	*0*
4	*53.19*	*0*	*54.88590*	*0*
5	*57.83*	*0*	*52.41420*	*0*
6	*51.36*	*0*	*54.13314*	*0*
7	*50.64*	*0*	*48.02974*	*0*

The results from the granger causality test suggest that the minimum temperature helps in predicting the maximum temperature. The test is implemented by regressing the data on the 7 past values of the minimum temperature and 7 past values of the maximum temperature. An F-test is then used to determine whether the coefficients of the past values of the minimum temperature and maximum temperature are jointly zero. This is shown by the values of the p values of the tests done in cross from one to seven lag. This is a gate way to the effective use of the reduced VAR model to model the data. Our results p values were less than the alpha value of 0.05 and shows that both variables granger cause each other. Table 6 presents the

Lag information criterion of the data from which the best lag of the VAR model to be used was selected. It was observed that the lag 3 has the minimal information criteria. This shows that the best model to be used in modeling the data is the VAR (3).

4.2 Further Analysis

Table 6: *Lag Selection Information Criterion Statistics*

LAGS	AIC	BIC	HQIC
1	0.565	0.743469	0.633908
2	0.504885	0.708851	0.583637
3	0.471396	0.70635	0.565485
4	0.476889	0.726353	0.569836
5	0.479669	0.760121	0.587953
6	0.486379	0.792327	0.604507
7	0.490352	0.821796	0.618324
8	0.493037	0.849977	0.630853
9	0.498387	0.880822	0.646047
10	0.503573	0.911503	0.661077

Using the two variables, $Y_{1,t}$ and $Y_{2,t}$, representing respectively the minimum temperature and the maximum temperature, the autoregressive models for forecasting the temperature data was represented by:

$$Y_{1,t} = 0.36\, Y_{1,t-1} + 0.02Y_{2,t-1} + 0.19Y_{1,t-2} - 0.05Y_{2,t-2} + 0.19Y_{1,t-3} - 0.02Y_{2,t-3} + 7.74 + SD_{1,i}$$

$$Y_{2,t} = 0.01\, Y_{1,t-1} + 0.26Y_{2,t-1} - 0.02Y_{1,t-2} + 0.02Y_{2,t-2} + 0.09Y_{1,t-3} + 0.06Y_{2,t-3} + 21.16 + SD_{2,i}$$

Stacking these two equations, an order-3 VAR model of the data is presented from the two equations:

$$Y_t = \begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} = \begin{bmatrix} 7.74 \\ 21.16 \end{bmatrix} + \begin{bmatrix} 0.36 & 0.02 \\ 0.01 & 0.25 \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{bmatrix} + \begin{bmatrix} 0.19 & -0.05 \\ -0.02 & 0.02 \end{bmatrix} \begin{bmatrix} Y_{1,t-2} \\ Y_{2,t-2} \end{bmatrix} + \begin{bmatrix} 0.19 & -0.02 \\ 0.09 & 0.06 \end{bmatrix} \begin{bmatrix} Y_{1,t-3} \\ Y_{2,t-3} \end{bmatrix} + \begin{bmatrix} SD_{1,i} \\ SD_{2,i} \end{bmatrix}$$

Where $SD_{2,i}$ is the seasonal difference corresponding to each season. In terms of model criterion, it is shown that our model forecasts the temperature with highly statistical significance. We can also conclude that the co-integration effect agrees well with our intuition in three aspects: the mean, the alternation, and the short-term observations, which verifies the validity of the model. This method and result are less complex and feasible than the stochastic forecast method shown in [23].

	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec
Min	1.45	4.19	6.26	5.65	3.36	1.47	1.11	1.59	1.78	2.01	-0.001	0.001
max	0.02	2.41	2.88	1.85	-0.65	-3.07	-4.15	-4.24	-2.81	-0.07	1.50	1.55

Finally, modeling multivariate time series modeling is suitable and permits the forecast of three years ahead using systems of equations [24].

Table 7 *Forecasted Minimum Monthly temperature*

Month	2015			2016			2017		
	lower	forcast	upper	lower	forcast	Upper	lower	forcast	upper
January	17.87	20.02	22.17	17.18	19.88	22.58	17.16	19.87	22.58
February	20.08	22.38	24.67	19.58	22.28	24.99	19.56	22.27	24.988
March	22.91	25.30	27.69	22.52	25.23	27.93	22.51	25.22	27.93
April	23.68	26.19	28.70	23.42	26.13	28.83	23.41	26.12	28.83
May	22.55	25.12	27.69	22.36	25.07	27.78	22.35	25.06	27.77
June	20.91	23.52	26.13	20.77	23.48	26.19	20.76	23.47	26.18
July	20.00	22.64	25.28	19.89	22.60	25.31	19.89	22.60	25.31
August	19.79	22.45	25.11	19.71	22.42	25.13	19.70	22.41	25.12
September	19.56	22.23	24.91	19.50	22.21	24.91	19.49	22.20	24.91
October	19.59	22.28	24.96	19.54	22.25	24.96	19.54	22.25	24.96
November	17.52	20.21	22.90	17.48	20.19	22.90	17.48	20.19	22.90
December	16.62	19.32	22.02	16.59	19.30	22.01	16.59	19.30	22.01

Table 8 *Forecasted Maximum Monthly temperature*

Month	2015			2016			2017		
	lower	forcast	upper	lower	forecast	Upper	lower	forcast	upper
January	33.29	35.61	37.93	33.10	35.54	37.98	33.10	35.54	37.98
February	35.59	38.00	40.38	35.44	37.8	40.32	35.44	37.88	40.32
March	36.47	38.87	41.28	36.41	38.85	41.29	36.41	38.85	41.29
April	35.77	38.19	40.62	35.73	38.17	40.61	35.73	38.17	40.61
May	33.43	35.86	38.29	33.40	35.84	38.28	33.40	35.84	38.28
June	30.69	33.12	35.55	30.66	33.11	35.55	30.66	33.10	35.54
July	28.89	31.32	33.76	28.87	31.31	33.75	28.87	31.31	33.75
august	28.05	30.49	32.93	28.04	30.48	32.92	28.04	30.49	32.92
September	28.93	31.37	33.81	28.92	31.36	33.80	28.92	31.36	33.80
October	31.70	34.14	36.57	31.69	34.13	36.57	31.68	34.13	36.57
November	33.90	36.37	38.81	33.92	36.36	38.81	33.92	36.36	38.81
December	33.07	35.51	37.95	33.07	35.51	37.95	33.07	35.51	37.95

3. CONCLUSION

Even though the Vector Auto regressive has mostly been used in the analysis of economic data, their applicability is by no means restricted to such data. In this paper, a Vector Autoregressive model was used in forecasting

Temperature values. The project illustrates how the VAR (3) model was fitted to the data after the parameters were estimated using R software based on the Lag selection for the model using the AIC, SIQ and BIC. The Unit root hypothesis was rejected concluding that the data was stationary, the Johansen test of co integration and the Granger causality test shows the bilateral causality of the data. Interest is paid to the properties of VAR model, to the estimation of the parameters of the model and to the determination of the number of co integration vectors. The study was carried on data of monthly temperature from January 1954 to December 2014 and finally the study permits the forecast of three year forecast ahead which were very adequate. The descriptive statistic of the data from this study of maximum and minimum monthly temperature from January 1954 to December 2014 (Table1 through Table 5) shows that the area of study is one of the warmest areas on planet earth with the maximum temperature sticking out beyond 40^{o}C. Before forecasting the future temperature and after precise exploration of the statistical characteristics of the data, a VAR (3) model was fitted to the data. The results revealed that both temperatures are increasing and this call for an alarm. The seasonal effect of the data was also detected and included in the model. Finally, the results conclude that the relationship between the minimum and maximum temperature is a bilateral causality since both are co-integrated and granger cause. Given that only one component of the forecaster's role (accuracy) was considered the above results must not be overgeneralized. But climate variation has been the source of many discomfort and threat on the living habitat have sound the alarm for an increase since the models shows a positive coefficient.

Declaration: The authors no conflict of interest

4 Acknowledgement
The authors wish to thank the Ghana Meteorological Agency for the temperature data they provided over the period 1954 to 2014

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APPENDICE

***Appendix 1**: Yearly Summary Statistics of the Minimum Monthly Temperature in ^oC*

YEAR	AVERAGE	MIN	MAX	MEDIAN	VAR	SD	KURTOSIS	SKEWNESS
1954	22.08	18.50	25.00	22.10	4.16	2.04	0.06	-0.57
1955	21.98	18.00	25.00	22.30	5.27	2.30	-0.68	-0.47
1956	21.91	18.90	25.10	21.50	3.42	1.85	-0.50	0.37
1957	22.35	18.70	26.10	22.45	4.26	2.06	0.03	-0.08
1958	22.63	19.50	25.70	22.45	3.67	1.92	-0.33	0.24
1959	22.60	18.50	26.70	22.35	4.86	2.20	0.36	0.12
1960	22.45	19.60	25.70	22.45	3.75	1.94	-0.80	0.23
1961	21.95	17.50	25.70	22.05	5.83	2.42	-0.33	-0.15
1962	21.98	17.00	25.30	22.20	6.14	2.48	0.63	-0.92
1963	22.09	17.60	25.20	22.55	5.97	2.44	-0.40	-0.84
1964	22.21	19.30	25.50	22.05	4.29	2.07	-0.89	0.48
1965	21.90	17.00	25.00	22.30	5.75	2.40	0.17	-0.85
1966	21.90	17.90	25.40	22.05	5.92	2.43	-0.76	-0.16
1967	22.22	18.85	25.58	22.13	5.08	2.25	-0.84	-0.12
1968	15.81	13.30	18.33	15.78	2.80	1.67	-0.86	-0.13
1969	21.51	18.10	24.84	21.45	4.91	2.22	-0.84	-0.11
1970	22.43	18.90	26.60	22.30	5.83	2.42	-0.76	0.08
1971	22.23	18.00	25.80	22.10	6.22	2.49	-0.68	-0.01
1972	22.42	19.00	25.80	22.45	4.97	2.23	-0.79	-0.06
1973	22.57	19.30	26.10	22.55	4.72	2.17	-0.51	0.12
1974	22.09	18.20	25.80	21.85	5.56	2.36	-0.80	0.01
YEAR	AVERAGE	MIN	MAX	MEDIAN	VAR	SD	KURTOSIS	SKEWNESS
1975	21.90	18.35	26.10	21.75	5.31	2.30	-0.60	0.26
1976	22.12	17.90	25.30	22.30	4.23	2.06	0.56	-0.56
1977	23.08	19.50	27.00	22.65	4.64	2.15	-0.36	0.18
1978	22.49	19.50	25.30	22.50	3.40	1.84	-0.54	-0.03
1979	22.85	19.80	27.00	22.75	5.03	2.24	-0.30	0.62
1980	23.13	19.10	26.50	23.00	5.85	2.42	-0.53	-0.35

1981	23.28	19.40	26.90	23.40	5.32	2.31	-0.14	-0.38
1982	22.26	13.65	26.92	22.75	13.42	3.66	1.72	-1.11
1983	23.52	17.80	27.70	23.65	9.09	3.02	-0.35	-0.31
1984	23.06	19.10	26.60	22.65	4.56	2.13	-0.06	0.04
1985	23.08	18.80	27.30	22.55	7.13	2.67	-0.58	0.35
1986	22.63	18.30	27.20	22.60	7.63	2.76	-0.64	-0.08
1987	23.07	19.80	27.30	22.95	5.47	2.34	-0.31	0.34
1988	23.07	19.30	26.90	22.65	6.05	2.46	-0.67	0.40
1989	22.19	19.60	27.00	22.10	4.97	2.23	0.48	0.86
1990	23.07	20.80	26.50	22.60	3.06	1.75	-0.32	0.71
1991	23.08	19.70	26.20	23.15	4.20	2.05	-0.45	-0.18
1992	22.35	15.20	26.30	22.50	8.97	3.00	2.21	-1.02
1993	23.34	19.10	26.90	22.95	6.13	2.48	-0.28	-0.52
1994	22.98	19.20	27.20	23.00	5.76	2.40	-0.31	0.00
1995	23.69	18.60	29.10	23.10	8.91	2.98	-0.33	0.15
1996	22.55	17.60	26.50	22.70	8.28	2.88	-0.49	-0.41

YEAR	AVERAGE	MIN	MAX	MEDIAN	VAR	SD	KURTOSIS	SKEWNESS
1997	22.81	19.30	25.70	23.05	4.53	2.13	-0.81	-0.28
1998	23.08	18.60	28.10	23.10	6.93	2.63	0.31	0.18
1999	22.80	18.70	26.10	22.50	4.74	2.18	-0.17	-0.08
2000	22.52	18.30	27.20	22.30	5.83	2.41	0.44	0.24
2001	23.21	18.60	26.40	23.35	5.58	2.36	-0.14	-0.51
2002	22.92	19.60	27.40	22.55	6.63	2.57	-0.81	0.57
2003	23.14	19.10	26.60	23.10	4.63	2.15	0.01	-0.11
2004	22.84	20.70	25.60	22.75	2.00	1.42	0.23	0.19
2005	23.73	20.40	28.30	23.00	6.91	2.63	-0.87	0.47
2006	23.28	19.40	26.90	23.40	5.32	2.31	-0.14	-0.38
2007	23.02	19.40	26.00	23.00	3.85	1.96	-0.28	-0.31
2008	22.63	18.10	26.00	22.70	5.94	2.44	-0.27	-0.53
2009	23.13	19.10	26.50	23.00	5.85	2.42	-0.53	-0.35
2010	23.23	18.20	27.40	23.20	8.27	2.88	-0.34	-0.25
2011	23.05	19.40	26.70	23.20	5.72	2.39	-0.64	-0.08
2012	23.23	19.90	26.40	23.10	3.54	1.88	0.07	-0.10
2013	23.23	20.00	27.00	22.80	4.64	2.15	-0.41	0.23
2014	23.36	19.40	26.30	23.80	4.47	2.12	-0.27	-0.53

Appendix II presents the descriptive statistic of the monthly maximal observation of each year. It is shown that in 2014, the average maximal temperature was 35.64, the minimum maximal temperature was 31.6 the maximum maximal temperature was 25 while the sample standard deviation of the minimal temperature in 1954 was 2.04

Appendix II: *Yearly Summary Statistics of the maximum Monthly temperature in ^oC*

YEAR	AVERAGE	MIN	MAX	VAR	SD	KURTOSIS	SKEWNESS
1954	34.28	29.00	38.60	10.61	3.26	-1.31	-0.41
1955	33.95	29.60	37.90	9.68	3.11	-1.42	-0.42
1956	34.01	29.10	37.80	9.10	3.02	-1.26	-0.39
1957	34.02	29.80	38.30	8.54	2.92	-1.41	-0.05
1958	34.30	30.50	39.40	8.61	2.93	-1.04	-0.04
1959	34.47	29.00	39.00	11.22	3.35	-1.00	-0.40
1960	34.52	30.70	38.20	7.83	2.80	-1.45	-0.20
1961	34.29	29.50	38.30	9.25	3.04	-1.20	-0.55

1962	34.15	29.70	39.30	9.11	3.02	-1.00	0.01
1963	34.35	30.30	38.10	6.78	2.60	-1.34	-0.20
1964	34.31	29.30	38.80	9.92	3.15	-0.99	-0.15
1965	34.66	29.90	39.40	8.61	2.93	-0.85	-0.13
1966	34.73	29.90	39.30	9.18	3.03	-1.28	-0.30
1967	34.64	29.90	38.80	8.37	2.89	-1.05	-0.26
1968	34.60	29.90	38.70	8.17	2.86	-1.06	-0.30
1969	34.66	29.90	39.00	8.56	2.93	-0.91	-0.27
1970	35.15	29.60	40.00	10.52	3.24	-0.69	-0.42
1971	34.33	29.40	38.20	9.51	3.08	-1.24	-0.26
1972	34.36	30.40	38.80	6.72	2.59	-0.81	0.04
1973	35.15	30.00	39.30	9.43	3.07	-1.03	-0.30
1974	34.33	30.10	38.50	8.83	2.97	-0.95	-0.24

YEAR	AVERAGE	MIN	MAX	VAR	SD	KURTOSIS	SKEWNESS
1975	34.45	30.00	38.70	9.30	3.05	-1.04	-0.23
1976	34.21	30.30	38.60	7.50	2.74	-1.06	0.32
1977	34.93	30.20	38.80	7.88	2.81	-1.04	-0.34
1978	34.44	30.30	38.80	8.05	2.84	-1.40	0.02
1979	34.75	30.70	39.70	10.14	3.18	-1.20	0.38
1980	35.34	31.00	39.70	9.01	3.00	-1.43	-0.08
1981	35.63	31.00	40.70	10.16	3.19	-0.97	0.05
1982	34.57	27.55	39.08	10.70	3.27	0.55	-0.64
1983	36.26	32.00	40.70	8.40	2.90	-0.96	0.37
1984	33.92	26.10	39.40	11.68	3.42	1.67	-0.72
1985	34.78	30.20	39.30	10.45	3.23	-1.18	-0.19
1986	34.77	30.50	39.50	10.20	3.19	-1.20	0.14
1987	35.74	31.10	40.20	10.32	3.21	-1.59	-0.13
1988	34.88	30.10	40.10	11.23	3.35	-1.32	-0.04
1989	34.66	30.60	38.40	7.51	2.74	-1.14	-0.13
1990	35.36	31.90	38.90	5.35	2.31	-1.01	-0.25
1991	34.68	30.40	39.40	9.54	3.09	-1.31	0.24
1992	34.46	30.00	39.60	9.53	3.09	-1.00	0.11
1993	35.11	31.00	39.20	9.39	3.06	-1.33	-0.05
1994	34.73	30.00	39.80	10.33	3.21	-0.96	0.28
1995	35.49	30.00	40.10	10.34	3.22	-1.06	-0.21
1996	35.36	30.80	39.90	11.73	3.42	-1.74	-0.18
1997	34.98	31.60	38.40	5.54	2.35	-1.14	-0.28

YEAR	AVERAGE	MIN	MAX	VAR	SD	KURTOSIS	SKEWNESS
1998	34.36	30.60	38.90	7.72	2.78	-1.29	0.05
1999	35.26	30.10	40.80	11.11	3.33	-0.81	-0.09
2000	34.91	31.00	39.10	8.33	2.89	-1.44	-0.30
2001	36.50	32.00	40.40	6.13	2.48	-0.27	-0.23
2002	35.63	30.70	40.90	9.94	3.15	-0.93	-0.03
2003	35.55	31.00	40.00	11.00	3.32	-1.62	-0.12
2004	35.16	30.90	38.50	8.73	2.96	-1.60	-0.46
2005	35.88	30.80	41.10	13.11	3.62	-1.45	-0.04
2006	35.63	31.00	40.70	10.16	3.19	-0.97	0.05
2007	35.08	29.90	40.20	9.69	3.11	-0.79	-0.02
2008	35.03	30.30	39.60	9.95	3.15	-1.35	-0.12

2009	35.34	31.00	39.70	9.01	3.00	-1.43	-0.08
2010	35.50	30.80	40.40	12.87	3.59	-1.63	-0.03
2011	35.43	30.70	40.50	9.02	3.00	-0.77	0.11
2012	34.90	30.70	39.70	9.19	3.03	-1.29	-0.02
2013	34.91	30.30	40.10	9.02	3.00	-0.75	0.22
2014	35.64	31.60	39.80	6.75	2.60	-0.84	-0.23

Appendix III is the descriptive statistic of the minimum observations taking in months. It is observed that the average temperature for the Januarys is 19.84 with a standard deviation of 1.7, a minimum observation of 13.38 and a maximum observation of 27.7. It can be observed that the observations in Januarys and in Decembers are at the bottom.

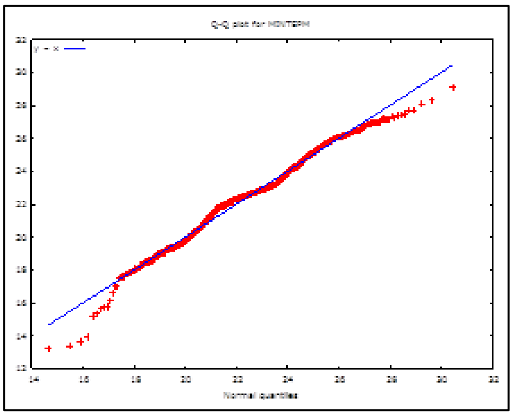
Appendix III: *Months Summary Statistics of the minimum temperature in ^{o}C*

MONTH	AVERAGE	MIN	MAX	VAR	SD	KURTOSIS	SKEWNESS
JANUARY	19.84	13.38	27.70	2.90	1.70	9.45	0.79
FEBRUARY	22.27	15.37	25.50	2.24	1.50	6.33	-1.51
MARCH	25.20	17.59	27.50	2.11	1.45	11.44	-2.33
APRIL	26.11	18.33	28.30	1.69	1.30	20.78	-3.48
MAY	25.05	17.89	27.30	1.38	1.17	22.90	-3.71
JUNE	23.46	16.67	24.80	1.11	1.06	28.68	-4.49
JULY	22.59	16.10	24.20	1.13	1.06	24.94	-4.47
AUGUST	22.41	15.80	24.40	0.99	0.99	33.36	-4.90
SEPTEMBER	22.20	15.60	23.30	1.02	1.01	30.44	-4.76
OCTOBER	22.25	15.75	23.50	1.15	1.07	22.43	-3.97
NOVEMBER	20.19	13.65	26.40	3.10	1.76	6.61	-0.79
DECEMBER	19.37	13.30	29.10	4.41	2.10	8.96	1.75

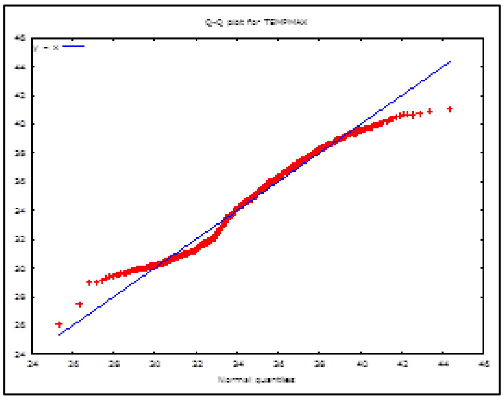
Appendix IV is describes the statistic of the maximum observations taking in months. It is observed that the average temperature for the March is 38.84 the maximum among all the months with a standard deviation of 2.14, a minimum observation of 26.1 and a maximum observation greater than 41. It can be observed that the observations from Februarys to Marchs are at the top.

Appendix IV: *Months Summary Statistics of the maximum temperature in ^{o}C*

MONTH	AVERAGE	Min	max	median	VAR	SD	KURTOSIS	SKEWNESS
JANUARY	35.54	32.80	40.70	35.30	1.70	1.30	2.86	0.92
FEBRUARY	37.87	35.60	40.00	37.80	0.92	0.96	-0.42	-0.10
MARCH	38.84	26.10	41.10	39.30	4.60	2.14	22.10	-4.15
APRIL	38.16	33.00	40.60	38.40	1.88	1.37	2.35	-1.05
MAY	35.84	32.20	39.00	35.80	1.50	1.22	0.95	-0.25
JUNE	33.10	31.30	35.70	33.00	1.11	1.05	-0.19	0.60
JULY	31.31	29.60	34.10	31.30	0.68	0.83	1.09	0.41
AUGUST	30.48	29.00	32.80	30.40	0.61	0.78	0.44	0.48
SEPTEMBER	31.36	29.60	35.80	31.20	1.15	1.07	7.63	2.27
OCTOBER	34.13	32.00	36.60	34.10	0.82	0.91	0.97	0.50
NOVEMBER	36.36	27.55	38.20	36.50	2.30	1.52	18.48	-3.42
DECEMBER	35.51	33.60	38.10	35.45	1.12	1.06	-0.18	0.45



Appendix V: *QQ Plot of the Minimum Average Monthly Temperature*



Appendix VI: *QQ Plot of the Maximum Average Monthly Temperature*