

Dynamic Harmonic Regression Modelling with the Minimum/Maximum Temperatures of Umuahia

B.C. Offorha¹, C.C. Nwokike², O. Uche-Ikonne³, M. Obubu⁴ and F.C. Onwunmere⁵

¹Department of Statistics
Abia State University, P.M.B 2000, Uturu
Email: mrofforha@gmail.com

²Department of Statistics
Abia State University, P.M.B 2000, Uturu
Email: chukwudikenwokike@gmail.com

³Department of Mathematics and Statistics
Lancaster University, Lancaster, UK
Email: kezboss3@gmail.com

⁴Department of Statistics
Nnamdi Azikiwe University, Awka, Nigeria
Email: maxwellobubu@gmail.com

⁵Department of Statistics
Abia State University, P.M.B 2000, Uturu
Email: onwunmere.fidelia@abiastateuniversity.edu.ng

ABSTRACT

Air surface temperature is one of the most important environmental factors that serve as a climate change indicator. A separate analysis on the minimum and maximum temperatures would be more informative than on the average temperature. The data used spanned over 30 years (1988 - 2017) separately available for minimum and maximum temperatures. Dynamic harmonic regression methods were successfully applied to the minimum/maximum temperature series where the error components were allowed to correlate but with innovations that follows a WN distribution. Minimum temperature series was detected to have a linear trend, double seasonal periods of 6 months (semi-annual) cycle and 12 months (annual) cycle, this multiple seasonality is usually ignored by most traditional time series methods, however, this was adequately handled using Fourier series. The increase in mean surface air temperature in Umuahia metropolis and its environs is believed to be due to the increase in the minimum temperatures rather than in the maximum temperatures, the minimum temperature was found to be increasing at the rate of 0.024°C yearly and 0.7°C over 29 years period, whereas the maximum temperature was significantly stable over the said period.

Keywords: Minimum and maximum temperatures, multiple seasonality, ARIMA, Fourier series, climate change.

Mathematics Subject Classification: 62P12

1. INTRODUCTION

Maximum and minimum temperatures are two of the most standard climatic elements that equally serve as climatic indicators used to assess the effect of climate change in a geographical area. The climate is a measure of the average weather condition of the atmosphere over a long period of time, usually 30 - 35 years. Climate change is, therefore, an abnormal variation in the average weather condition of the

atmosphere over a long period of time. This, which is also known as global warming, is occasioned by an increase in the average temperature of the earth's surface.

The impacts of climate change are numerous and real, almost all nations of the world are affected directly or indirectly. The burden of these impacts on Nigeria as a developing country is devastating due to its vulnerability and slow adaptation. In recent years, Nigeria has increasingly suffered from the adverse effect of climate change, evident in the occasioned heat waves, incessant flooding (Chukwuma, 2018), negative economic growth (Ogbuabor and Egwuchukwu, 2017), increased health risk (During, 2017) and environment challenges (Olaniyi et al., 2014).

Different factors aid meteorologist in understanding climatic conditions, especially forecasting weather conditions. Statistical approaches have been used to forecast rainfall frequencies (Akpanta et al., 2015) and different forecast methods have been compared with good effect in Umuahia metropolis (Offorha et al., 2018), however extreme circumstances have not been taken into account.

The seasonality of data can be broken down into amplitudes, phases and frequencies which is similar to the Fourier analysis, hence we consider using this methodology in weather forecasting. The Fourier analysis has been used in different sectors like the fashions sales (Fumi et al., 2013), showing that the method is an efficient and cost effective method in forecasting and also in call centers (Lewis et al., 2003), which showed greater accuracy in forecasting call volumes. Omekara and Okereke (2012) constructed a Fourier seasonal analysis (FSA) model for forecasting, where the rainfall data for Umuahia was transformed and fitted adequately in a multiplicative model but not in recent years.

This research is aimed at detecting the periodicity in the minimum and maximum temperature series, modelling the variations in minimum and maximum temperatures by applying the Fast Fourier Transform algorithm (FFT) for the weather forecast of series with multiple seasonality and correlated error component. These can aid in environmental decisions making and policy formulation.

2. MATERIALS AND METHODS

Here, we consider the combination of deterministic and stochastic processes in modelling a time series data. This is achieved by decomposing the series into the various component of a time series analysis as shown by equation 1 below:

$$y_t = T + S + E \quad (1)$$

where; T is the trend component. S is the periodicity/seasonality component which models the seasonal patterns present in the data. E is the error component of the general model.

2.1. Spectral analysis

Spectral analysis is a switch from time domain analysis to frequency domain analysis, this provides us with tools to explore the frequency properties of any time series data.

Fourier method as one of the tools of spectral analysis is one of the best approach used in modelling any series with multiple seasonality (with hidden periods) and lengthy seasonality. Any seasonal series could be expressed as a sum of an underlying sine and cosine functions of different frequencies, this is helpful in determining frequencies that appear particularly relevant. Fourier transform converts a series

from a time domain to frequency domain. From Cryer and Chan (2008); to fit a single cosine wave to a discrete time series data, this cosine function could be written as:

$$y_t = R \cos(2\pi f t + \Phi) \quad (2)$$

Where, R is the amplitude, f the frequency, and Φ the phase of the curve. Since the curve makes a complete oscillation at every $1/f$ time units. $1/f$ is known as the period of the cosine wave. Equation 2 could be rewritten linearly using trigonometric identity as

$$y_t = A \cos(2\pi f t) + B \sin(2\pi f t) \quad (3)$$

where

$$A = R \cos(\Phi), B = -R \sin(\Phi) \quad (4)$$

Equation 3 could be thought of as a multiple regression model with A and B as the parameters of the explanatory variables; $\cos(2\pi f t)$ and $\sin(2\pi f t)$. Equation 4 is useful when determining the periodogram of a time series data.

Given a time series with n data points and fixed frequency f , the parameters of equation 3, A and B , can be estimated using the ordinary least squares regression method, hence, a general linear combination of m orthogonal trigonometric identities (also known as Fourier representation) with arbitrary amplitudes, frequencies and phases could be written as

$$y_t = A_0 + \sum_{j=1}^m [A_j \cos(2\pi f_j t) + B_j \sin(2\pi f_j t) + e_t] \quad (5)$$

and estimated by

$$\hat{y}_t = a_0 + \sum_{j=1}^m [a_j \cos(2\pi f_j t) + b_j \sin(2\pi f_j t)] \quad (6)$$

where n = sample size, $a_0 = \bar{y}$, $m = n/2$, $a_j = \frac{2}{n} \sum_{t=1}^n y_t \cos(2\pi f_j t)$, $b_j = \frac{2}{n} \sum_{t=1}^n y_t \sin(2\pi f_j t)$, $f_j = \frac{j}{n}$ is the j th harmonic frequency of the fundamental frequency $1/n$ at period $= p_j = n/j$ and e_t is the error term of which might not be a *White Noise (WN)* process.

2.1.1. The Periodogram

In spectral analysis one of the main objectives is detecting important period(s) present in a time series data, one useful tool in achieving this is the periodogram (see Cryer and Chan, 2008). If $n = 2k + 1$, that is an odd number, the periodogram p at frequency j for $j = 1, 2, \dots, K$ is given as

$$p_j = \frac{2}{n} (a_j^2 + b_j^2) \quad (7)$$

Where k is any positive integer. If the sample size is even, $n = 2k$, equation 7 still applies but for $j = 1, 2, \dots, k - 1$. However, f varies from 0 to $k/n = 1/2$ and equation 7 at the extreme frequency of $1/2$ becomes

$$p_1 = n(a_k)^2$$

For large data set the periodogram can be obtained using the Fast Fourier Transform (FFT) algorithm, which makes use of fewer computer resources.

2.2. ARIMA (p, d, q) process

If y_t and x_t represent the original and transformed (differenced) series respectively, then y_t is an ARIMA (p, d, q) process hence $x_t = (1 - B)^d y_t$ is a causal and invertible ARMA (p, q) process (Brockwell and Davis, 2002). Given the above definitions, y_t could be expressed using a difference equation of the form

$$\phi_p(B)(1 - B)^d y_t = \theta_p(B)\eta_t, \quad \eta_t \sim WN(0, \sigma^2) \quad (8)$$

And ARIMA (p, q) of the form

$$\phi_p(B)y_t = \theta_p(B)\eta_t, \quad \eta_t \sim WN(0, \sigma^2)$$

Where: $\phi_p(B)$ and $\theta_p(B)$ are the ordinary Autoregressive (AR) and Moving Average (MA) polynomials of degrees p and q , respectively, and $\phi \neq 0$ for $|e| \leq 1$, d is a non negative integer that measures how many times a series was differenced, $d = 0$ for a stationary series and ≥ 1 for non stationary series (Brockwell and Davis, 2002). B is the backward shift operator: $B(y_t) = y_{t-1}$, η_t are independent identically distributed random variables and follows a white noise process, $WN(0, \sigma^2)$ distribution.

2.3. Modelling strategy

The idea here is to fit the deterministic part as a multiple regression model comprising of the linear trend term and the periodic component, while ARIMA probability model will be used to model any remaining pattern in the residuals obtained from the deterministic part (Ye et al., 2013; Hughes et al., 2006).

2.3.1. Modelling steps

1. Establish the presence or not of a linear trend and periodicity using time-plot, KPSS & ADF tests, periodogram (for order of periodicity) and the ACF plot.
2. If a linear trend is detected, the coefficients are estimated using the ordinary least squares method and the series is detrended as follows; $\hat{e} = y_t - (\hat{\beta}_0 + \hat{\beta}_1 t)$.
3. The residuals in step 2 becomes the new data for further analysis. A seasonal model is fitted to $\hat{e}$ using Fourier method and then deseasonalised as follows; $\hat{e}'_t = \hat{e} - (a_0 + \sum_{j=1}^m [a_j \cos(2\pi f_j t) + b_j \sin(2\pi f_j t)])$.
4. The new residuals obtained in step 3 are tested for WN features, if rejected, ARIMA model is used to account for the remaining pattern. Hence, the proposed model is of the form

$$y_t = \beta_0 + \beta_1 t + \sum_{j=1}^m [A_j \cos(2\pi f_j t) + B_j \sin(2\pi f_j t) + \epsilon_t] + e_t \quad (9)$$

$$\text{where } e_t = \phi_p(B)y_t = \theta_q(B)\eta_t, \quad \eta_t \sim WN(0, \sigma^2)$$

Step 3 & 4 can be automated simultaneously using the *auto.arima* command in forecast (Hyndman and Khan, 2008) package of R (R Core Team, 2018) programming language by passing the Fourier term as an external regressor of the ARIMA error component.

3. RESULTS

RStudio was used as the computing platform, all statistical hypothesis tests were conducted at a significance threshold of 5%. Mean monthly minimum and maximum temperatures measured in degree centigrade ($^{\circ}\text{C}$) from 1988 to 2017 (30 years) was obtained from the National Root Crop Research Institute (NRCRI), Umudike, Abia State-Nigeria. NRCRI is recognized in the world as a synoptic station with an operational number of 0507.23.

For the purpose of validation, the data was divided into “training set” and “testing set”. The training set span from 1988 to 2016 and was used to build the model while the testing set span from 2016 to 2017 which was used as a validation tool.

3.1. Preliminary analysis of minimum temperature

Here, we carried out some descriptive analysis on the monthly minimum temperatures, this formed the basis for further statistical analysis.

Table 1: Summary by month of minimum temperature series

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean ($^{\circ}\text{C}$)	21.3	22.9	23.5	23.7	23.2	22.7	22.5	22.5	22.5	22.6	22.9	21.6
Std. Dev. ($^{\circ}\text{C}$)	(1.69)	(1.21)	(0.94)	(0.92)	(0.77)	0.59)	(0.69)	(0.83)	0.63)	0.83)	0.90)	.27)

From Table 1 the lowest average minimum temperature were recorded in the month of January and December. January seems to be the coldest month of the year (21.3°C) while the highest average minimum temperatures were recorded in April, March and May. Table 1 shows that there exist a plausible yearly pattern in the series; as months that are close together tend to have somewhat similar values for instead, July, August and September have a constant value of 22.5°C . January seems to be the most unstable (standard deviation = 1.69) month followed by December. The most stable month is June then September, the range of the entire series of the minimum temperature is (17°C , 27°C).

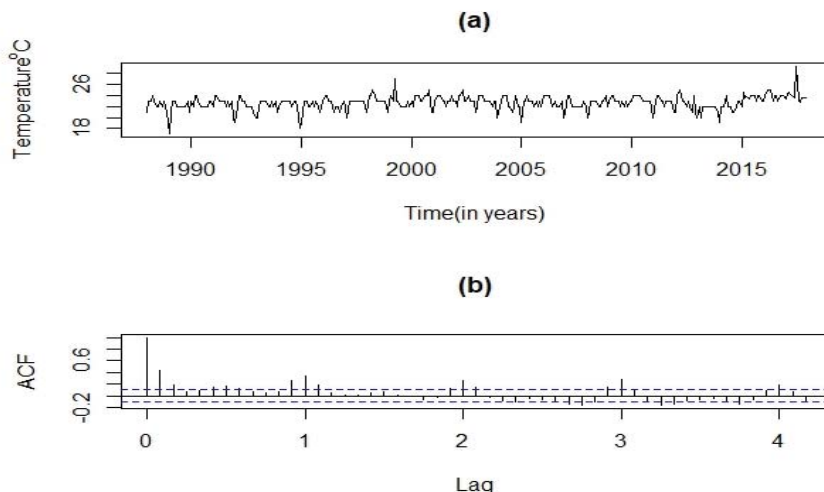


Figure 1. (a) Time plot of monthly minimum temperatures (1988 - 2017). (b) ACF of monthly minimum temperature.

3.2 Time series analysis of minimum temperature

Figure 1a shows a slow rise in the trend of minimum temperature which is clearer from 2010 to 2017, this subtle linear trend is substantiated by a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) (Kwiatkowski et al., 1992) trend stationary test. With a p -value of 0.041 the null hypothesis, H_0 : the series is trend stationary, is rejected. The wavelike pattern of the ACF plot in Figure 1b shows the presence of seasonality in the series.

3.2.1 Linear trend estimation of minimum temperature

A simple linear regression model is fitted to the minimum temperature series using the ordinary least squares method, Table 2 shows the estimated coefficients of the linear trend parameters.

Table 2: Coefficients for the trend part of minimum temperatures model

Variable	Coef.	Std. error	t-statistic	p – value
Intercept	22.33	0.1255	177.898	<0.0001
t	0.0019	0.0006234	3.058	0.00241

In Table 2 the respective p -value of the coefficients are highly significant, hence there is approximately 0.002°C increase in monthly minimum temperature as a result of a unit increase in month. The fitted regression equation is $y_t = 22.33 + 0.0019t + e_t$, hence the estimates of the residuals, e_t , is obtained by $\hat{e}_t = y_t - (22.33 + 0.0019t)$. The values of $\hat{e}_t$ becomes our new series for further analysis.

3.2.2. Spectral analysis and ARIMA modelling of minimum temperature

The periodogram plot of Figure 2 shows two significant high spikes indicating somewhat a series with double seasonality. The two most maximum frequencies, f_j and $f_{j'}$, are 0.167 and 0.083 respectively, where $j = 60$ and $j' = 30$. The periodograms corresponding to these frequencies are 71.27966 and 58.28338 respectively. These frequencies and periodograms correspond to the periods, $p_j = \frac{j}{n} = \frac{0.167}{348} = 6$ months and $p_{j'} = \frac{0.083}{348} = 12$ months. This indicates semi-annual and annual periods, in other words, the observations make a complete cycle at every 6th and 12th months respectively. The period, 6 months, is the primary season while 12 months is the secondary season. Let p_1 and p_2 represent the 6-month and 12-month periods respectively, the order of terms in p_1 and p_2 , j and j' , must not exceed $p/2$, where p is the detected period(s).

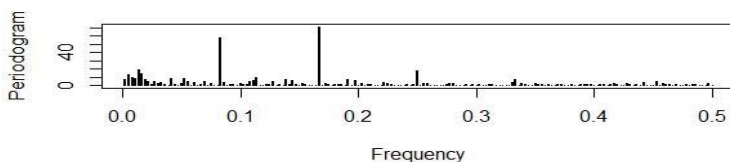


Figure 2. Periodogram of detrended series of minimum temperature.

Hence, for p_1 the terms in it must not exceed 3 (i.e., $6/2$) while the terms in p_2 must not exceed 6 as well, this will be fitted in collaboration with an ARIMA model with order p, d, q for the error component. Table 3 shows all possible models considered by permuting the orders of the terms, j and j' , in the respective periods, p_1 and p_2 of the Fourier representation. Among all the candidate models, model 8 has the least AIC of about 907.5 as indicated by the double asterisk (**).

Table 3: Respective orders for each full model for minimum temperature with their corresponding AIC value.

Model	Orders of Fourier term		Orders of ARIMA model			AIC
	j	j'	p	d	q	
1	3	6	2	1	1	909.43
2	3	5	2	1	1	909.43
3	3	4	2	1	1	911.24
4	3	3	2	1	1	911.24
5	3	2	1	1	1	934.84
6	3	1	1	1	1	934.84
7	2	6	2	1	1	909.43
8	2	5	2	1	1	907.46**
9	2	4	2	1	1	909.26
10	2	3	2	1	1	909.26
11	2	2	1	1	1	932.88
12	2	1	1	1	1	932.88
13	1	1	2	1	1	943.72

Hence, the best fitted model for minimum temperature is made up of a linear trend, Fourier term with double seasonal periods of orders, $j = 2$ and $j' = 5$, and an error term with ARIMA structure of orders ($p = 2, d = 1, q = 1$) represented mathematically as

$$\begin{aligned}
 y_t = & \frac{22.33}{(0.1255)} + \frac{0.0019t}{(0.00062)} - \frac{0.4563 \sin\left(2\pi \frac{1}{6}t\right)}{(0.0641)} - \frac{0.4444 \cos\left(2\pi \frac{1}{6}t\right)}{(0.0640)} - \frac{0.1923 \sin\left(2\pi \frac{2}{6}t\right)}{(0.0529)} \\
 & - \frac{0.0851 \cos\left(2\pi \frac{2}{6}t\right)}{(0.0529)} + \frac{0.3363 \sin\left(2\pi \frac{1}{12}t\right)}{(0.0814)} - \frac{0.4802 \cos\left(2\pi \frac{1}{12}t\right)}{(0.0811)} \\
 & - \frac{0.3113 \sin\left(2\pi \frac{1}{12}t\right)}{(0.0555)} - \frac{0.0788 \cos\left(2\pi \frac{3}{12}t\right)}{(0.0555)} - \frac{0.1239 \sin\left(2\pi \frac{5}{12}t\right)}{(0.0534)} \\
 & - \frac{0.0402 \cos\left(2\pi \frac{5}{12}t\right)}{(0.0534)} + e_t \\
 e_t = & \frac{0.2353}{(0.0681)} e_{t-1} + \frac{0.0916}{(0.0640)} e_{t-2} - \frac{0.2353}{(0.0405)} \eta_{t-1} + \eta_t; \eta_t \sim WN(0, 0.7646)
 \end{aligned} \tag{10}$$

In brackets below the coefficients, are the standard errors of the coefficients of equation 10, the standard errors of $\hat{\beta}_s$ indicates that the parameter β_s , are highly significant. This explains the point that there is a significant increase in minimum temperatures.

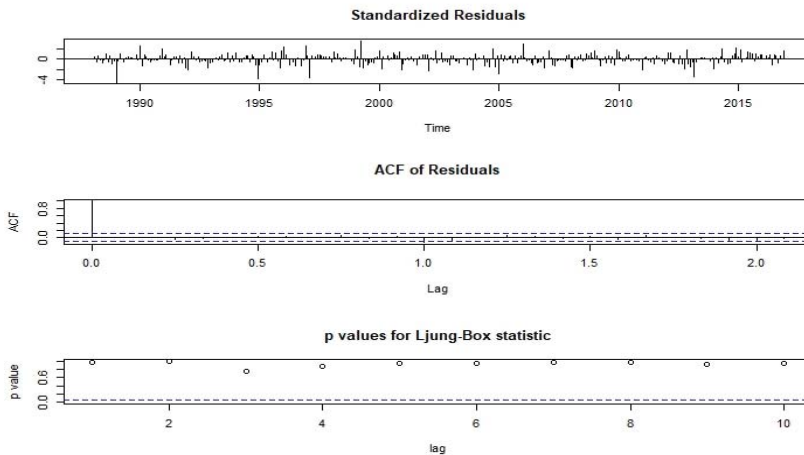


Figure 3. Diagnostic plots of the best fitted model for minimum temperature.

Figure 3 shows a standardized residuals plot that has a zero mean and constant variance of 1, the ACF plot shows almost no significant protruding spike from the blue dashed lines of the 95% confidence interval bounds, indicating lack of serial dependence. The plotted p-values from the Ljung-Box statistics are highly non significant at all lags, indicated by the small circles which are well above the $p=0.05$ significance threshold.

Figure 4 was used to evaluate the forecast performance of model 8, in Figure 4c the fitted values as shown by the broken line depicts the fluctuations in the true observed values (solid line), from 1988 to 2016, to a reasonable extent. To substantiate this good forecast performance of model 8, out of sample forecast of Figure 4d shows a reasonable closeness between the forecast values and training set, from Jan. 2017 to Dec. 2017. Except for July 2017 that has a large discrepancy between the forecast value and the training set value, this is a clear case of an outlying value. This might be a mistake during record entry. In Figure 4d, 2017.0 represent Jan. 2017, and 2017.1 represent Feb. 2017 and so on.

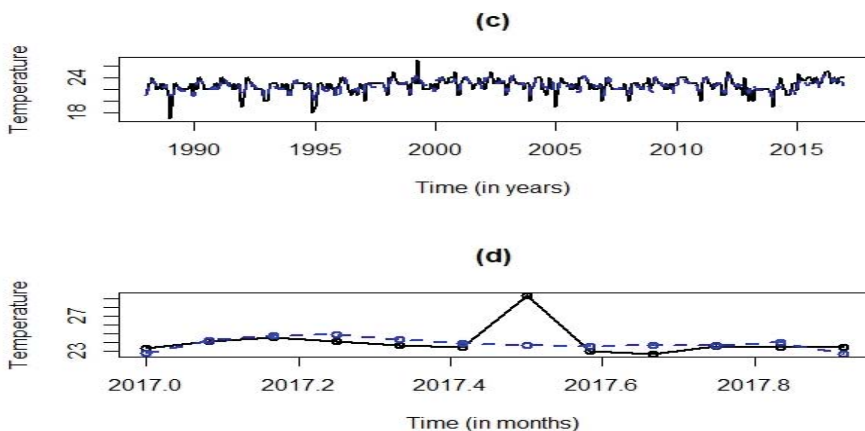


Figure 4. (c) Time plot between fitted values (broken line) of model 8 and observed values (solid line) of monthly minimum temperatures from 1988 to 2016. (d) One step ahead out of sample forecasts of minimum temperatures, from Jan. 2017 to Dec. 2017. Solid line is the training values while broken line is the forecasts.

3.3. Preliminary analysis of maximum temperature

Similarly to minimum temperature, we carried out some descriptive analysis on the monthly maximum temperatures. The highest average maximum temperatures were recorded in February, March, April and January

Table 4. Summary by month of maximum temperature series

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean ($^{\circ}\text{C}$)	32.7	34.1	33.6	32.7	31.7	30.2	29.0	28.9	29.7	30.5	31.6	31.9
Std. Dev. ($^{\circ}\text{C}$)	(0.892)	(1.9)	(1.18)	(0.866)	(0.954)	(0.511)	(0.923)	(0.693)	(0.614)	(0.634)	(0.820)	(1.22)

with February being the hottest month (34.1°C). The lowest average maximum temperatures were recorded in August, July and September respectively. The range of the series is (27.00°C , 37.00°C). Table 4 shows a yearly cycle. December (standard deviation = 1.22°C) seem to be most unstable followed by February and March. The most stable month is June (standard deviation = 0.511°C).

3.4. Time series analysis of maximum temperature

As shown by Figure 5e there appear to be no systematic fluctuations in the mean of the maximum temperature series this is confirmed using the KPSS test, and with a p -value of 0.1 we fail to reject the null hypothesis of trend stationary. There is clearly a strong seasonal variation as indicated by the wavy ACF plot of Figure 5f.

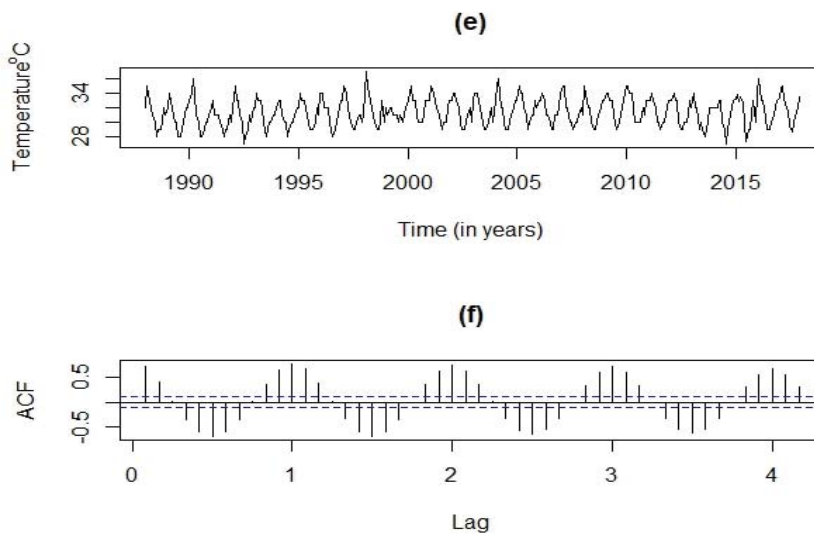


Figure 5. (e) Time plot of monthly maximum temperature (1988 - 2017). (f) ACF plot of monthly maximum temperature.

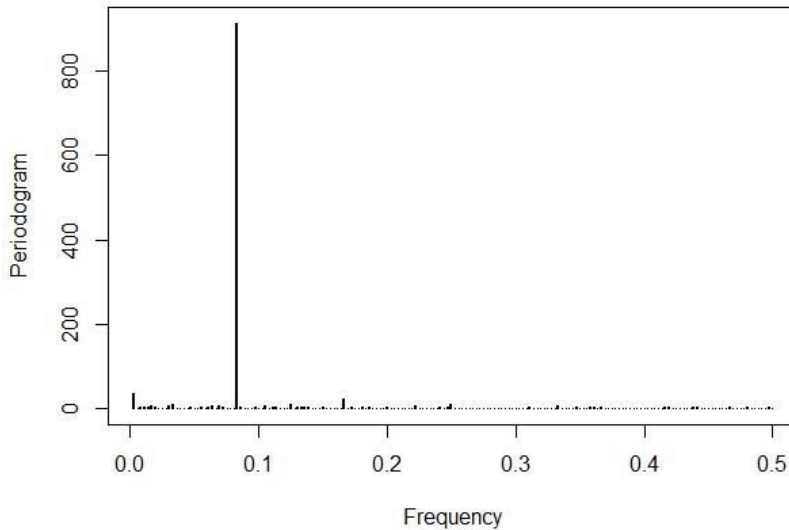


Figure 6. Periodogram of maximum temperatures

From the periodogram plot of Figure 6, there is clearly one significant high spike. This highest spike occurred at the frequency, $f_j = 0.0833$ and the periodogram is 913.4643, where $j = 30$. The period corresponding to this frequency and periodogram is $p_j = \frac{0.0833}{348} = 12\text{months}$, which is an annual seasonal cycle.

Table 5. Respective orders for each full model for maximum temperature with their corresponding AIC value.

Model	Orders of Fourier term	Orders of ARIMA model			AIC
	j	p	d	q	
1	6	2	1	1	881.35
2	5	2	1	1	879.36**
3	4	2	1	2	881.48
4	3	2	1	2	891.47
5	2	2	1	2	904.06
6	1	2	1	1	925.14

The best fitting model is model 2 which has the least AIC value of 879.36. Hence, the full model is made up of a Fourier term of order $j = 5$ and an ARIMA error component of orders, $p = 2, d = 1, q = 1$ with no trend component, this fitted final model is expressed mathematically as

$$\begin{aligned}
 y_t = & \underset{(0.0748)}{2.0463} \sin\left(2\pi \frac{1}{12} t\right) + \underset{(0.0746)}{1.0450} \cos\left(2\pi \frac{1}{12} t\right) - \underset{(0.0639)}{0.2441} \sin\left(2\pi \frac{2}{12} t\right) - \underset{(0.0638)}{0.2820} \cos\left(2\pi \frac{2}{12} t\right) \\
 & - \underset{(0.0569)}{0.0335} \sin\left(2\pi \frac{3}{12} t\right) - \underset{(0.0569)}{0.2456} \cos\left(2\pi \frac{3}{12} t\right) - \underset{(0.054)}{0.201} \sin\left(2\pi \frac{4}{12} t\right) \\
 & - \underset{(0.0541)}{0.0444} \cos\left(2\pi \frac{4}{12} t\right) - \underset{(0.0536)}{0.1124} \sin\left(2\pi \frac{5}{12} t\right) + \underset{(0.0536)}{0.0067} \cos\left(2\pi \frac{5}{12} t\right) + e_t \\
 e_t = & \underset{(0.0574)}{0.1911} e_{t-1} + \underset{(0.0571)}{0.0562} e_{t-2} - \underset{(0.0202)}{0.9564} \eta_{t-1} + \eta_t; \eta_t \sim WN(0, 0.7034)
 \end{aligned} \tag{11}$$

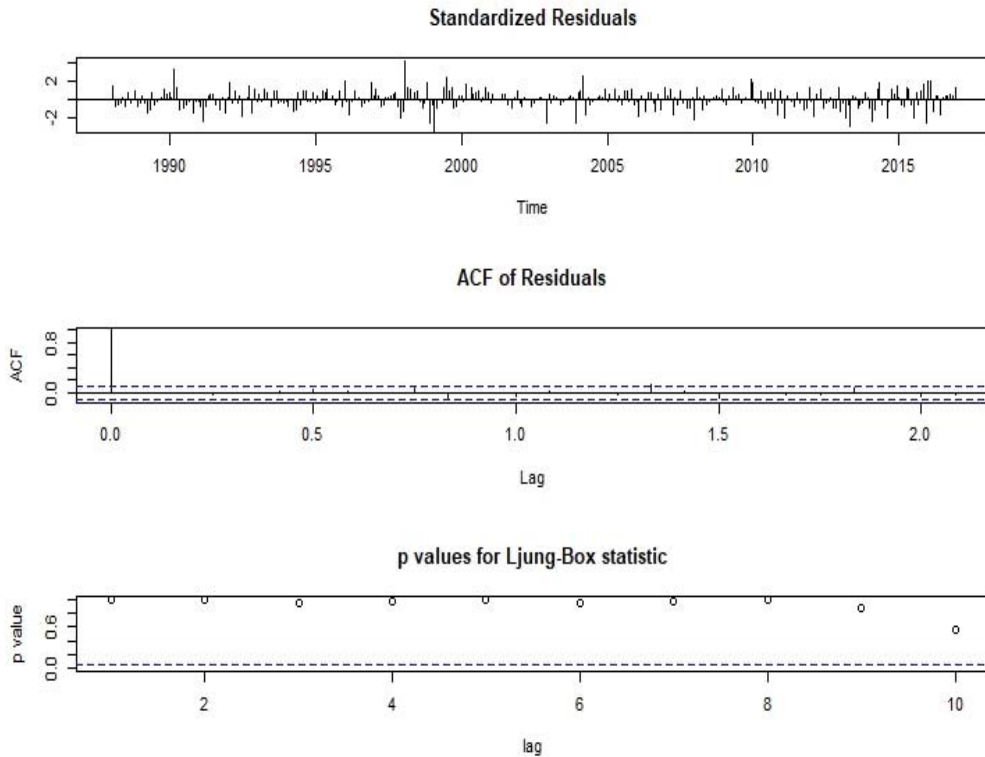


Figure 7. Diagnostic plots of the best fitted maximum temperature model.

From Figure 7, the standardized residuals plot shows that the residuals of equation 11 follow a standard normal distribution with. Similarly, the ACF plot shows that the residuals are not correlated at all lags, this is confirmed with the p-values plot for Ljung-Box statistics that are higher at all lags than the conventional $p = 0.05$ significance threshold.

Figure 8g shows a close agreement between the predicted values using model 2 and the true observed values of maximum temperatures from 1988 to 2016. Similarly, in Figure 7h, the forecast values (broken line) from model 2 depicts the variation in the true values from Jan. 2017 to Dec. 2017.

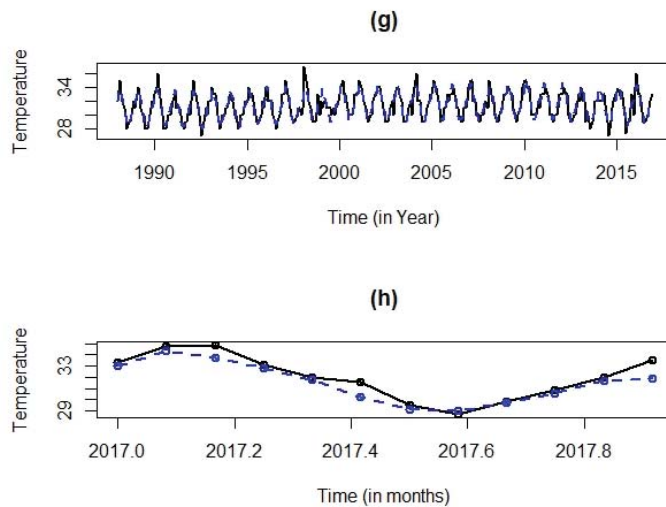


Figure 8. (g) Time plot between predicted values (broken line) of model 2 and observed values (solid line) of monthly maximum temperatures from 1988 to 2016. (h) One step ahead out of sample forecasts of maximum temperatures, from Jan. 2017 to Dec. 2017. Solid line is the training values while the broken line is the forecasts.

4. DISCUSSION AND CONCLUSION

Although Ye et al. (2013) carried out a similar analysis on global monthly absolute temperature using almost similar methods used in this study, Hughes et al. (2006) suggested a separate analysis on the minimum and maximum temperatures since analysis on average temperature over smooth out the variation and hence might be less informative. Our study is based more on the methods used by Hughes et al. (2006) than Ye et al. (2013). We carried out a separate analysis on the minimum and maximum temperatures successfully, using dynamic harmonic regression methods of which the variations in minimum and maximum temperatures were explained by linear time series models with innovations following a WN distribution. Although the minimum and maximum temperatures had the same range, 10oC, however, the minimum temperatures show a bit more dynamic behaviour than the maximum temperatures. An increasing linear trend was observed in the minimum temperature at the rate of 0.024oC yearly and 0.7oC over 29 years period, this values seem small but was found to be significant and will definitely have a detrimental effect on the environment, marine life, agriculture, health, education and hydrology of Umuahia and its environ over a long period of time. No significant trend was established in the maximum temperatures, which is similar to the result of Hughes et al. (2006).

Double seasonality was detected in the minimum temperature series, a semi-annual cycle of 6 months and an annual cycle of 12 months which was adequately handled using the Fourier series, most conventional time series methods ignore this feature, hence leading to inadequate modelling of the variation present in the series, hence leading to poor forecast performance. A single seasonality of an annual cycle of 12 months was detected in the maximum temperature series.

The in-sample fitting and out of sample forecasts from the best fitted models for minimum and maximum

temperatures were very close to the true observed values indicating the adequacy of the models.

In conclusion, we found out that January seems to be the coldest month of the year while the hottest month is February in Umuahia. The increase in the overall temperature is as a result of the increase in the minimum temperature suggested by the presence of a linear trend rather than in the maximum temperature which was quite stable over the years. This increase over time could cause serious climate change hazards if not handled appropriately.

However, the series used in this study is not large enough nor were other environmental factors considered to make any strong conclusions, but this study could serve as a pilot study to researchers, climatologists, meteorologists and other stakeholders. Due to this observed increase in minimum, this study is a wake-up call to all stakeholders concerned with climate change and environmental decisions making, cause an increase in minimum temperature might be more detrimental than an increase in the overall temperature(Hughes et al., 2006).

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