MODELLING AND FORECASTING MONTHLY MAXIMUM TEMPERATURE IN OGBOMOSO, SOUTH-WEST NIGERIA

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Abstract

Temperature variation may have long-lasting effects on environment and economy. This study examined the maximum temperature in South-West Nigeria using monthly climate variability data obtained from the Nigeria Meteorological Agency (NiMET) for the period 2013-2023. The data were statistically analyzed to identify the patterns in maximum temperature. The time plot revealed a pattern of peaks and troughs, indicates strong seasonality in temperature variations over the study period. An appropriate Seasonal Autoregressive Integrated Moving Average SARIMA model was fitted and used to forecast maximum temperature. The forecast results suggest a gradual but steady rise in maximum temperature, highlighting a potential warming trend in the study area. These findings provide valuable insights for climate monitoring and environmental planning in South-West Nigeria.

Keywords: Maximum Temperature; Climate Variability; SARIMA model; Climate Change

1.0 Introduction

Global climate change refers to local and regional changes that directly affect people and ecosystems and are of immediate concern to scientists, managers, and policymakers (Girvetz et al. 2009). Winconsin Department of Natural Resources (2024), describes long-term shifts in temperatures and weather patterns, primarily driven by increasing greenhouse gas emissions from human activities since the 1800s. Rising global temperatures have been associated with extreme weather events, agricultural disruption, infrastructural damage, and ecological imbalance.

Pavlasek et al. (2015) describe temperature as a central variable in meteorology, particularly in weather forecasting and climate determination, as it serves as a direct indicator of global climatic trends. According to the Intergovernmental Panel on Climate Change (IPCC, 2018), global warming induced by human activity has already increase by approximately 1.0°C over pre-industrial level, with projections indicating a rise to 1.5°C between 2030 and 2052 if current trends continue. Changes in temperature over time are important indicators of climate change, and monitoring these changes help identify potential impacts on ecosystems, agriculture, and human health (FAO, 2021).

Nigeria has experienced adverse climate conditions characterized by droughts, flooding, irregular rainfall patterns, and increasing temperatures, which have significantly affected agriculture, water resources, and human welfare. Several studies have documented rising temperature trends across different regions of Nigeria. Abatan et al. (2015) found that Nigeria is experiencing an increase in the frequency of extreme heat events and a decrease in cold extremes. Oluwatobi (2016) also reported a significant increase in temperature trends in Ijebu-Ode. Emetere et al. (2021) examined seasonal temperatures in Agege-Lagos and reported evidence of climate change over several decades. Similarly, Ayeni and Oloukoi (2022) analyzed temperature trends in Akure and observed consistent warming patterns.

Despite the growing body of research, there remains a need for localized assessments of temperature variability over relatively short timeframes to identify region-specific trends. Such localized studies are essential for informed adaptation and mitigation planning.

This study, therefore, aims to assess the trend and variability of monthly maximum temperature in Ogbomoso, South-West Nigeria, over an eleven-year period (2013–2023). Specifically, the study seeks to analyze variability, fit an appropriate time series model, and forecast maximum temperature for the subsequent three years.

2.0 Methodology

2.1 Time Series Methods

In time series analysis, it is crucial to select a model that adequately captures the underlying structure of the series in order to make reliable predictions. Time series methods serve various purposes. In some cases, the objective may be to control the data-generating process, understand the mechanism that produces the series, or obtain a concise summary of its key features. This section describes the time series methods used in the analysis.

2.2 White noise

A white noise process serves as the foundation for time series models. A time series is said to follow a white noise process if

$$\varepsilon_t \sim i.i.d.N(0, \sigma_\varepsilon^2) \quad (1)$$

where mean is zero and variance is σ_ε^2

2.3 Basic Autoregressive Moving Average models (ARMA)

In many studies, a class of models that formed as a linear combination of white noise processes is considered (Cochrane, 2005). The ARIMA model has been extensively used in forecasting financial budget (Arowolo et al., 2022), electricity accessibility (Oguntola et al., 2024) among others. The different models are represented as follows;

Autoregressive Model (AR(p)): $$X_t = \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_p X_{t-p} + \varepsilon_t \quad (2)$$

Moving Average Model (MA(q)): $$X_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \quad (3)$$

Autoregressive Moving Average (ARMA (p, q)): $$X_t = \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \quad (4)$$

Seasonal Autoregressive Integrated Moving Average (SARIMA): $$Z_t = (1-L)^d (1-L^s)^D X_t \quad (5)$$

where X_t and Z_t are the time series, β's are the autoregressive model parameters, θ's are the moving average model parameters, p, q, d, and D are nonnegative integers, $\boldsymbol{s}$ is the seasonal period and ε_t is a white noise process with mean zero and variance σ_ε^2.

Box and Jenkins (1976) methodology consist of three steps for modelling ARMA processes, namely; model identification, parameter estimation and diagnostic checking.

2.5 Forecasting

An important objective of time series analysis is to predict future values of a series. Most forecasting results are derived from the general theory of linear prediction developed by Kolmogorov (1939, 1941), Kalman, (1960), Whittle (1983), among others.

2.5.1 Minimum Mean Square Error Forecast

The objective of forecasting is to produce an optimal forecast with minimal error, leading to a minimum mean square error (MSE) forecast. The stationary ARIMA model is given by:

$$\phi(\beta)X_\tau = \theta(\beta)\varepsilon_\tau \tag{6}$$

which implies: $X_\tau = \frac{\theta(\beta)\varepsilon_\tau}{\Phi(\beta)}$ and $\frac{\Theta(\beta)}{\Phi(\beta)}$ *is replaced by* $\Psi(\beta)$

Then:

$$\begin{aligned} X_\tau &= \Psi(\beta)\varepsilon_\tau \\ &= \Sigma\Psi_j\beta'\varepsilon_\tau \\ &= \varepsilon_\tau + \Psi_1\varepsilon_{\tau-1} + \Psi_2\varepsilon_{\tau-2} + \cdots \end{aligned} \tag{7}$$

When:

$$\Psi_o = 0 \; and \; t = n + 1$$

$$\begin{aligned} X_{n+1} &= \varepsilon_{n+1} + \Psi_1\varepsilon_{n+\iota-1} + \Psi_2\varepsilon_{n+\iota-2} + \cdots \\ &= \Sigma\Psi_j\beta'\varepsilon_{n+1-j} \end{aligned} \tag{8}$$

We have:

$$X_{\tau-1}, X_{\tau-1}, X_{\tau-2}, \ldots \; at \; time \; t.$$

$$then \; to \; forecast \; 1 step \; ahead \; of \; future \; values \; X_{n+1,}$$

$$X_n(1) = X_1\varepsilon_n + \Psi^*_{1+1}\varepsilon_{n-1} + \Psi^*_{1+2}\varepsilon_{n-2}\ldots$$

The mean square error of the forecast is;

$$E\big(X_{n+1} - X_n(1)\big) = \sigma_t^2\Sigma\Psi_j^2 + \sigma_t^2\Sigma(\Psi_{i+j} - \Psi^*_{i+j}) \tag{9}$$

3.0 Results

Monthly time series data on maximum temperature (ºC) in Ogbomoso, South-West Nigeria, from 2013 to 2023 were analyzed. The data were retrieved from Nigeria Meteorological Agency (NiMET) database. Table 1 shows that the monthly maximum temperature had a mean of 32.9°C, a median of 33.3°C, and a standard deviation of 2.44°C. The minimum and maximum recorded temperatures were 28.2°C and 38.0°C, respectively. Time plot of the series is presented in Figure 1.

Table 1: Descriptive Statistics of Maximum Temp (°C)

Variable	Mean	Median	S.D.	Min	Max
Max. Temp (°C)	32.9	33.3	2.44	28.2	38.0

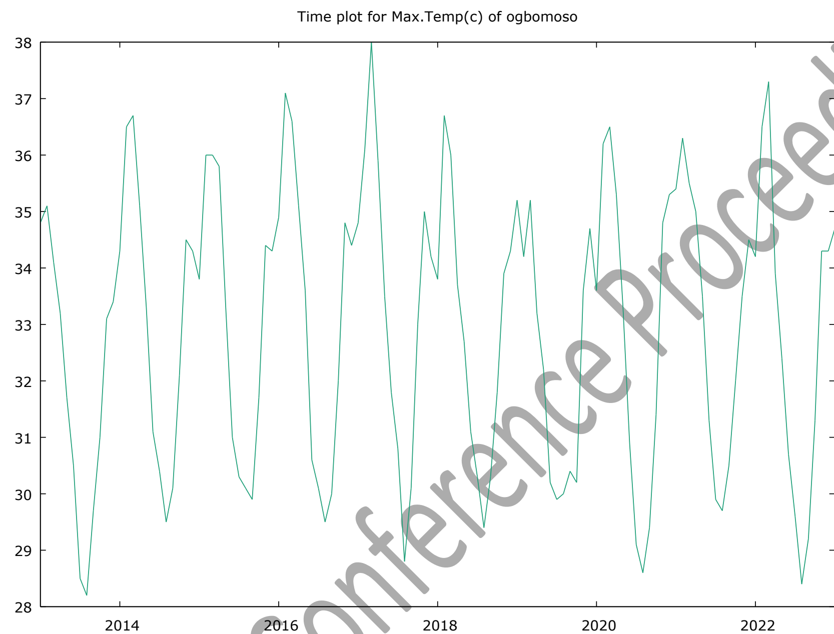

Figure 1: Time plot for Maximum Temperature (°C)

The time plot in Figure 1 shows a recurring pattern peaks and troughs. Although the series fluctuates, it exhibits a relatively stable mean with slight upward movement over time.

3.1 Stationarity Test for Maximum Temperature

The stationarity of the series was tested using the Augmented Dickey Fuller (ADF) Test

H_0: The series is not stationary.

H_1: The series is stationary.

Table 2: Stationarity Test Results for Maximum Temperature (°C)

	Intercept	Intercept and Trend
ADF	-3.17828	-3.47935
P-value	0.02131	0.04157

The Augmented Dickey-Fuller test statistic was -3.17828 (p = 0.02131) with an intercept, and -3.47935 (p = 0.04157) with Intercept and trend. Since the p-values are less than 0.05, the null hypothesis of non-stationarity is rejected. The series is therefore stationary at level.

3.2 Model Identification

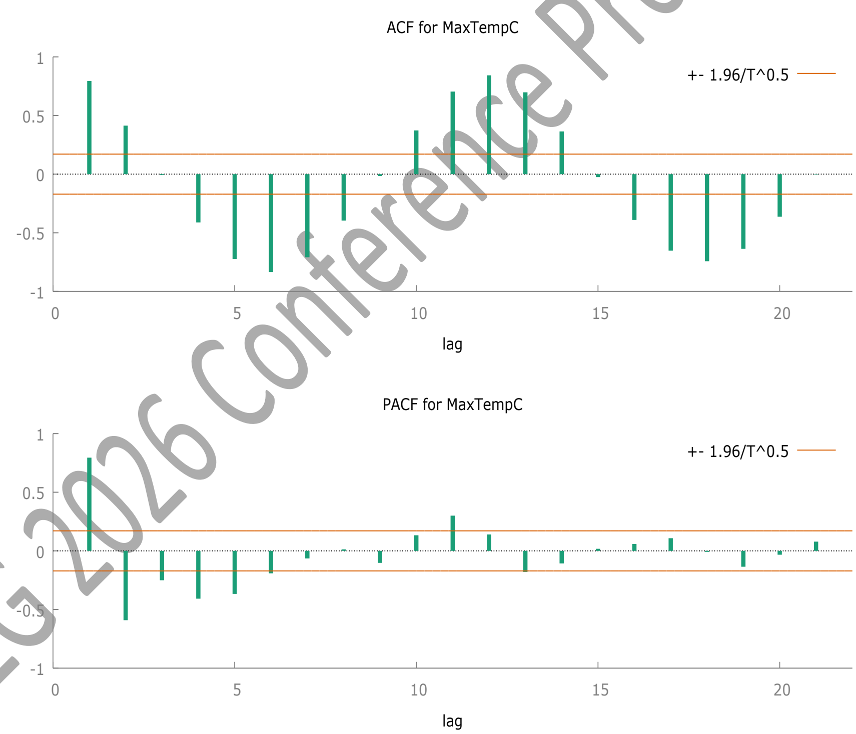

Figure 2: ACF and PACF Plots of Max.Temp (°C)

The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are typically used to guide model identification, though they do not directly determine the exact order of parameter estimates. From the ACF and PACF plot in Figure 2, an AR (2) process is initially suggested, as the ACF decay exponentially while the PACF cut off after lag 2.

Table 3: Parameter Estimates for ARMA Model

	Coefficient	std. error	z	p-value
Const	32.8968	0.0749	438.8	0.000***
β_1	1.16036	0.1357	1269	0.000***
β_2	−0.6057	0.1667	−3.635	0.0003***
β_5	−0.2773	0.1025	−2.705	0.0068***
θ_1	−0.4243	0.1249	−3.396	0.0007***
R-squared	0.858946	Adjusted R-squared	0.853349	

Noted that the order 3 and order 4 were removed because their coefficients were not statistically significant.

Although the ACF and PACF initially suggested an AR (2) structure, further model selection using information criteria (AIC, Hannan-Quinn) indicated that an ARMA (5,1) model provided a better fit.

The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Hannan-Quinn Criterion (HQC) were used to determine the best fitting model. Based on these criteria (AIC = 370.0678; HQC = 379.4393), the ARMA (5,1) model was selected as the preferred model. All retained parameters were statistically significant at conventional levels.

$$X_t = 32.8968 + 1.1604X_{t-1} - 0.6057X_{t-2} - 0.2773X_{t-5} - 0.4243\varepsilon_{t-1}$$

Table 4: Estimation of SARIMA Model

AR1	MA1	SAR1	SMA1
0.4230	0.0880	-0.1764	-0.9983
σ^2	Log-likelihood	AIC	HQC
0.3637	-184.52	379.04	384.67

The SARIMA $(1,0,1)(1,1,1)_{12}$ model yielded the lowest values based on the selected criteria (Hannan Quinn = 384.67; AIC = 379.04). Hence, the SARIMA $(1,0,1)(1,1,1)_{12}$ model was selected as the best fit for the data. The model is expressed as

$$(1 - 0.423L)(1 - 0.176L^{12})(1 - L^{12})X_t = (1 + 0.088L)(1 - 0.998L^{12})\varepsilon_t$$

3.3 Diagnostics Checking

Model diagnostic was conducted to assess the adequacy of the selected model. The following hypotheses were tested: is applied to the residual.

H_o: The residuals are not autocorrelated

H_1 : The residuals are autocorrelated

Table 5: Box-Ljung Results

Process	Box-Ljung test	Df	p-value
Max Temp	9.84	12	0.63

Table 5 shows a P-value greater than α = 0.05, indicating no significant autocorrelation in the residuals. Thus, the model adequately fits the data.

H_0: The residuals follow normal distribution

H_1**:** The residuals do not follow a normal distribution

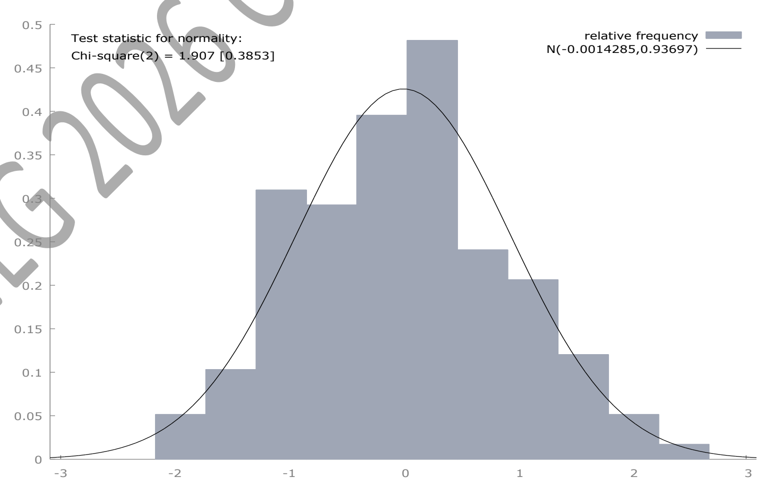

Figure 3: Residual Diagnostic of Maximum Temperature (°C)

The residual normality test yielded a chi-square value of 1.907 with p = 0.3853 at α = 0.05. Since the p-value exceeded 0.05, the null hypothesis that residuals followed a normal distribution cannot

not rejected. Therefore, the residuals are approximately normally distributed, indicating that the model is adequate for forecasting.

3.4 Forecast Evaluation

Once a model has been fitted, future values of the time series can be forecast. Table 6 shows the forecast of maximum temperature for the next three (3) years with the confidence interval of 95%.

Table 6: Forecast of Maximum Temperature (°C) for Three Years

For 95% confidence intervals, z(0.025) = 1.96			
Observations	Prediction	std. error	95% interval
2024:01	35.2185	0.911788	(33.4315, 37.0056)
2024:02	35.3644	1.13216	(33.1454, 37.5834)
2024:03	34.8951	1.15459	(32.6322, 37.1581)
2024:04	33.7095	1.15459	(31.4465, 35.9724)
2024:05	32.4119	1.15774	(30.1427, 34.6810)
2024:06	31.3714	1.21044	(28.9990, 33.7438)
2024:07	30.751	1.33256	(28.1392, 33.3627)
2024:08	30.6554	1.42636	(27.8598, 33.4510)
2024:09	31.1596	1.45812	(28.3018, 34.0175)
2024:10	32.1239	1.46068	(29.2610, 34.9868)
2024:11	33.2459	1.4667	(30.3712, 36.1206)
2024:12	34.2198	1.50612	(31.2678, 37.1717)
2025:01	34.8189	1.57519	(31.7316, 37.9062)
2025:02	34.9054	1.63481	(31.7012, 38.1095)
2025:03	34.4644	1.66178	(31.2074, 37.7214)
2025:04	33.6281	1.66461	(30.3655, 36.8906)
2025:05	32.6345	1.66897	(29.3634, 35.9057)
2025:06	31.7485	1.69655	(28.4233, 35.0736)
2025:07	31.1924	1.74384	(27.7745, 34.6102)
2025:08	31.098	1.78702	(27.5955, 34.6005)
2025:09	31.4747	1.80827	(27.9306, 35.0188)

2025:10	32.2074	1.81085	(28.6582, 35.7566)
2025:11	33.0917	1.81369	(29.5369, 36.6464)
2025:12	33.8922	1.83323	(30.2991, 37.4852)
2026:01	34.4048	1.86766	(30.7443, 38.0653)
2026:02	34.5072	1.90025	(30.7828, 38.2316)
2026:03	34.1875	1.91703	(30.4302, 37.9449)
2026:04	33.5445	1.91934	(29.7827, 37.3064)
2026:05	32.7573	1.92116	(28.9919, 36.5227)
2026:06	32.0354	1.93525	(28.2424, 35.8284)
2026:07	31.5639	1.96096	(27.7205, 35.4073)
2026:08	31.4559	1.98604	(27.5633, 35.3485)
2026:09	31.726	1.99945	(27.8072, 35.6449)
2026:10	32.2901	2.0015	(28.3672, 36.2130)
2026:11	32.9908	2.00266	(29.0657, 36.9159)
2026:12	33.6411	2.01295	(29.6958, 37.5864)

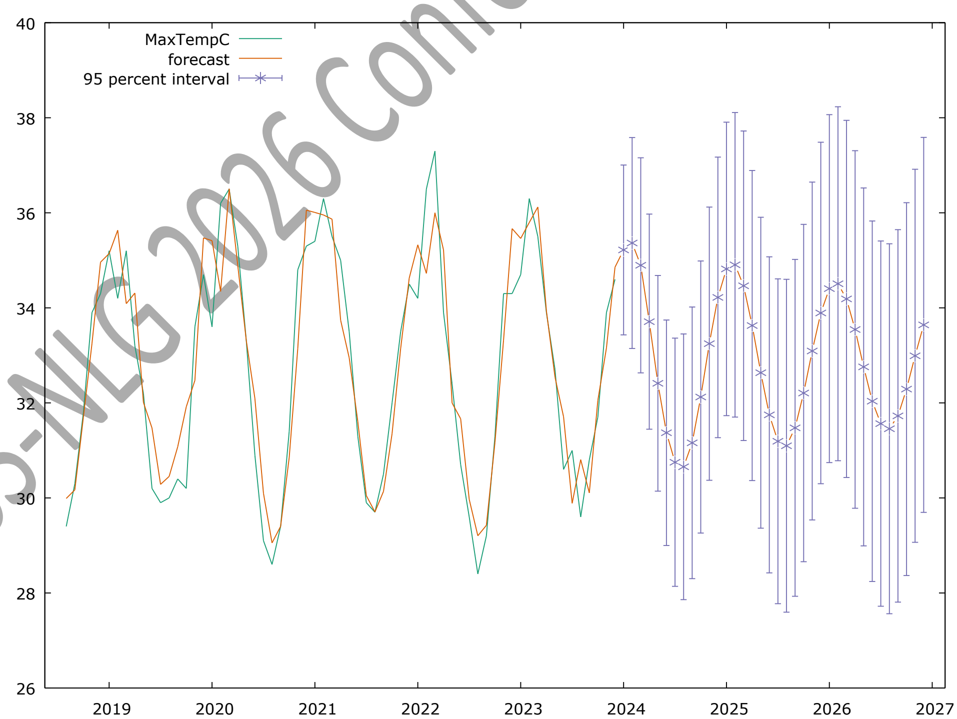

Figure 4: Forecast of Maximum Temperature (°C) for Three Years

The forecasts from January 2024 to December 2026 indicated continued fluctuations with a slight upward trend in maximum temperature. The shaded areas around the predicted values represent the 95% confidence intervals, indicating the range within which the actual temperature values is likely to fall, with 95% probability. The width of the intervals varies across months, with wider intervals indicating greater uncertainty in the forecast.

Conclusion

This study examined the monthly maximum temperature series for Ogbomoso, South-West Nigeria, over the period 2013-2023 using time series approach. The results from the Augmented Dickey-Fuller test confirmed that the series is stationary at the level. The time plot revealed recurring peaks and troughs, suggesting the presence of seasonal fluctuations alongside a mild upward trend. Based on the Box–Jenkins modelling framework and information criteria, the SARMA (1,0,1) $(1,1,1)_{12}$ model was selected as the most appropriate model for the data. Diagnostic checks further confirmed the adequacy of the model, as the residuals were normally distributed and free from significant autocorrelation. The forecast results for the period 2024–2026 indicate continued fluctuations in maximum temperature with a gradual upward movement, suggesting a potential warming pattern in the study area. This finding aligns with existing evidence on climate variability and rising temperatures across Nigeria.

The study provides localized empirical support for climate change trends and offers useful insights for environmental monitoring and policy planning. However, the relatively short data span may limit long-term generalization.

References

Abatan, A. A., Abiodun, B. J., Lawal, K. A., and Gutowski, W. J. (2015). Trends in extreme temperature over Nigeria from percentile-based threshold indices. *International Journal of Climatology, 36*(6), 2527–2540. https://doi.org/10.1002/joc.4510

Arowolo, O. T., Akinade, T. A., Ekum, M. I., Ogunsanya, A. S. and Oguntola, T. O. (2022). ARIMA Model and its Application to Budget Performance. Ilorin Journal of Science 9(1), 33 – 49.

Ayeni, O. D., and Oloukoi, G. (2022). Analysis of temperature trend as an indicator of climate change using Land Surface Temperature (LST) and meteorological data in Akure, southwest Nigeria. *Journal of Research in Forestry, Wildlife & Environment, 14*(3).

Box, G. E. P. and Jenkins, G. M. (1976). *Time Series Analysis, Forecasting and Control.* Revised Edition, Holden Day, San Francisco.

Emetere, M., Afolalu, S., and Peters, U. (2021). Evidence of climate change using seasonal temperatures over Agege-Lagos, Nigeria. *E3S Web of Conferences, 259*, 01005. https://doi.org/10.1051/e3sconf/202125901005

FAO. (2021). Climate change and food security in Africa: A review of the status, challenges and opportunities. Rome, Italy.

Girvetz, E. H., Zganjar, C., Raber, G. T., Maurer, E. P., Kareiva, P., and Lawler, J. J. (2009). Applied climate-change analysis: The climate wizard tool. *PLOS ONE*. https://doi.org/10.1371/journal.pone.0008320

IPCC (2018). Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. Transactions of the ASME-Journal of Basic Engineering, 82(Series D), 35-45.

Kolmogorov, A. N. (1939). On the Shannon theory of information transmission in continuous time. Izv. Acad. Sci. USSR, Ser. Math, 3, 3-14.

Kolmogorov, A. N. (1941). Local structure of turbulence in incompressible viscous fluid for very large Reynolds numbers. Dokl. Akad. Nauk SSSR, 30, 299-303.

Oguntola, T. O., Adesina O. A, Oke S. A., and Oladimeji L. A. (2024). Modelling the Accessibility to Electricity in Nigeria using Time Series Technique. *African Journal of Mathematics and Statistics Studies,* 7(2), 183-191. DOI:10.52589/AJMSSJYWHCHDQ.

Oluwatobi, A. (2016). Analysis of trend and variability of atmospheric temperature in Ijebu-Ode, Southwest Nigeria. *International Research Journal of Arts and Social Sciences, 6*(2).

Pavlasek, P., Merlone, A., Musacchio, C., Olsen, A. F., Bergerud, R. A., & Knazovicka, L. (2015). Effect of changes in temperature scales on historical temperature data. *International Journal of Climatology, 36*(2), 1005–1010. https://doi.org/10.1002/joc.4404

Whittle, P. (1983). Prediction and regulation by linear least-square methods. University of Cambridge, Statistical Laboratory.

Wisconsin Department of Natural Resources “Climate Change- The Science, Impact and Solutions” dnr.wisconsin.gov/climate change. Retrieved on April 24, 2024.