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## Predicting A Monotonic Trend of The Surface Air Temperature Using Generalized Additive Model (Gam) Over North-Eastern Region of Nigeria

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### Abstract

Given the growing global concern over climate change, understanding how temperature patterns evolve over time is increasingly important. Analyzing long-term temperature data can provide valuable insights into these trends, helping researchers and policymakers assess climatic shifts and their potential impacts. Monthly temperature records spanning several decades offer a robust foundation for identifying such patterns, revealing both seasonal fluctuations and broader climatic trends. Traditionally, linear regression models have been widely employed to analyze temperature data due to their simplicity and interpretability. While these models can effectively capture annual temperature variations, they have significant limitations in representing long-term trends, especially when those trends are non-linear. Climate systems often exhibit complex, non-stationary behavior that linear models fail to adequately capture, necessitating more flexible modeling approaches. Generalized Additive Models (GAMs) provide a powerful alternative by fitting smooth, non-linear functions to the data, allowing for a more nuanced representation of temperature patterns. Unlike rigid linear assumptions, GAMs adapt to the underlying structure of the data, making them particularly useful for detecting seasonal variations and gradual climatic shifts over extended periods. This study explores how GAMs can enhance the modeling of temperature trends by applying them to a 41-year dataset (1981-2022) obtained from the Nigerian Meteorological Agency (NiMet). The analysis demonstrates that GAMs offer superior flexibility in capturing both seasonal cycles and long-term warming trends. Graphical representations of smoothed model estimates reveal a clear rise in regional temperatures over the past four decades, aligning with broader observations of global warming. While GAMs are highly effective in identifying non-linear relationships, their performance depends on the careful selection of smoothing functions. The choice of basis functions and smoothing parameters must align with both the data characteristics and the modeling objectives to ensure accurate and interpretable results. By leveraging GAMs, this study underscores their utility in climate research, providing a more refined tool for analyzing temperature trends in a warming world.

### Keywords

Monthly mean temperature, Generalized Additive Models (GAMs), Generalized linear models (GLMs), Long-term trend, Non-linear effects, Climate change.

## 1. INTRODUCTION

A sequence of observations taken one after the other over an extended period of time is called a time series (Pole et al., 2018). This statistical series shows how the data have behaved historically, currently, and perhaps in the future. All it is, in essence, a technique that forecasts values in the future  $y_{t+1}$  using observable information from the past  $y_{t-1}$ , present  $y_t$ , and one time lag  $t_1$  (Bauer et al., 2020). The values of a variable  $Y$  (temperature) at times  $t_1, t_2, t_3$ , mathematically describe a time series. As a result,  $Y = F(t)$  indicates that  $Y$  is a function of  $t$  (Seydel, 2010).

The topic of discussion at the worldwide conference is climate change. In all countries across the world, governments and environmental non-governmental organizations consider them to be among the primary threats concerning their potential long-term effects on sustainable economic growth (Starikova & Shamanina, 2021). Understanding climate variability is crucial in the modern world. The Earth's climate is shifting, resulting in a rise in extreme weather phenomena such as droughts, floods, and unusually high or low temperatures (Lopes et al., 2014).

Surface air temperature analysis is a crucial topic that can aid in our understanding of climatic variability (Rahman & Lateh, 2015). With this understanding, proactive measures for

preventing and mitigating the anticipated harmful effects of global warming and the temperature effect on people, animals, and plants can be developed (Katopodis & Sfetsos, 2019; Nath & Behera, 2010).

## 2. LITERATURE REVIEW

Various approaches have been utilized in the examination of temperature time-series, such as: Alkasim et al., (2018) calculate the land surface temperature using the Landsat-7 ETM+ satellite image in Yola, North Eastern Nigeria, Mushore et al., (2017) use cellular automata Markov chain analysis to predict future changes in land surface temperature, land use, and land cover in order to ascertain how urban growth would affect Harare's future microclimate. Tyoh et al., (2021) used estimates of heat flows to investigate subsurface geothermal gradients in relation to the near-surface air temperature, and Ofure et al., (2021) used geothermal gradients in the Bornu-Chad Basin to predict the air temperature throughout Nigeria by using an artificial neural network and downscaling to the outputs from the Doubled CO2 scenario.

Similarly, To statistically calibrate surface air temperature estimates for East Asia, Lyu et al. (2021) used pattern projection techniques. The Ashanti area of Ghana's monthly mean surface air temperature was predicted by Asamoah-Boaheng, (2014) using the SARIMA model.

In their study, Pan et al. (2012) employed WRF to dynamically downscale near-surface air temperature at the basin scale, utilizing the Chinese Heihe River Basin as a case study. The predictions of air temperature using machine learning techniques are examined by Cifuentes et al. (2020). The Sylhet district's surface air temperature trend was established by Ishaque et al. (2021), The trend analysis was done using Sen's slope estimator and the Mann-Kendall trend test.

Moreover, Zhu et al., (2021) applied Sub-Seasonal Surface Air Temperature Forecasting using Super ensemble Methods: Pilot Studies across Northeast Asia in 2018. Tran et al., (2021) reviewed Neural Networks for Air Temperature Forecasting. Araghi et al., (2017) Forecasted soil temperature based on surface air temperature using a wavelet artificial neural network. Ustaoglu et al., (2008) applied three artificial neural network techniques to forecast the daily mean, maximum, and minimum temperature time series. Kim & Suh, (2013) explored the possibility of calibrating one-month surface air temperature forecasts for South Korea using Bayesian model averaging.

Drawing from existing work, the authors concentrate on multiple methods for identifying patterns in time series data. Nevertheless, there hasn't been any

research done in the literature on the North-Eastern Region of Nigeria on using the Generalized Additive Model (GAM) to find a monotonic trend for the annual mean temperature. Applying and evaluating the models' performance in the research field is the goal of this study.

The aim of this study was to explore the rise in local temperature over the North Eastern Region of Nigeria using the Generalized Additive Model (GAM) and recommend preventive actions for the food industry, tourism, and other sectors.

### 3. METHODOLOGY

Time series prediction can be an efficient method for forecasting temperature datasets. The atmosphere's average worldwide temperature is rising (Moazami et al., 2019). Thus, for the following regions it covered, temperature prediction could be aided by the time series prediction model developed by this research:

#### 3.1 Generalized Additive Models (GAM)

The statistical community has been using a novel class of models called Generalized Additive Models (GAM) to model observable data (T. Hastie & Tibshirani, 1990; Li, Lord, & Zhang, 2010). The Generalized Analytical Model (GAM) is a linear predictor that involves the sum of smooth functions of variables (McKeown &

Sneddon, 2014). *GAMs* are essentially a class of statistical models that model and capture the non-linearity in the data by substituting multiple non-linear smooth functions for the typical linear relationship between the response and the predictors. (Ankinakatte, Norberg, Løvendahl, Edwards, & Højsgaard, 2013).

A way to expand the generalized linear model is through the use of generalized additive models, or *GAMs* (T. Hastie &

$$g(\mu) = \beta_0 + s_1(x_1) + s_2(x_2) + \dots + s_k(x_k),$$

Where  $g(\mu)$  is the link function,  $\beta_0$  is a constant,  $s_k$  is the smoothing parameter to be estimated, and  $x_k$  is the explanatory variable.

Relapse techniques that are nonlinear and smoothing, like *GAM*, rely on information rather than constraining the reaction state to a certain parametric framework. Selecting a proper degree of smoothing by restricting the degrees of freedom is a crucial step in fitting a *GAM*, as it allows for accurate capture of data volatility without running the risk of overfitting. *GAM's* intention to restrict the total cross-validation model (T. J. Hastie, 2017).

Tibshirani, 1990). It is possible to incorporate smooth terms in *GAMs* that are functions of the input variables. As a result, the linear predictor is the total of the input variables' smooth functions. (Ankinakatte S. et al., 2013). Due to their great flexibility, generalized additive models can fit well when there is substantial noise in the predictor variables and nonlinear interactions. *GAMs* possess the structure (T. J. Hastie, 2017; T. Hastie & Tibshirani, 1990).

(1)

Because *GAMs* are so flexible, it follows that the appropriateness work's state is highly sensitive to the opportunities used for the smoothing capacity. In particular, one needs to be careful not to overfit the data; while a complicated model with lots of degrees of freedom will fit the data well, it is unlikely to have strong predictive power in post-approval evaluations (T. J. Hastie, 2017).

## 4. RESULT

### 4.1. Descriptive Statistics of the Temperature Series.

Descriptive statistics of the monthly mean temperature series of the North-Eastern Region of Nigeria	
Mean	31.09225
Median	31.70000
Mode	35.70000
Maximum	38.70000
Minimum	22.70000
Std. Dev.	0.194479
Skewness	- 0.13348
Kurtosis	- 1.31176
Sum	15639.4
Sample Variance	19.02446
Observations	503
Confidence Level (95.0%)	0.382093

For the northeastern Nigerian region under consideration in this study, Table 1 showed the descriptive statistics of the monthly mean temperature series. The area has a tiny standard deviation of 0.194479 and a mean temperature of 31.09225 °C, which suggested that there was less variability and that the data points are generally close to the mean. Temperatures throughout the distribution range from a minimum of 22.70 °C to a maximum of 38.70 °C. The distribution is skewed to the left, with a value of -

0.13348 for Skewness and -1.31176 for kurtosis, suggesting that the distribution was less peaked and has thinner tails than a normal distribution and that the data was more dispersed toward the lower end of the scale. This suggested that compared to a regularly distributed distribution, the data has fewer extreme values, or outliers. As such, the distribution was platykurtic and asymmetric.

Figure 1 showed a visualization of the temperature series' histogram and a

normalcy test. The distribution appears to be less peaked and have shorter tails than a normal distribution, according to the figure, which suggested that there are less extreme values (outliers) in the data than in a normal distribution. The behaviour of the temperature series is depicted in the scatterplot of the temperature series in Figure 2. Because

outliers have the potential to skew and distort the patterns and relationships within the data, their presence in the series indicates that it is non-linear and affects predicting accuracy. Thus, managing outliers is usually advised before to undertaking a forecasting analysis, which is one of the study's goals.

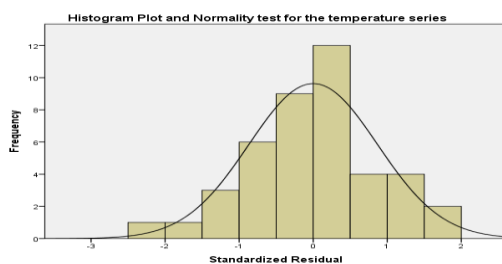


Figure 1: Histogram plot and normality test for the temperature series

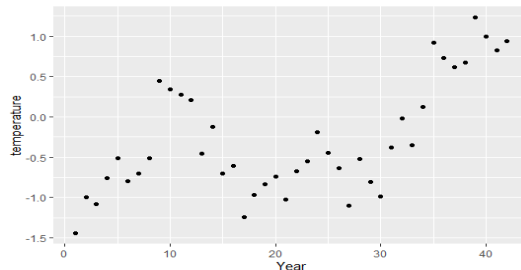


Figure 2: Scatter plot of the annual north-eastern temperature series

The series' plot in Figure 3 displays a random walk, which denotes data cycles, as well as a pattern of seasonality at the level of the series. To comprehend the long-

term behavior of the variable, it is crucial to validate seasonality and determine whether the data show an overall trend over time.

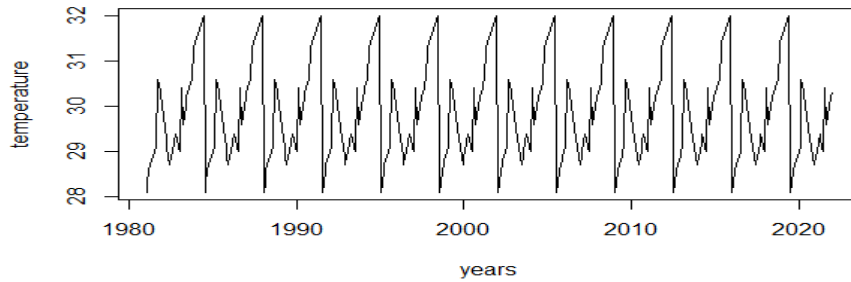


Figure 3: Time Plot for the Mean Monthly Temperature Data.

As indicated in Figure 4, we first look into confirming the serial correlation of the monthly mean temperature data before applying the *Generalized Additive Model (GAM)* to the time series of the data.

With the aid of R programming software, a generalized additive model was utilized to take into consideration the serial correlation seen in the monthly mean temperature data in this study.

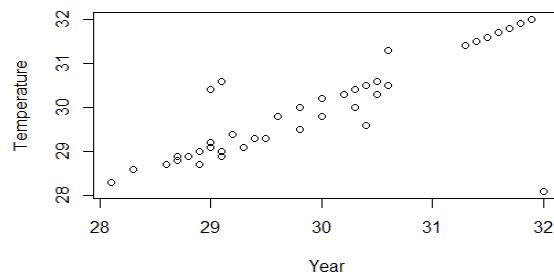


Figure 4: Scatter plot of the serial correlation of the temperature series

The link between the variables is shown in Figure 4's scatter plot. Since both variables' values rise simultaneously, the figure demonstrates a positive correlation. From left to right, the points create an upward-sloping pattern. Furthermore, the plot indicates a high correlation by presenting both the correlation's direction and intensity.

In Figures 4 and 5, we plot residual ACF and PACF, respectively, to validate seasonality, cyclicity, and trend in the series data. The time series' temporal structure was precisely captured using the ACF and PACF plots, which enhances forecasting precision.

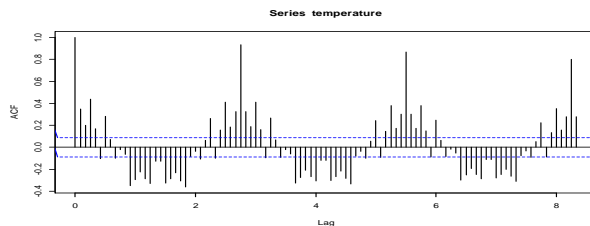


Figure 5: Residual ACF Plot

Figure 5 displayed the plot of the residual ACF, which accounts for the seasonal components, along with correlation coefficients at different lags. Significant spikes are usually visible at the seasonal

lags in this plot; the fact that the significant spikes appear at lag 12 suggested that the pattern is seasonal with an annual cycle.

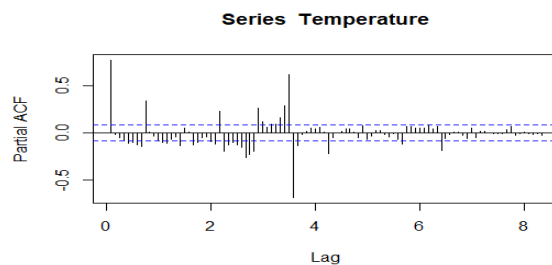


Figure 6: Residual PACF Plot

A partial correlation coefficient at different lags, controlling the intermediate lags, including the seasonal lags, was displayed in the plot of the residual PACF in Figure 6. This suggested that partial autocorrelation and seasonal autocorrelation are present.

Significant correlations were seen in the plots of the ACF and PACF in Figures 5 and 6, respectively, indicating that the time series data was non-stationary and that the seasonal influence must be removed in

order to achieve stationarity. A thorough comprehension of seasonality may not be possible from the plot of the ACF and PACF with seasonal effects alone. It could take further research and analysis with a generalized additive model to properly identify and represent the seasonal component.

Generalized additive models (GAMs) have the potential to eliminate autocorrelation and minimize its effect on time series data, which can enhance the test for



series that exhibit it. By fitting a GAM model with terms for seasonal patterns, this can be accomplished. The residual signal can then be examined for trends or other interesting patterns after this

seasonal pattern has been modelled and eliminated (Morton & Henderson, 2008). As seen in Figure 7, we attempt to fit the normal linear model before fitting the GAM model.

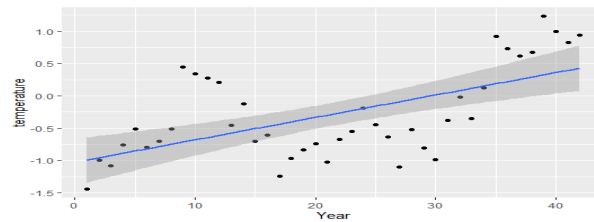


Figure 7: Time plot of the fitted normal linear model

It is evident from the graphic in Figure 7 that a nonlinear relationship in the time series may not fit well into a conventional linear model. The coefficients might not, however, correctly reflect the actual relationship between the predictors and the response in the case of nonlinear series. Additionally, the residuals might

show a pattern or departure from randomness, indicating that the nonlinear relationship and the entire variability explained by the nonlinear component are not well captured by the linear model. We examine the residual plot in Figure 8 to make sure.

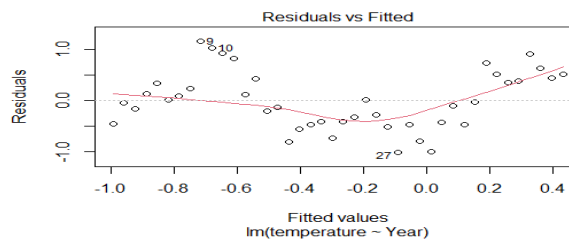


Figure 8: Residual plot of the fitted values of the temperature series

Figure 8 illustrated how the residuals are not dispersed equally among temperature series values. The graphic indicated that the linear model was not fully capturing

the nonlinear connection between the predictors and the response because the residuals consistently deviate from zero in particular directions or within particular

ranges of fitted values. Furthermore, there is a distinct pattern or systematic link between the residuals and the fitted values rather than a random scatter, which suggested that the linear model is inadequate in capturing the nonlinear relationship.

The residuals showed a nonlinear trend or curved pattern, indicating that the linear model is not the best match for the data. There are certain data points that drastically deviate from the residuals' predicted range. These anomalies could hint to significant findings or data points that the linear model does not well fit. Outliers in the residuals plot may indicate that the linear model was unable to appropriately reflect the variability of the response across the predictor values or to capture extreme observations in the setting of nonlinear data. Furthermore, there appears to have been a breach of

the independence assumption since the linear model was unable to fully represent the connected structure in the data.

As a result, this research suggested utilizing a generalized additive model as opposed to a normal linear model. The model may be fitted more precisely and the nonlinear patterns in the data are better captured. In order to improve the model, we look at how `gam()` describes the additional material model as a blended effects model because of the significant equality between splines and subjective impacts, as well as how `lme` fits the model(). This considered the relational frameworks of the residuals. In order to model and capture the nonlinear relationship and lessen the impact of outliers in the dataset, we first extract the fitted values from the time series data.

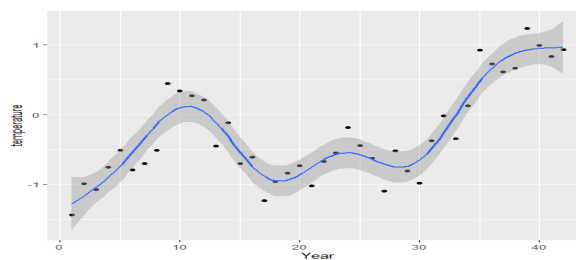


Figure 9: Plot of the fitted values of the temperature series using `mgcv` package

Time series data can be made less affected by outliers by using *GAM* to capture the nonlinearity present in the data, as shown in Figure 9. When analyzed

in conjunction with additional diagnostic tools, including extra residual diagnostics, the plot revealed that the model suited the data more accurately.

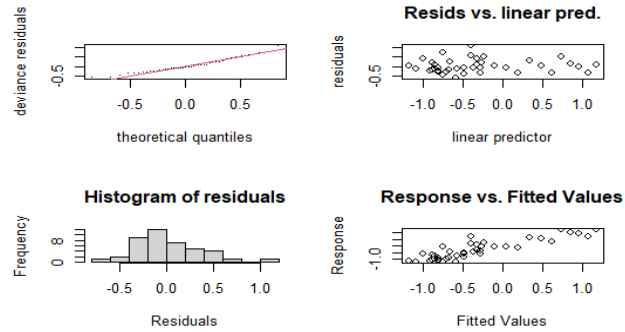


Figure 10: Residuals Diagnostics checks of the fitted values

Table 2: Approximate significance of smooth terms:

	Estimate	R-sq.(adj)	Standard error	T value	p-value
Intercep	-0.31709	0.739	0.05767	-5.498	3.29e-06 ***
†					

Deviance explained = 89%, n = 42

In this study, a diagnostic residual plot was used to evaluate the *GAM* model's performance and determine how well the model fit the data. To look for consistent departures from the *GAM*'s premise, we analyzed the model residuals' trends.

Since there was no discernible pattern surrounding the zero line, the random scatter points in the residuals and the linear predictor indicated that the model effectively captured the variability in the data (Li et al., 2010). The absence of any curved pattern in the residuals' form with respect to the fitted values suggested that the model accurately represented the nonlinear connection. The majority of the outliers are well contained within the residuals' predicted range. The residual

plot's histogram showed that the data are independent and regularly distributed. This suggested that the dataset meets the requirement for errors to be regularly distributed.

The significance of the smooth term and any parametric terms, as well as the variance explained, are provided by using a summary with the model object, as indicated in Table 2.

According to Table 2, the p-value was  $3.29e-06 < 0.05$ . It implied that there is overwhelming evidence to refute the null hypothesis. This suggests that the smooth term is statistically significant and that the model fits the data better when the nonlinearity and flexibility it reflects are

incorporated. This implied that the smooth term's addition to the *GAM* greatly enhances the model's fit to the data and captures a strong nonlinear link between the response and the predictor variable that the smooth term represents. To guarantee the proper interpretation and application of the *GAM* results, this study took into account the relevance of a

smooth term in conjunction with other relevant data, such as the diagnostic measures and the overall goodness-of-fit of the model.

First we extract the set of *basis functions* (that is, the  $b_j(x_j)$  part of the smooth term). Then we plot the first and second basis functions as shown in figure 10.

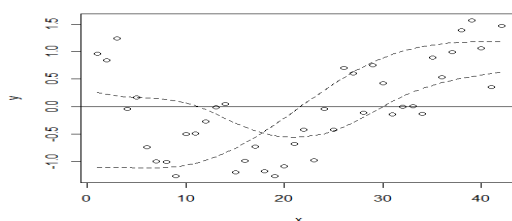


Figure 11: Plot of the first and second basis functions

Visualizing the nonlinear relationship that the *GAM* is recording is made possible by plotting the first and second basis functions. We can gain insight into how the basis functions affect the response variable in the model by using it to determine the basis functions' smoothness and form. An intricate and nonlinear relationship is represented by the basis function. Because there are fewer sharp shifts or oscillations in the plot, the basis function appears to be smoother and the function changes more smoothly and gradually.

Through the use of *GAMs*, this study offers a more thorough examination of

time series data by identifying trends and describing their characteristics. The relationship between the predictor variable and the response is directly revealed by the plot of all the basis functions in Figure 11, which also identifies the existence of a trend. It is vital to evaluate the basis function's contribution within the framework of the entire model, taking into consideration additional variables and any interactions, in order to completely comprehend its effect. As a result, we plot each basis function as it is displayed in Figure 11 and then include it in the forecasts.

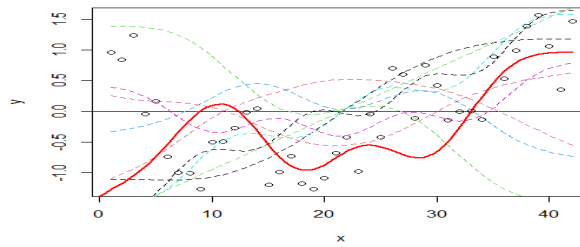


Figure 12: basis functions and prediction plot

GAM calculated a coefficient ( $\beta_j$ ) for each of the dotted lines ( $b_j$ ) in Figure 12, and the sum indicated the contribution for the relevant function  $f(x)$ . Because we just

model temperature ( $y$ ) as a function of the smooth term, it's nice and straightforward for this study and pretty applicable.

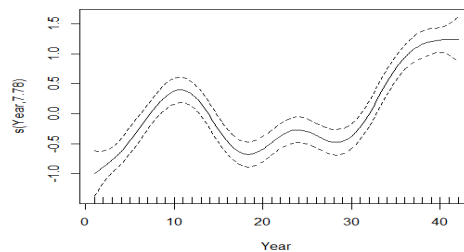


Figure 12: the smooth terms plot

Figure 12 displayed a rather good fit. The generalized additive model's (GAM) smoothing function makes the data appear smoother by lowering noise in the data. The model's ability to capture the nonlinear interactions between variables is demonstrated by the predicted values obtained by GAM on the {gam} data. The

figure displays the observed data points in addition to the anticipated values derived from the GAM model. It illustrates how well the model matches the observed data and provides insights into the overall trend and pattern in the data. As demonstrated in Figure 13, we employ the basis functions and the estimated coefficients for the fitted smooth term to demonstrate that.

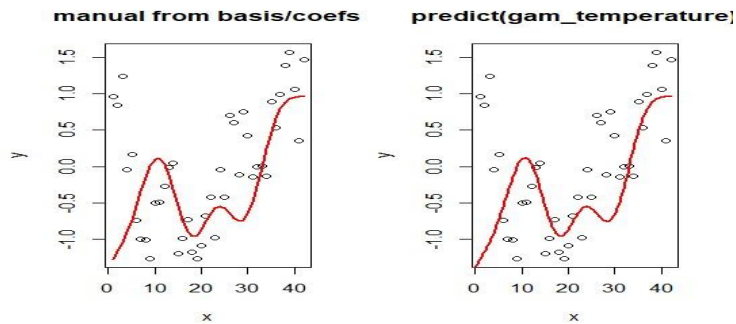


Figure 13: Basis functions and the estimated coefficients to the fitted smooth term plot

Once the smooth term has been taken into consideration, the fitted smooth term plot demonstrates a strong correlation between the response variable and the predictor variable(s). After combining the basis functions with the appropriate estimated coefficients, it presents the

estimated smooth curve. A deeper comprehension of the data is made possible by the plot, which sheds light on the non-linear relationship between the predictors and the response. It may also highlight significant patterns and trends.

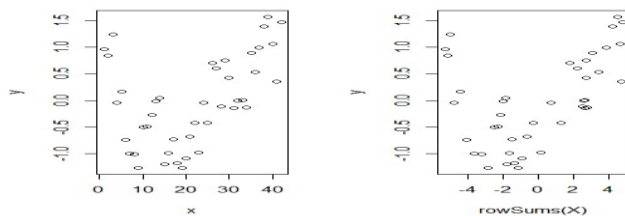


Figure 14: A rowsums plot

A rowsums plot was employed in this study to provide a graphical depiction of each predictor variable's contribution to the smooth term in the model. When all other factors are held constant, it shows the distinct impact of each predictor variable on the response variable. Understanding the general pattern and the connections between each predictor variable and the

response variable is possible with the help of the rowsums plot. It enables us to observe how each predictor variable's variation affects the smooth term. Every predictor variable in the graphic is shown on the x-axis. Each predictor's contribution to the smooth term is shown on the y-axis.

## 5. CONCLUSION

In this study, trends were identified and evaluated across time using the Generalized Additive Models (GAM). To ascertain whether there is a noteworthy increasing or declining trend, it examines the ranks of data over several time periods. But generalized additive models tell us something about the trend's size or form.

In contrast, the study employed generalized additive models (GAM), which are adaptable regression frameworks, to describe non-linear patterns in the temperature data of the northeastern Nigerian region. GAMs provided estimates of trends, confidence intervals, and other model diagnostics in the study and were utilized to represent complex interactions between the response variable and predictor factors.

These results appear to have some business implications and can be applied to real-world data. By offering an automated forecasting method to lower temperature prediction errors, this work advances the discipline.

Based on the whole time series' prediction results, a number of issues have been identified. Specifically, when the time series is overfitted, the approach breaks down. Because of this requirement, the model is unable to precisely match the time series' unanticipated turning points. The results suggest that the novel

approaches based on Generalized Additive Models are practical, suitable, and reliable methods for estimating the average temperature.

In order to address the issue of overfitting in time series analysis, this paper concludes by suggesting possible extensions or modifications of the generalized additive models, such as hybrid techniques.

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