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RESEARCH ARTICLE

DESCRIBING LONG-TERM TRENDS IN TEMPERATURE OF JOS REGION OF NIGERIA, USING GENERALIZED ADDITIVE MODELS (GAMS)

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ABSTRACT

Descriptions of how temperature patterns change through time can be relevant in light of the present worry about climate change. These trends can be deduced from monthly temperature data collected over the past few decades. To model temperature patterns, generalized linear models are frequently utilized. These models can represent temperature variations over the course of a year, but they have limitations when it comes to predicting long-term trends, especially when they are non-linear. By fitting smooth functions to the data, generalized additive models (GAMs) provide a framework for modeling non-linear connections. Using data from the Department of Meteorology and Climatology University of Jos from January 1986 to December 2023, this research illustrates how GAMs can enhance the flexibility of models to reflect seasonal patterns and long-term trends in temperature. Smoothed model estimations provide useful graphical depictions of a rise in temperature patterns at this area during the previous 38 years. GAMs are very useful for looking for non-linear correlations in data. Smooth functions must be chosen with care to ensure that they are appropriate for the data and modeling goals.

KEYWORDS

Monthly temperature, generalized additive models (GAMs), Generalized linear models (GLMs), Long-term trend, Non-linear effects, Climate change.

1. INTRODUCTION

Being able to express seasonal temperature trends over a lengthy period of time rather than just the average pattern is necessary when discussing climate change (Moazami et al., 2019). Time series are normally ordered chronologically, or in terms of some equally spaced time intervals (John et al., 2010). Temperature is an example of a daily, monthly, and annual time series (Adnan and Layla, 2019). Temperature data is one of the many areas where time series is utilized to observe, analyze, and anticipate the future using various models.

Climate change is one of the most serious environmental hazards to food production, water availability, forest biodiversity, and livelihoods in many countries throughout the world (Jui and WenChun, 2011). It is critical to understand climate variability in today's world. The Earth's climate is changing, and extreme weather events such as floods, droughts, and unusual temperatures are becoming more often. The average temperature of the Earth's surface has risen by around 0.8 degrees Celsius since the early twentieth century, and several climate model estimates suggest that the average temperature will rise by between 1.1 and 6.4 degrees Celsius this century (Antonio et al., 2013).

The study of mean monthly temperature time series is a crucial topic that can aid in our knowledge of climatic variability (Wenbiao et al., 2007). This information can be utilized to design proactive efforts for both preventing and mitigating the projected harmful effects of global warming (Antonio et al., 2013; Wenbiao et al., 2007). Climate change has an impact on food production in particular. This is due to the fact that crop yields are directly influenced by factors such as wing speed, temperature, and rainfall patterns. Even slight increases in temperature in tropical places will reduce the number of crops harvested. Higher temperatures will result in significant decreases in crop production. (Example rice, wheat,) production around the world (Ahmad et al., 2015).

In the study of temperature time-series, several methodologies have been used, including: They apply well-established methods like generalized additive models and MaxEnt, along with others that have gained attention more recently, such as regularized regressions, point-process weighted regressions, random forests, XGBoost, support vector machines, and the ensemble modeling framework, to reanalyse the same data set (225 species from six different regions) and explore patterns in predictive performance across methods (Valavi et al., 2022). Applied the Multidimensional scaling (MDS) approach to investigate the complex correlations between global temperature time series (Adnan et al., 2019).

Similarly, in this work, research gaps were identified and the various machine learning algorithms for temperature forecasting that are currently being used in the literature were reviewed (Cifuentes et al., 2020). This study demonstrates how machine learning methods may be used to reliably predict temperatures using a collection of input features, such as historical temperature, relative humidity, sun radiation, rain, and wind speed readings, among others (Wenbiao et al., 2007). Used time series Poisson regression and seasonal auto-regression integrated moving average (SARIMA) models to examine the potential impact of weather variability on the transmission of cryptosporidiosis.

In order to anticipate future monthly temperatures, the majority of the authors use the time series SARIMA Model (Manon et al., 2006). As a result, temperature data contains nonlinearities, and real-world situations are often complicated and nonlinear (Gruss et al., 2017). If the time series exhibits nonlinear behavior, standard methods may be inadequate. As a result of global warming, the temperature fluctuates (King, 2019). Several

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alternative strategies for nonlinear models have been developed to address the problem of nonlinearity, such as GAMs, ANNs, Big data, and Open data, among others, where Generalized Additive Models are used. (GAMs) have become one of the most significant methods because they are extremely versatile and may deliver outstanding results even when nonlinear interactions are present.

GAMs models may approximate a nonlinear mapping of any complexity and without prior knowledge of problem solution, making them appealing for predicting applications (Gruss et al., 2017). Classical prediction models have been extensively compared to Generalized Additive Models. In their respective applications, several writers concur on the superior performance of GAMs over standard linear models (Underwood, 2008). The methodology for estimating linear and nonlinear relationships was investigated in this study, and a framework for measuring nonlinear change was devised. Finally, a case study regional analysis of linear and nonlinear change was performed to demonstrate how the methodology might be used to investigate temperature increases.

2. Literature Review

In a semi-arid area of north-eastern South Africa, this study tried to predict when there will be a drought (Fhumulani et al., 2020). The study's findings showed how effective GAMs are at forecasting short- and medium-term droughts. Use Generalized Additive Models (GAM) to examine the global impact of local climatic conditions on the leatherback turtle hatchling output and to investigate the non-linear link between local cli-mates and hatching success and emergence rate (Vincent et al., 2015). In this study, tweedie's generalized additive model (GAM) was used to develop a climate-niche species distribution model to quantify the correlations between scallop abundance and important environmental factors and assess spatiotemporal changes in Atlantic sea scallop in the Gulf of Maine's coastal waters (Michael et al., 2019).

For the purpose of simulating the particle number concentration (PNC) of outdoor, airborne ultrafine particles in Helsinki, Finland, Generalized Linear Model (GLM) and Generalized Additive Model (GAM) were compared (Clifford et al., 2011). They look at the temporal trends in PNC and the connections between it and factors including precipitation, wind direction and speed, humidity, temperature, and sun insolation. The Akaike Information Criterion (AIC) is used to select the model. When fitting models with the same covariates and equivalent degrees of freedom, they have demonstrated that the Generalized Additive Model (GAM) offers a better fit than the corresponding Generalized Linear Model (GLM).

A group researchers built and validated a generalized additive model (GAM) for forecasting wheat output using a sizable yield data set gathered from experiments on regularly planted types in Western Australia (Kefei et al., 2019). Using demersal trawl survey data and geographic (latitude and longitude) and environmental (depth, temperature, bottom dissolved oxygen, and sediment type) features, delta generalized additive models (GAMs) were developed to predict the spatial distribution of different size classes of South African hakes, Merluccius capensis and M. paradoxus (Gruss et al., 2016).

A group researchers compared the three techniques for spatial prediction: residual kriging (GK), generalized additive models (GAM), and kriging with external drift (KED) (Juha et al., 2012). The bias and normalcy of the prediction error are now described by statistical key values that are now included with every interpolation file. The cross-validation findings indicated that GAM was the most accurate method for predicting mean temperatures, with only very minor variations when compared to the other methods. KED and GK produced the most accurate forecasts for mean precipitation, respectively (Michael and Cameron, 2013). In this study, a generalized additive modeling (GAM) approach is utilized to explain the abundance of 40 species groupings (i.e., functional groups) over the Gulf of Mexico (GoM) utilizing a large fisheries independent data set (SEAMAP) and climatic scale oceanographic variables. A group researchers applied Generalized Additive Model to describe the estimated relationship between Melbourne, Australia's local-scale weather and daily air pollutant concentrations (John et al., 2010).

Used the generalized additive model (GAM) framework, the links between meteorology and pollution have been evaluated after accounting for seasonality, long-term trends, weekly emissions, regional variation, and temporal persistence (Pearce et al., 2011). Uses data from Mauritius from 1962 to 2001 to explain how GAMs can increase the flexibility of models to predict seasonal patterns and long-term trends in the occurrence and intensity of daily rainfall (Underwood and Fiona, 2009). Estimate the contributions of automobiles to pollution levels close to roadways using time-series and simulation models (Kai and Batterman, 2010). Generalized additive models (GAMs) were employed in the time-series model to match the pollutant measurements to traffic counts and weather factors.

3. Methodology

3.1 Generalized Additive Models (GAM)

GAMs are a novel form of model for modeling observed data that has recently been introduced into the statistical field (Xiugang, 2010; Hastie and Tibshirani, 1990). A model that makes use of a linear predictor and the accumulation of smooth covariate functions is known as a generalized linear model (GLM) (Raul et al., 2012). GAMs are essentially a category of statistical models where several non-linear smooth functions are used to simulate and capture the non-linearity in the data instead of the more typical linear relationship between the response and the predictors (Roel et al., 2014). These are also a flexible and smooth strategy that aids in the fitting of linear models that can be either linear or non-linearly reliant on numerous predictors xi to capture non-linear relationships between response and predictors (Simon et al., 2017).

GAMs (Generalized Additive Models) are a way of extending the generalized linear model (GLM) (Hastie and Tibshirani, 1990). Smooth terms that are functions of the input variables are possible to incorporate in GAMs. As a result, the linear predictor is the sum of smooth input variable functions (Ankinakatte et al., 2013). In the presence of nonlinear interactions and significant noise in the predictor variables, Generalized Additive Models are quite flexible and can produce an outstanding match (Anish, 2017). GAMs have the form (Hastie and Tibshirani, 1990; Juha et al., 2012).

$$g(\mu) = \beta_0 + s_1(x_1) + s_2(x_2) + \ldots + s_k(x_k), \qquad (1)$$

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

Information-driven nonlinear and smoothing relapse techniques, such as GAM, do not confine the state of the reaction to any parametric framework. When fitting GAM, one of the most critical steps is to determine an appropriate level of smoothing by limiting the degrees of freedom; this allows the variation in the data to be accurately recorded while reducing the risk of overfitting (Juha et al., 2012). GAM intends to keep the total cross-approval model to a minimum (Simon et al., 2017).

$$〚nD/(n - DoF)〛^2 \qquad (2)$$

Where D is the deviation, n is the number of data points, and DoF is the effective degrees of freedom in the model. Because of GAMs' adaptability, the state of appropriateness work is particularly sensitive to the degrees of opportunity used for smoothing capability. Specifically, one must be aware of the dangers of overfitting information; Although a sophisticated model with numerous degrees of freedom will produce a strong fit to the data, it is unlikely to have great predictive power in aftereffect approval tests (Hastie and Tibshirani, 1990; Davey et al., 2007).

4. Result

In this study, R software was used to create an algorithm based on the GAMs model. The link between the covariates and the reaction variable was unknown, at least to the maker, prior to fitting. One argument for the use of GAMs is that they give a straightforward tool for inspecting these relationships. The graphs in figure 1 could be utilized to offer a realistic framework for the variables. The nonlinear (and linear) correlations discovered in the original data are modelled using the GAMs model. Using the gamm () functionality, we start with AR (1) errors and later test a model with AR (2) errors to calculate the residuals of the models. The more complicated AR (2) errors model shows limited support in a generalised likelihood ratio test. Table 1 demonstrates that the AR (1) has successfully modelled the majority of the residual correlation with a P-value of 0.4138.

Table 1: A Generalised Likelihood Ratio Test

	Model	Df	AIC	BIC	LogLik	Test	L.Ratio	P-value
Model 1	1	5	131.2194	138.7020	-60.60971	1 vs 2	0.667928	0.4138
Model 2	2	6	132.5515	141.5306	-60.27575			

The mean temperature data of the Jos city within the period of Thirty-seven years (1986 - 2023) was adopted in this study to generate time series analysis. The plot of the series in figure 1 and 2 respectively shows a random walk indicating cycles in the series, and also shows a pattern of seasonality in the series at level. It is therefore important to confirm seasonality and assess whether there is overall trend in the data over time in other to understand the long-term behaviour of the variable.

Figure 3 shows that, the PP plot of the mean deviates significantly from a straight line, it indicate that the mean values do not follow a normal distribution. This suggests that the temperature series distribution is skewed, have heavy tails, or otherwise deviate from normality. The detrended PP plot of the mean in figure 4 shows a clear systematic pattern, it suggests that the deviations from normality are not solely due to the underlying linear relationship. This indicates that the data's mean values may not follow a purely normal distribution, and further investigation may be needed.

To confirm seasonal, cyclical, and trend in the series data, we plot a residual ACF and PACF as shown in figure 5 and 6 respectively. The ACF and PACF plot is used to capture the temporal structure of the time series. In other to improve the forecasting accuracy, the plot of the residual ACF in figure 5 shows correlation coefficients at various lags, taking into account the seasonal components. In this plot, the significant spikes occur at lag 12 suggesting a seasonal pattern with an annual cycle. The plot of the residual PACF in figure 6 shows partial correlation coefficient at various lags, controlling the intermediate lags including the seasonal lags. This indicates the presence of seasonal autocorrelation and partial autocorrelation.

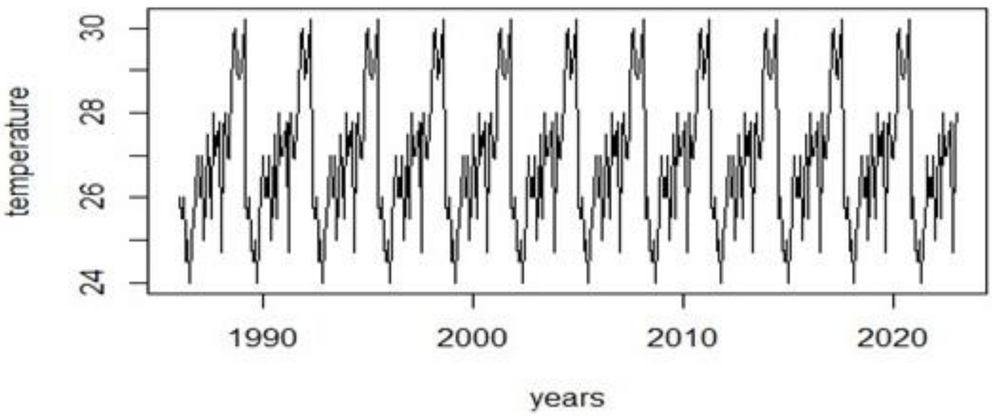

Figure 1: Time Plot of the Mean Monthly Temperature

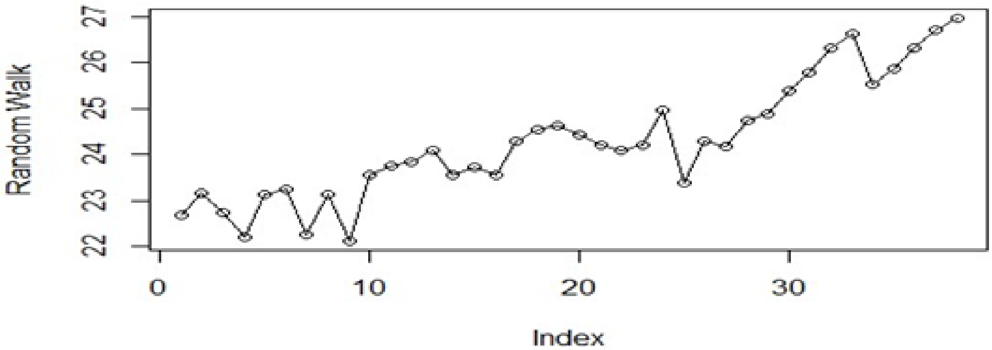

Figure 2: Time Plot for the random walks of the series

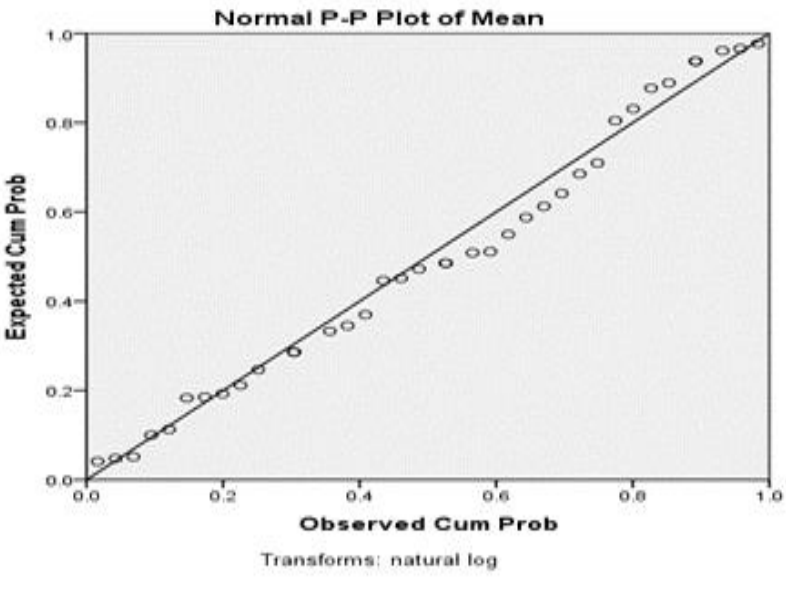

Figure 3: Normal probability plot of the for the temperature series

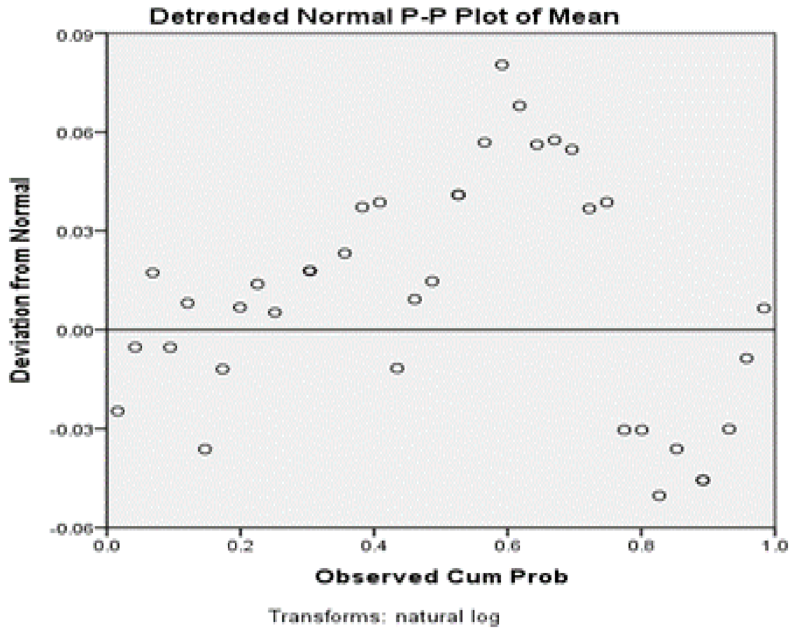

Figure 4: Detrended normal probability plot temperature series

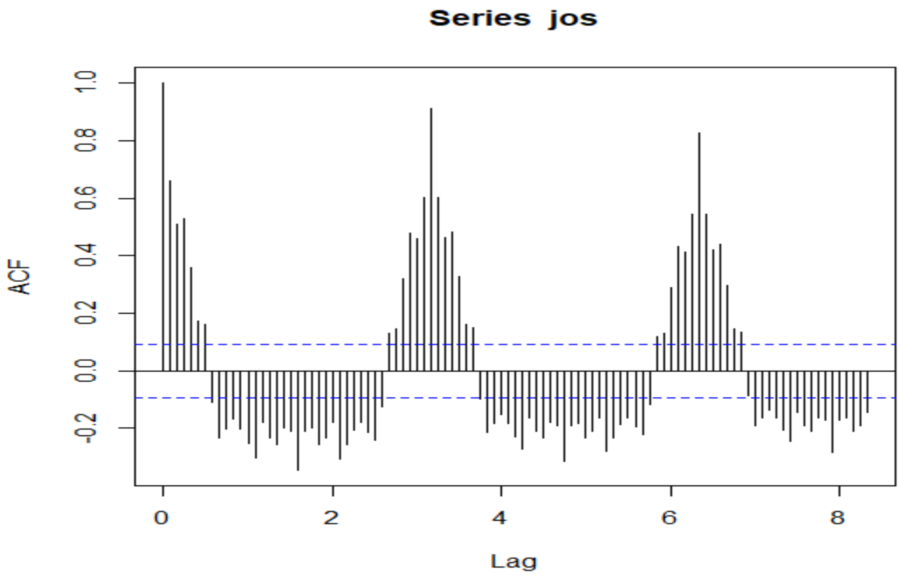

Figure 5: ACF plot of the temperature series

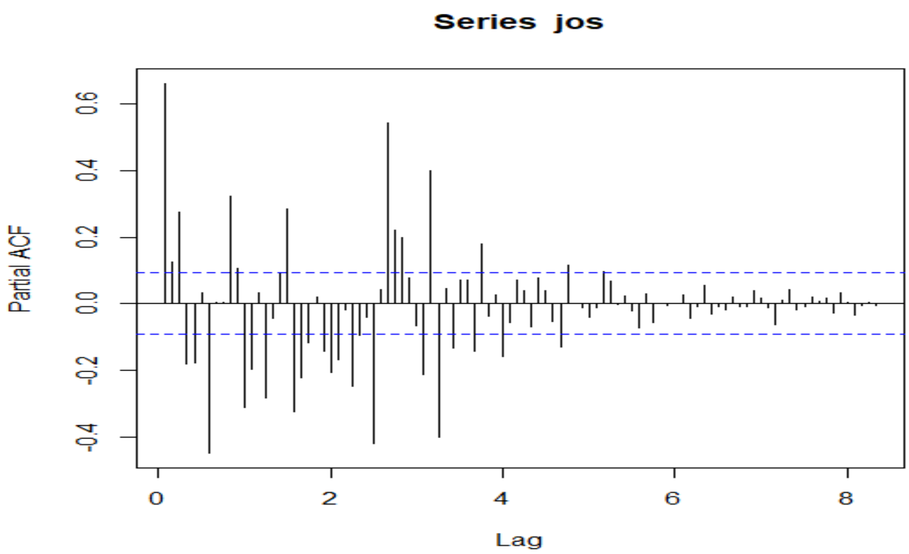

Figure 6: PACF plot of the temperature series

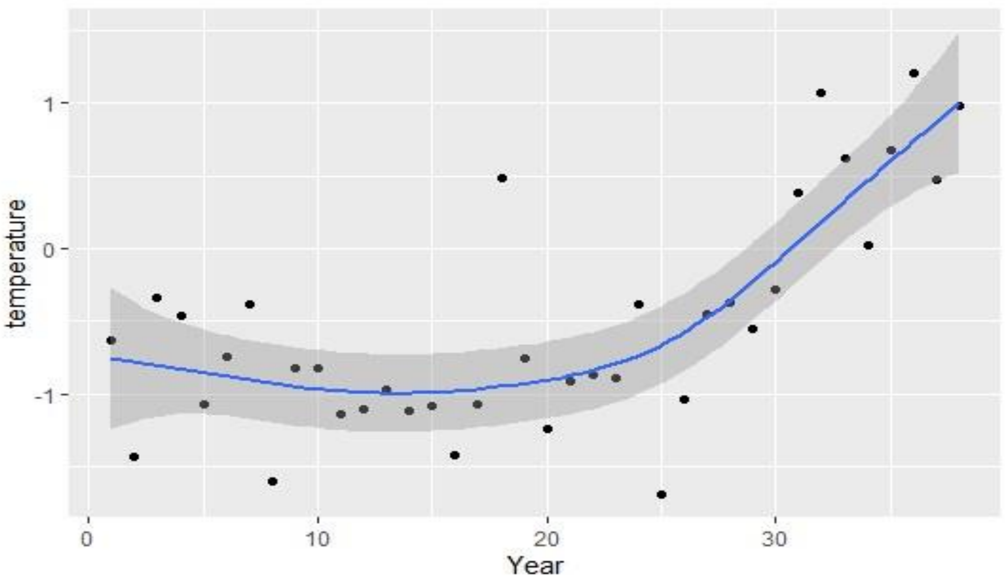

Figure 7: Plot of the fitted values of the temperature

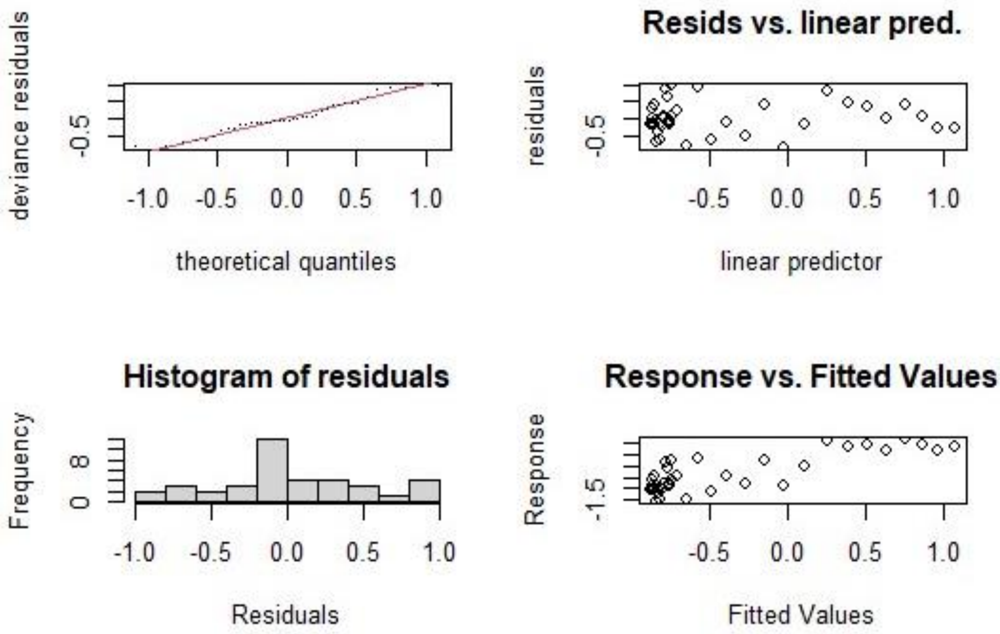

Figure 8: Residuals Diagnostics checks of the fitted values series using mgcv package

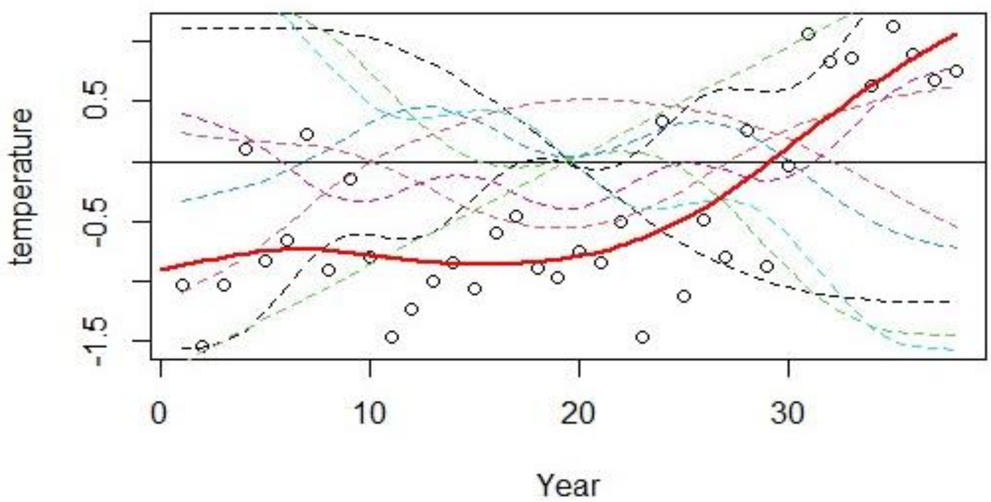

Figure 9: basis functions and prediction plot

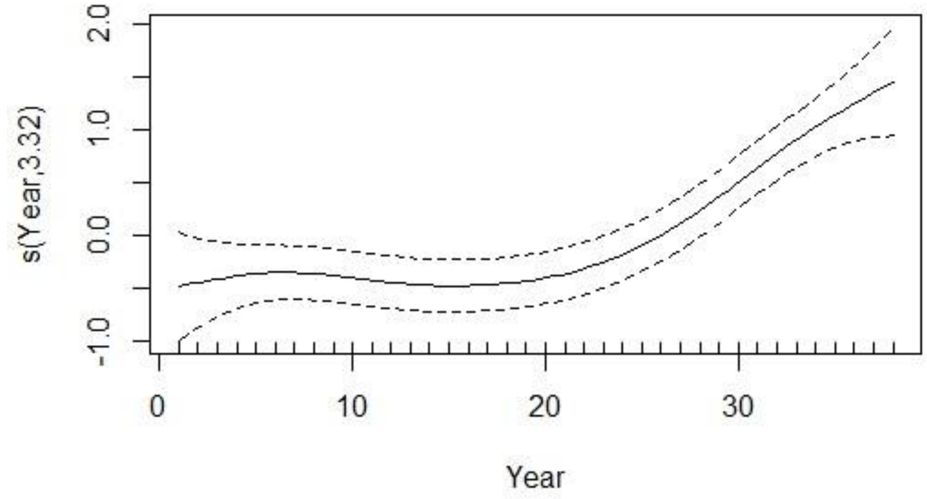

Figure 10: The smooth terms plot

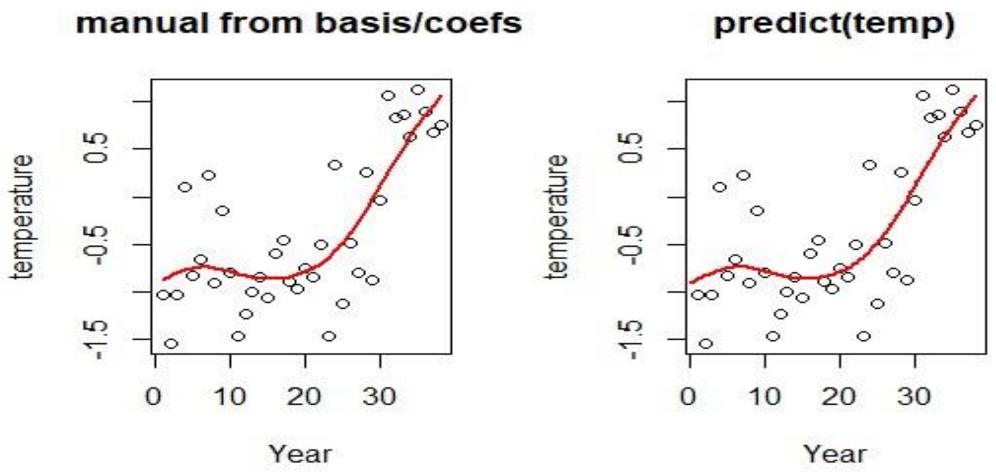

Figure 11: Basis functions and the estimated coefficients to the fitted smooth term plot

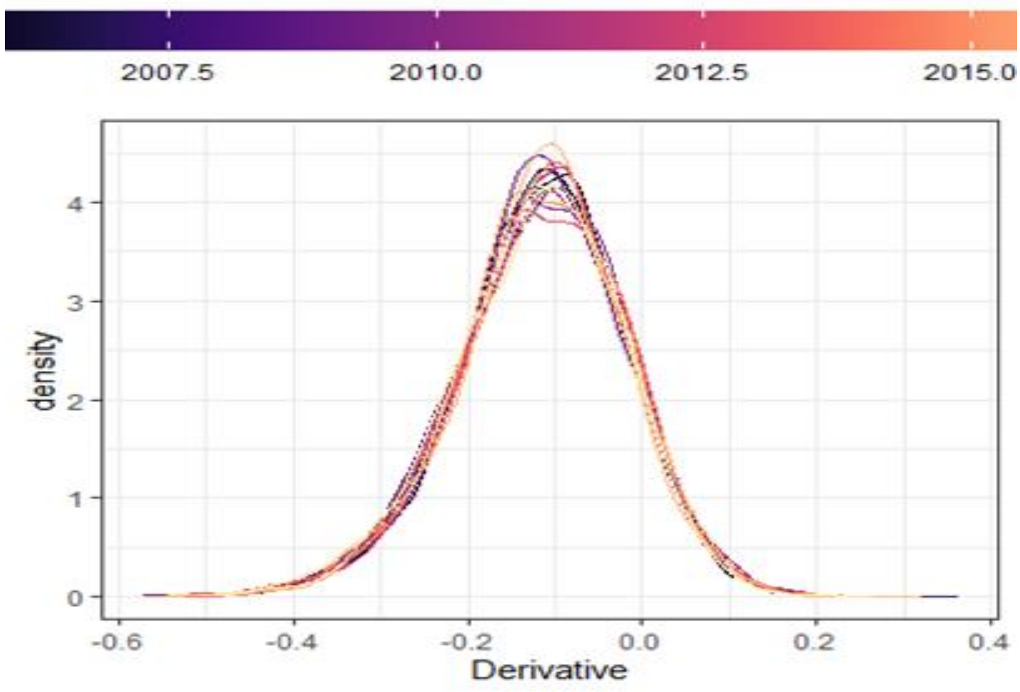

Figure 12: Kernel density estimates of the first derivative for particular years from the fitted trend

Figure 7 displayed how gam is capable of capturing nonlinearity in time series data which reduces the impact of outliers in a time series data. As you can see from figure 7 the model is better fit to the data, the plot was interpreted in conjunction with other diagnostic tools, such as additional residual diagnostics. A diagnostic residual plot was carried out in this research to assess the performance of GAM model and understand the accuracy of the model fit (see figure 8). We examine the patterns of the model residuals to check for systematic deviations from the assumptions of the GAM.

The random scatter points in residuals and linear predictor suggest that the model is adequately captured the variability in the data since there is no visible pattern around the zero line. The shape of the residuals with respect to the fitted values did not show any curved pattern which indicates that the model captured the nonlinear relationship properly. Most of the outliers fall significantly within the expected range of the residuals. The histogram of the residual plot indicates that the data are normally distributed and are independent. This indicates that the dataset satisfies the assumption of normally distributed errors.

To fully understand the effect of the basis function, it is necessary to consider its contribution in the context of the full model, taking into account other variables and potential interactions. Therefore, we plot all of the basis functions as shown in figure 9, and then add that to the predictions. Each of those dotted lines from figure 16 above represents a function (b_j) for which GAM estimates a coefficient(β_j), and when you sum them you get the contribution for the corresponding f(x). It's nice and simple for this study, because we model temperature (y) only as a function of the smooth term, so it's fairly relatable.

The smoothing function from generalized additive model (GAM) clearly reduces the noise in the data and makes the data appear smoother. The predicted values from GAM on the `predict(temp)` data indicate that the model captured the nonlinear relationships between variables. The plot shows the predicted values based on the GAM model, along with the observed data points. It gives insights into the overall trend and pattern in the data and shows how well the model fits the observed data. To prove that we uses the basis functions and the estimated coefficients to the fitted smooth term as shown in figure 10.

The fitted smooth term plot shows a good relationship between the predictor variable(s) and the response variable after accounting for the smooth term. It displays the estimated smooth curve, which is obtained by combining the basis functions with their corresponding estimated coefficients. The plot provide insights into the non-linear relationship between the predictors and the response, allowing for a better understanding of the data and potentially revealing important patterns and trends. Finally, we create kernel density estimate plots that are faceted by year after performing some processing to put the derivatives into a format that can be shown using ggplot. The slopes of the trends predicted using the posterior distribution of the model show relatively little change across years, as expected. Jos city's temperature is expected to rise, according to the additive model.

5. Conclusion

The goal of this study was to see if GAMs could be used to model long-term temperature patterns. Fitting smooth functions of time to GAMs can describe long-term trends. Separate smooth's can be fitted to see if various patterns emerge in the long-term trend when temperature rises or falls. GAMs can also be used to model average seasonal trends in temperature. Finally, GAMs can be used to model various covariates to see if effects are linear or non-linear.

GAMs are a useful addition to GLMs since they let you examine the relationship between covariates and response variables and decide whether it is linear or non-linear. As a result, when no previous information is available, they work best for describing uncertain connections between covariates and response variables. It appears to be more acceptable to fit this functional form directly within a GLM if the functional connection is known prior to fitting, as is the case when modeling the seasonal pattern with Fourier series. It might be a good idea to use GAMs as an exploratory tool to find functional forms that can subsequently be explicitly retrofitted, especially if the functional form can be articulated.

Although GAMs are useful, when choosing the base dimension for smooth terms, caution is required. The selection of a base dimension is critical, but it is also fairly subjective. When data is highly variable, a high-dimensional basis allows for a great deal of freedom in describing precise patterns in the data. When the data is highly changeable, using a lower-dimensional foundation will only explain very smooth patterns. The choice of basis is less critical if the variability in the data is low, allowing the trend to dominate the data, as long as the basis is large enough. This explains the discrepancies in smooth behavior between the occurrence and intensity models. The usage of a high-dimensional basis did not produce smooth long-term trends due to the great variability of intensity.

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