

## Forecasting the Monthly Mean Temperature of Jos Northern Region of Plateau State using the SARIMA-GAM Hybrid Model

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**Abstract.** In reality, meteorologists create their periodic weather forecasts for variables like humidity, average temperature, precipitation, and other atmospheric factors using a variety of statistical techniques. The goal of the current study was to examine the temporal variations in the monthly mean temperature of Jos City based on a hybrid SARIMA and Generalized Additive Models (GAM) technique (SARIMA-GAM), using data from the Department of Geography of the University of Jos Meteorology Unit from 1986 to 2023. This study evaluated a suitable forecasting model for the monthly and annual mean temperature of the Jos North Region. The SARIMA and GAM models are used to capture both the linear and nonlinear components, respectively. This study benefits from the strengths of both SARIMA and GAM to improve forecasting accuracy. The hybrid model provides a more comprehensive analysis of the time series data by capturing nonlinearity using the GAM model and linearity using the SARIMA model. In conclusion, popular metrics like MSE, RMSE, MAE, and MAPE are used to assess and compare the predicted performance of various models. Principal results show that the hybrid SARIMA-GAM model outperforms the individual models in predicting the region's mean temperature in Jos City, Nigeria.

**Keywords:** Monthly mean temperature; Time series forecasting; SARIMA model; GAMs model; SARIMA-GAM hybrid models.

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### 1. Introduction

A time series is a collection of observations that are generated in a specific order across time. It's a statistical series that shows how data has behaved in

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the past, present, and maybe in the future (Becker *et al.*, 2015). In essence, it is a technique that combines observed data from the past  $y_{(t-1)}$  and present  $y_t$  to forecast future values  $y_{(t+1)}$  with a temporal lag of one (Jingjing, 2013). The numerical values of the variable  $Y$  (temperature) at the times  $t_1$ ,  $t_2$ , and  $t_3$  are known as a time series in mathematics.  $Y$  is a function of  $t$  as a result,  $Y = F(t)$  (Sake and Akhtar, 2019).

Discussions at the worldwide conference center on the problem of climate change. Regarding their potential long-term effects on sustainable economic growth, governments and environmental non-governmental organizations evaluate them as one of the major concerns across the globe (Starikova and Shamanina, 2021). Understanding the fluctuation of the climate is crucial in today's world. The Earth's climate is shifting, resulting in a rise in extreme weather occurrences 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 comprehension of climatic variability (Rahman and Lateh, 2015). Using this information, proactive measures can be developed to minimize the anticipated negative effects of global warming (Katopodis and Sfetsos, 2019; Nath and Behera, 2010). Climate change has an impact on food production in particular. This is because crop yields are directly influenced by factors such as wind 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 (e.g., rice, wheat) production around the world (Christenson *et al.*, 2006).

Temperature is an example of a time series with daily, monthly, and annual orders (Zhou *et al.*, 2019). Temperature data is one of the many data sets where time series are utilized to observe, analyze, and anticipate the future using various models. Data in a time series is normally arranged by time, and subsequent observations are usually dependent (Citakoglu, 2021). We look into the SARIMA-GAM time series in this work and attempt to identify forecasting series that are suitable for the research domain.

Several attempts have been made to model time series data that is trending and seasonal (Chulwoo and Myung, 2013). In the study of temperature time series, many methodologies have been used. For example, Dammo *et al.*, (2015) and Salaudeen *et al.*, (2021) studied temporal and seasonal variations in temperature over northeastern Nigeria. Trends in annual and seasonal temperature series were analyzed using the Mann-Kendall test. de Araújo and da Silva. (2022) studied monthly mean minimum and maximum temperatures as well as precipitation. The data used spans 100 years between 1901 and 2000. SARIMA(0,1,1)(0,1,1)<sub>12</sub> (with constant) and SARIMA(0,1,0)(0,1,1)<sub>12</sub> (with constant) were found to be the best suitable models for time series analysis of the two types of data.

Similarly, Ofure *et al.* (2021) utilized the SARIMA model to predict the monthly temperature in Ghana's northern area. The scientists used temperature information from January 1990 through December 2020. The SARIMA(1,0,0) is therefore the most accurate model for forecasting monthly temperatures in Ghana's northern area. Tran *et al.* (2021) applied the Seasonal Autoregressive Integrated Moving Average (SARIMA) method to create temperature forecast-

ing models for the state of Kerala. The model is developed using mean maximum and mean lowest monthly temperature data collected over 47 years from seven locations. SARIMA(2,1,1) was shown to be the best forecasting model for eight of the fourteen time-series datasets, according to the study.

Tao *et al.* (2021) investigated the accuracy of the Support Vector Regression (SVR) and SVR-FA models and compared it to that of the SARIMA stochastic model. It is advised to utilize SVR-FA rather than SVR models for temperature forecasting because of the efficiency of merging the SVR model with the Firefly optimization algorithm in predicting temperatures in Iran's climate. Meshram *et al.* (2020) used SARIMA time series analysis to examine how precipitation in Bangladesh varied across time and space. Lyu *et al.* (2021) suggested that the wavelet-ARIMA model is superior to the wavelet-ANN model when applied to monthly maximum and minimum temperature data in north-eastern Bangladesh. Nourani *et al.* (2018) identified possible trends in the variables and their dominating periods using Şen's technique and the nonparametric hybrid wavelet Mann-Kendall test.

According to many of the research findings for monthly mean temperature time series prediction, most of the studies simply used a single approach model for predicting temperature data (Ruiz-Aguilar *et al.* 2014). It is not easy to simulate many real-life time series using straightforward techniques, especially when high precision is needed (Araghi *et al.* , 2017). Numerous researchers have proposed hybrid models, such as: Chulwoo and Myung, (2013) who analyzed the seasonal additive trend data using GAMs and NNs. The SARIMA-GAM performed well consistently throughout the whole range of noise variance, while the SARIMA-NN only demonstrated high performance at minor noise levels. Ruiz-Aguilar *et al.* (2014) hybridized the autoregressive integrated moving averages (SARIMA) model to forecast the number of inspections. Based on a comparison of several hybrid techniques, it may be concluded that the hybrid models perform better than the individual models.

Based on the literature, nevertheless, no literature has yet examined the use of the SARIMA-GAM model for monthly mean temperature forecasting in the study area. This study's objective was to apply the SARIMA-GAM model to investigate and forecast the rise in local surface air temperature in the Jos region of Plateau State, and evaluated their effectiveness.

## 2. Materials and Method

This article compared and assessed SARIMA and SARIMA-GAM for different types of seasonal and trend time series data. Additionally, the ideas and mathematical formulations for the linear, nonlinear, and hybrid models are briefly discussed in the ensuing subsections.

### 2.1 Linear Models (SARIMA)

The SARIMA model (Box and Jenkins, 1976) is a popular linear forecasting scheme for seasonal and trend time series data. The seasonal ARIMA  $(p, d, q)$   $(P, D, Q)^S$  model is more appropriate for climate data that typically follows an annual cycle, i.e., a seasonal ARIMA ( $s = 12$  for an annual cycle), where  $P$  is

the order of the seasonal AR model,  $D$  is the order of the seasonal differencing (usually  $D = 12$  for monthly data),  $Q$  is the order of the seasonal MA model, and is the number of periods in the season. In backshift notation, the general form of such a seasonal ARIMA  $(p, d, q) (P, D, Q)^S$  model is expressed as:

$$\varphi_p(B)\Phi_p(B^S)(1-B)^d(1-B^S)^D(y_t - c) = \theta_q(B)\Theta_Q(B^S)\xi_t, \quad (1)$$

where  $c$  is a constant,  $\xi_t$  is typically a Gaussian white noise,  $p, d, q, P, D$ , and  $Q$  are integers, and  $\varphi_p(B)$  and  $\theta_q(B)$  of order  $p$  and  $q$  are the polynomials representing autoregressive and moving average components, respectively;  $\Phi_p(B^S)$  and  $\Theta_Q(B^S)$  of orders  $P$  and  $Q$  are the polynomials representing seasonal autoregressive and moving average components, respectively;  $d$  and  $D$  are orders of differencing;  $(1-B)$  and  $(1-B^S)$  are difference operators, and  $S$  is the length of the seasonal cycles.

If  $d$  and  $D$  are both at zero in (1), the SARIMA model is reduced to a seasonal autoregressive moving average (SARMA). Specifically, if  $p, q, P$ , and  $D$  are all at zero, the SARIMA model becomes autoregressive (AR). The AR model can be expressed as:

$$y_t = c + \sum_{j=1}^p \varphi_j (y_{t-j}) + \xi_t \quad (2)$$

where  $\varphi_j$  is the  $j^{th}$  weight and  $p$  is the order. This model is often expressed as  $AR(p)$ . Estimation and prediction will be carried out using the functions in the package of *R* program.

## 2.2 Nonlinear Models (GAM)

To simulate and capture the nonlinearity in the data, several non-linear smooth functions are substituted for the typical linear relationship between the response and the predictors in GAMs (Morton and Henderson, 2008). To capture the non-linear relationship between response and predictors, they are also a flexible and smooth technique that aids in the fitting of linear models that can be either linear or non-linearly reliant on many predictors ( $x_i$ ). Due to their extreme flexibility, Generalized Additive Models may fit nonlinear relationships and considerable noise in the predictor variables quite well (Underwood, 2009). GAMs possess the structure.

$$y_t = \beta_0 + \sum_{j=1}^m S_j (y_{t-j}) + \xi_t \quad (3)$$

In this case,  $S_j$  is the  $j^{th}$  additive function weight;  $m$  is the number of lags;  $\xi_t$  is the  $t$  error term, and  $\xi_t$  for all  $t$  are uncorrelated, and  $\beta_0$  is a constant.

A crucial step in fitting a GAM is determining the proper amount of smoothing by restricting the degrees of freedom. This allows for accurate capture of data

volatility without running the risk of overfitting (Ankinakatte, *et al.*, 2013). GAM intends to restrict the total cross-appraisal model.

### 2.3 The Hybrid (SARIMA–GAM) Model

Given the seasonality, variability, and complexity of the time series, temperature data exhibits both linear and nonlinear patterns. As a result, it might not be sufficient to fit linear or nonlinear patterns using SARIMA or GAMs, respectively. The suggested hybrid model is capable of modeling both structures. As a result, a hybrid strategy that applies both approaches can produce superior outcomes compared to using the models independently (Dini *et al.*, 2020). According to the hybrid model's conventional methodology, time series can be broken down into their sum of linear and nonlinear components (Jeong and Kim, 2013).

$$\hat{Y}_{t+1} = \hat{L}_{t+1} + \hat{N}_{t+1} \quad (4)$$

The observation at time  $t$  is represented by  $\hat{Y}_{t+1}$ , the linear component by  $\hat{L}_{t+1}$ , and the nonlinear component to be estimated at time  $t$  by  $\hat{N}_{t+1}$ .

$$L_{t+1} = f(y_{t-1}, y_{t-2}, \dots, y_{t-m}), \quad N_{t+1} = g(a_{t-1}, a_{t-2}, \dots, a_{t-m})$$

Therefore, the proposed hybrid (SARIMA–GAMs) model is given by

$$y_t = f(y_{t-1}, y_{t-2}, \dots, y_{t-m}) + g(a_{t-1}, a_{t-2}, \dots, a_{t-m}) + \xi_t \quad (5)$$

where  $f(x)$  is either a linear model (of AR, SARIMA) or an additive function in the GAM;  $g(x)$  is also either a linear model (of AR, SARIMA) or an additive function in the GAM;  $a_t^s$  are residuals from  $f(y_{t-1}, y_{t-2}, \dots, y_{t-m})$  and  $\xi_t$  is the error term at  $t$ , and  $\xi_t$  for all  $t$  are uncorrelated (Chulwoo and Myung, 2013). According to the hybrid SARIMA-GAMs model, the residuals dataset after fitting SARIMA contains only nonlinear component and can be properly modelled through GAM (Jeong and Kim, 2013). The GAM for residuals has the following form:

$$\hat{e}_{t+k} = f(e_t, e_{t-1}, \dots, e_{t-k}) + e_t \quad (6)$$

Where  $e_t$  is the random error,  $\hat{e}_{t+k}$  is the forecast value that relates to the model's anticipated error, and  $f$  is the nonlinear function as calculated by the GAM model. The combined forecast is then derived by:

$$\hat{Y}_t = \hat{L}_t + \hat{N}_t \quad (7)$$

Where  $\hat{L}_t$  denotes the linear component  $\hat{N}_t$  is the nonlinear component, and  $\hat{Y}_t$  is the forecast value.

### Performance Criteria

Several criteria have been considered to evaluate the performance of the proposed model and generate valid findings for making predictions, ensuring that the best model chosen is the ultimate goal. The MSE, RMSE, MAE, and MAPE performance indices are used to estimate the generalization error.

### 3. Results and Discussion

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

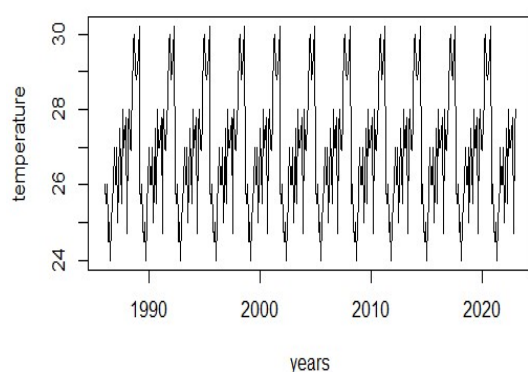


Figure 1: Time plot for the Mean Monthly Temperature series

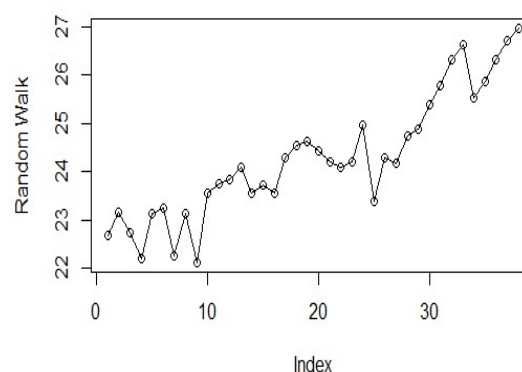


Figure 2: Time Plot for the random walk of the series

Before applying the hybrid model to the time series data, we first investigated to confirm the serial correlation of the temperature series. The scatter plot in Figure 3 displayed the relationship between the variables. The plot showed a positive correlation since the values of both variables increased together. The points form a pattern that slopes upward from left to right. In addition, the plot also provided the strength and direction of the correlation, suggesting a strong correlation. Secondly, a histogram plot and normality test for the temperature series were plotted to assess and examine the overall behavior of the temperature data. The result showed a slight level of variation, as shown in Figure 4.

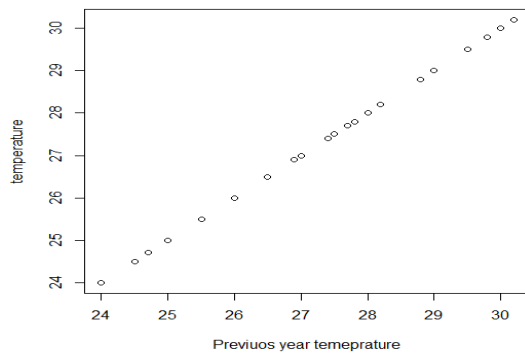


Figure 3: Scatter plot of the temperature series

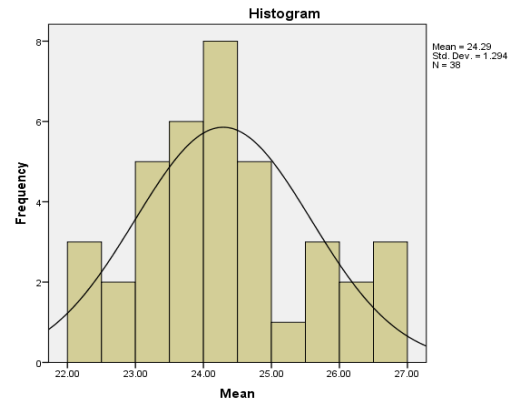


Figure 4: Histogram plot and normality test

Table 1:1 presents the descriptive statistics of the temperature series of the Jos region of Plateau

| Descriptive Statistics of the Annual Mean Temperature Series |              |
|--------------------------------------------------------------|--------------|
| Mean                                                         | 24.33288288  |
| Standard Error                                               | 0.21095002   |
| Median                                                       | 24.20833333  |
| Mode                                                         | 23.54166667  |
| Standard Deviation                                           | 1.283158878  |
| Sample Variance                                              | 1.646496705  |
| Kurtosis                                                     | -0.472041457 |
| Skewness                                                     | 0.371514842  |
| Range                                                        | 4.833333333  |
| Minimum                                                      | 22.125       |
| Maximum                                                      | 26.95833333  |
| Sum                                                          | 900.3166667  |
| Count                                                        | 37           |

From Table 1, the region has an annual mean temperature of  $24.33^{\circ}\text{C}$  and a standard deviation of 1.28, which indicated that the data points deviate from the mean by approximately 1.28 units (i.e., there was variability in the dataset). The distribution has a minimum temperature of  $22.125^{\circ}\text{C}$  and a maximum temperature of  $26.96^{\circ}\text{C}$ , respectively. The value for Skewness was 0.37, which indicated that the distribution was skewed to the right, and kurtosis was -0.47, which implied that the distribution was less peaked and has thinner tails compared to a normal distribution. This indicated that the data had fewer extreme values (outliers) than a normally distributed distribution. Therefore, the distribution was asymmetric and platykurtic.

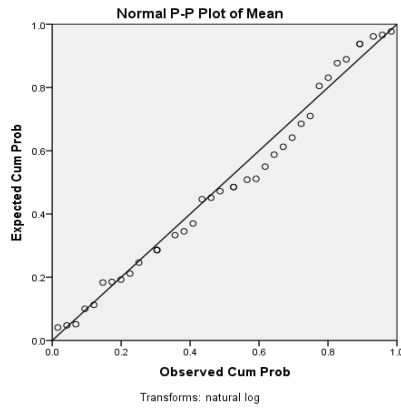


Figure 5: Normal probability plot of the series

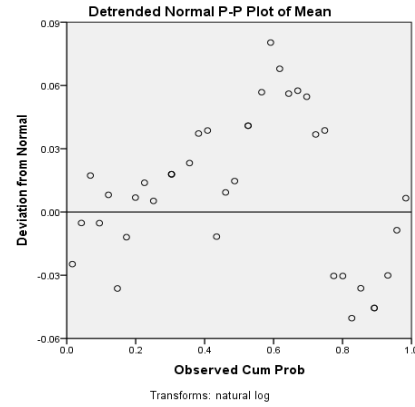


Figure 6: Detrended normal probability Plot of the temperature series

The PP plot of the mean in Figure 5 deviated significantly from a straight line, which indicated that the mean values do not follow a normal distribution. This suggested that the temperature series distribution was skewed, had heavy tails, or otherwise deviated from normality. The detrended PP plot of the mean in Figure 7 showed a clear systematic pattern, which suggested that the deviations from normality are not solely due to the underlying linear relationship. This indicated that the data's mean values may not follow a purely normal distribution, and further investigation may be needed.

To confirm seasonality, cyclicity, and trend in the series data, we plotted residual ACF and PACF as shown in Figures 7 and 8, respectively. The ACF and PACF plots were used to capture the temporal structure of the time series. The plot of the residual ACF in Figure 7 showed correlation coefficients at various lags, taking into account the seasonal components. Moreover, the significant spikes occur at lag 12, suggesting a seasonal pattern with an annual cycle. The plot of the residual PACF in Figure 8 showed the partial correlation coefficient at various lags, controlling the intermediate lags, including the seasonal lags. This indicated the presence of seasonal autocorrelation and partial autocorrelation.

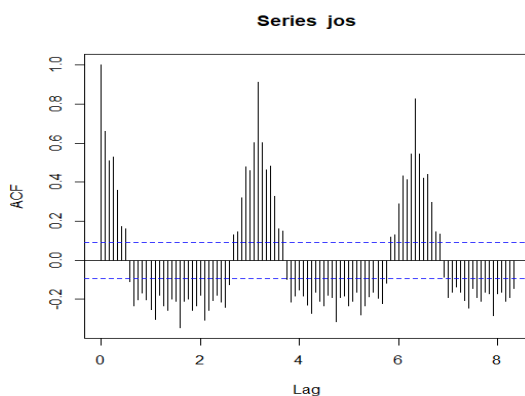


Figure 7: ACF plot of the temperature series

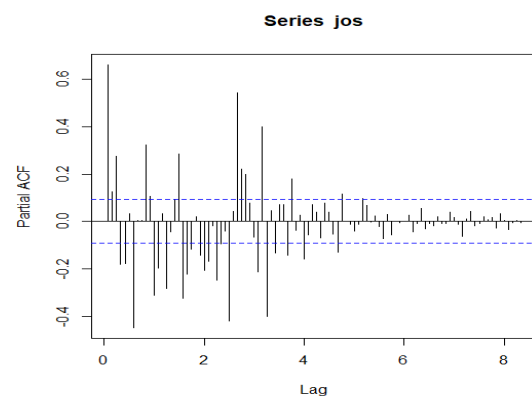


Figure 8: PACF plot of the temperature series

Since both the plots of the ACF and PACF in Figures 7 and 8 showed signifi-

cant correlations, the time series data was non-stationary and therefore needed to eliminate the seasonal effect for stationarity (Ruiz-Aguilar *et al.*, 2014). Further analysis using the SARIMA-GAM model may be necessary to capture and model both the seasonal and non-seasonal components accurately, which is crucial for building accurate forecasting models.

A generalized additive model was used to fit and capture the nonlinear patterns in the series. To have a better model, we examined how GAM refers to the added material model as a blended impacts model due to the substantial equality of subjective impacts and splines. This takes into account the residuals' relationship frameworks. We first extracted the fitted values from the time series data to model and capture the nonlinear relationship and reduce the effect of outliers from the dataset.

Figure 9 displayed how GAM was capable of capturing nonlinearity in time series data, which reduced the impact of outliers in time series data. The model was a better fit to the data as shown in the figure; 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 the GAM model and understand the accuracy of the model fit. We examined the patterns of the model residuals to check for systematic deviations from the assumptions of the Generalized Additive Model.

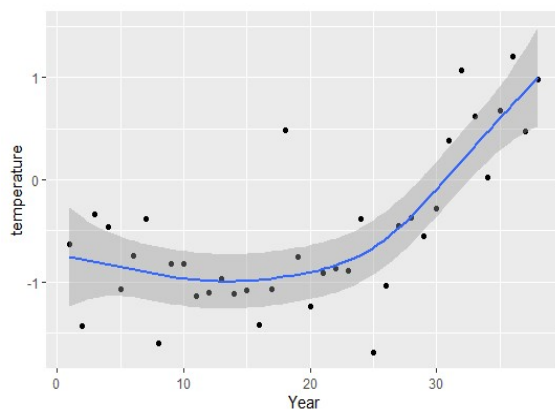


Figure 9: Plot of the fitted values of the series using GAM

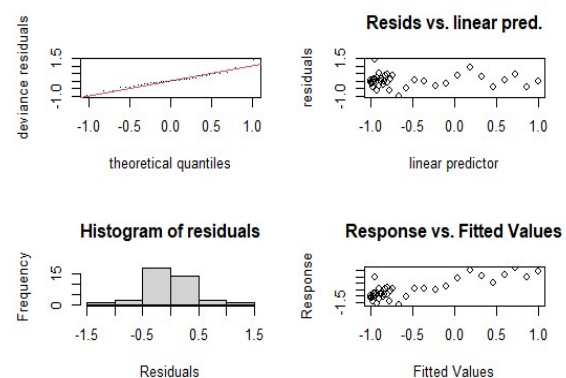


Figure 10: Residuals Diagnostics checks of the fitted values

The random scatter points in residuals and linear predictors in Figure 10 suggested that the model adequately captured the variability in the data since there was no visible pattern around the zero line. The shape of the residuals concerning the fitted values did not show any curved pattern, which indicated 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 indicated that the data are normally distributed and are independent, and therefore, the dataset satisfies the assumption of normally distributed errors.

According to Figures 11 and 12, obtained using R software, the majority of the spikes in the series move around the zero mean, indicating that the model had captured the underlying pattern of the data, which means they are independent of each other, implied that the series is stationary.

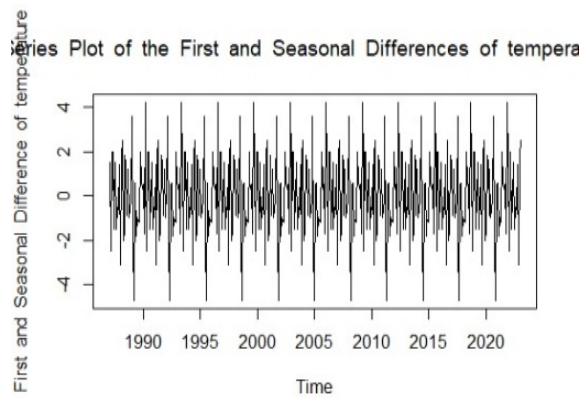


Figure 11: first and seasonal difference of the series

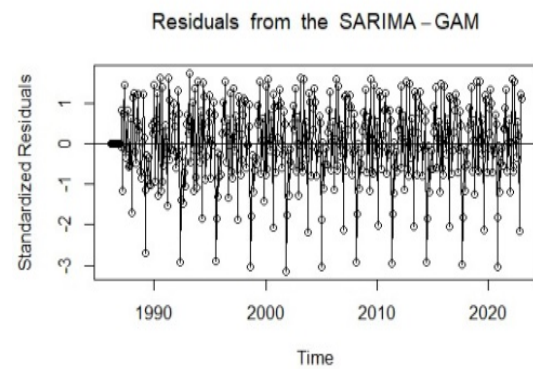


Figure 12: Residual plot from the hybrid model

The ACF of the first order difference in Figure 13 showed that there were no significant autocorrelation coefficients at certain lags (i.e., above the critical bounds), which suggested that no systematic patterns or dependencies are remaining in the data. Therefore, the time series model may provide a comprehensive forecast of the series.

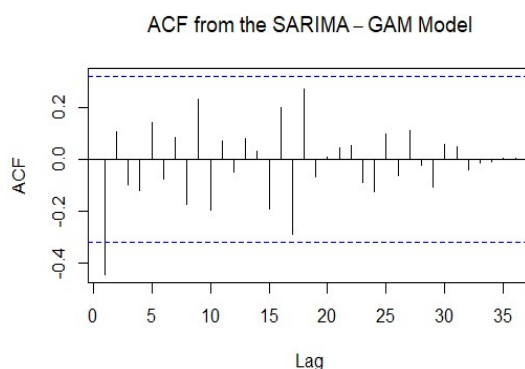


Figure 13: ACF of the first and seasonal difference

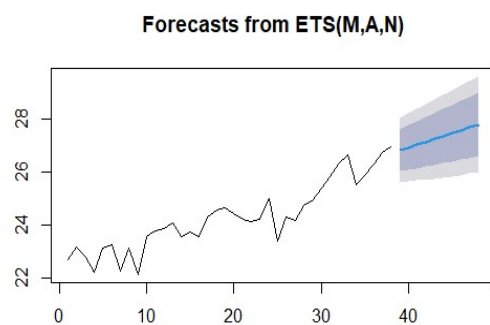


Figure 14: Forecast plot from the hybrid model of the series

Figure 14 showed the forecast plot from the hybrid model of the temperature series which provided the future outcome based on the historical data.

Table 2: SARIMA-GAM models identified

| Models         | Selected models                              | MSE           | RMSE          | MAE           | MAPE          |
|----------------|----------------------------------------------|---------------|---------------|---------------|---------------|
| Model 1        | SARIMA-GAM(0,1,1)(0,1,2) <sub>12</sub>       | 0.3423        | 0.4367        | 0.3526        | 1.3419        |
| Model 2        | SARIMA-GAM(1,1,3)(2,1,2) <sub>12</sub>       | 0.3250        | 0.4122        | 0.3343        | 1.2796        |
| Model 3        | SARIMA-GAM(1,1,1)(2,1,1) <sub>12</sub>       | 0.2974        | 0.4455        | 0.9342        | 1.3008        |
| Model 4        | SARIMA-GAM(0,1,2)(0,1,1) <sub>12</sub>       | 0.0983        | 0.4964        | 0.8543        | 1.6029        |
| <b>Model 5</b> | <b>SARIMA-GAM(1,1,2)(1,1,1)<sub>12</sub></b> | <b>0.0211</b> | <b>0.2861</b> | <b>0.2864</b> | <b>0.8539</b> |
| Model 6        | SARIMA-GAM(1,1,1)(1,1,0) <sub>12</sub>       | 0.3324        | 0.3690        | 0.4235        | 1.1430        |

The output for each configuration of different models was evaluated in Table 2. The model with the highest forecasting accuracy was chosen based on the output indexes (MSE, RMSE, MAE, and MAPE). Table 2 compiled the best templates for the hybridized models. The model with the highest output indexes was highlighted in bold. Furthermore, the results of the best hybrid model are compared to the forecasting results of the individual models in this analysis.

Table 3: Comparison of prediction error of the hybrid model and the individual models

| Models         | Selected models                              | MSE           | RMSE          | MAE           | MAPE          |
|----------------|----------------------------------------------|---------------|---------------|---------------|---------------|
| Model 1        | SARIMA(1,1,2)(1,1,1) <sub>12</sub>           | 0.3241        | 0.6213        | 1.0238        | 1.2125        |
| <b>Model 2</b> | <b>SARIMA-GAM(1,1,2)(1,1,1)<sub>12</sub></b> | <b>0.0211</b> | <b>0.2861</b> | <b>0.2864</b> | <b>0.8539</b> |

Table 3 summarized the forecasting effects of the aforementioned models. The hybrid model outperformed the SARIMA model. The MSE, RMSE, MAE, and MAPE values obtained by the hybrid models are slightly lower than those obtained by the other methods using R software.

#### 4. Conclusion

Breaking down a statistic into its linear and nonlinear components is the foundation of the hybrid technique for SARIMA-GAM models. Numerous investigations showed that the combined use of two models can already produce better results than they might individually.

This paper suggested hybrid forecasting models using SARIMA-GAMs as an alternative to those using SARIMA. The prediction performances of the suggested hybrid model were compared with SARIMA models via simulation studies. According to the simulation analysis results, the prediction performances between models seemed to depend on the type of time series data. On the other hand, once the time series data included any trend, the SARIMA models performed well and failed if there was nonlinearity in the series. The SARIMA-GAM seemed to be better than SARIMA for the time series data with an addi-

tive trend. These results can be applied to the corresponding real data, and some related business implications seemed to be available.

In general, a hybrid model outperforms a single model. It's worth noting that not all hybrid configurations boost the single models' prediction efficiency. The SARIMA-GAM model achieved the best output outcomes, according to the results of the experiments. The findings implied that the innovative hybrid SARIMA-GAM model approaches are viable, appropriate, and trustworthy techniques for predicting the mean temperature. This work added to the body of knowledge by offering an autonomous forecasting technique that lowers temperature prediction mistakes.

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