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Evaluation of time series Mann-Kendall Test model and Generalized Additive Model in simulation of non-stationary extremes values

Dayyab Abdulkarim Shitu [a] and Rashida Danjuma Idris [a]

[a] *Department of Mathematical Science. Abubakar Tafawa Balewa University Bauchi. Nigeria*

ABSTRACT
In order to forecast time-series data that have both linear and non-linear relationships such as average temperature, humidity, precipitation, and other atmospheric elements, time-series data analysts used a variety of statistical techniques to construct their forecasts. This research article aimed to evaluate the performance of the Mann-Kentrick test model and Generalized Additive Models (GAMs) techniques in the simulation of non-stationary extremes values. The Mann-Kendall test is a nonparametric statistical method that is used to find patterns in data over time. In contrast, generalized additive models (GAM) are a parametric statistical method used to model trends in time-series data. This study used monthly mean temperature data from the Nigerian Metrological Agency (NiMet) for the Northeastern Region of Nigeria over a 41-year period (1981 to 2022). To compare the expected performance of the models, well-known measures such as MSE, RMSE, MAE, and MAPE were employed. From the result of the trend test accuracy between Mann-Kendall's test and Generalized Additive Models (GAM), it has shown that the Mann-Kendall's test is good in trend detection but unable to capture nonlinear trend. Principal results with strong evidence from the plots showed that the Generalized Additive Model (GAM) outperforms the Mann Kendall test (MK) models both in capturing nonlinear relationship and modeling the time series trend.

KEYWORDS
Evaluation, Generalized Additive Models, Extreme values, Mann-Kendall Test.

1. Introduction

Many people agree that one of the most destructive natural phenomena is climate change, which causes significant environmental, social, and financial damage annually throughout the world, (Wang, T. et al. [23]. Climate change caused a direct economic loss of 24 billion USD, or 1-3% of GDP during that time. In 2017, combined damage from hurricanes and floods in the United States reached a record-breaking $300 billion (Gao, Y. et al. [5]. In the modern world, it is essential to understand how the climate fluctuates. As a result of the Earth's changing climate, extreme weather events, such as droughts, floods, and abnormally high or low temperatures, are becoming more frequent (Lopes, A. M., & Tenreiro Machado, J. A. [11]).

CONTACT Author[a]. Email: dayyababdulkarim@gmail.com

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Given this knowledge, preventive steps can be taken to stop and mitigate the harm that climate change and global warming are expected to cause to people, animals, and plants (Katopodis, T., & Sfetsos, A. [8]; Nath, P. K., & Behera, B. [14]).

Time series is a statistical series that provides information about the behavior of data in the past, present, and potentially the future. In short, they are a method that uses data from the past (y_{t-1}) and the present (y_t) to predict future values (y_{t+1}), with one being the time lag (Bauer, A. et al. [1]). The so-called stationary assumption that underpins the design of water infrastructure and flood mitigation projects has been called into question in recent years due to an increase in extreme weather (extreme values), which could result in an underestimation of flood quantiles and a higher risk of structural failure (Chen, M., Papadikis, K., & Jun, C. [2]). The analysis of non-stationary extreme values has advanced recently; non-stationary series show abrupt changes or jumps along with cyclic and trending components that are globally recognized as statistical parameters that vary over time (Dong, S. et al. [4]).

Time-series datasets have been analyzed using a variety of methods, such as: Dong, S. et al. [4] emphasizes using GAMLSS to build a probabilistic model that can handle periodic non-stationary variations and precisely estimate design wind speeds under non-stationary conditions using techniques like average design life level, equal reliability, design life level, and expected number of exceedances. Polnikov, V. G. et al. [18] employed a novel polynomial approximation technique to estimate wind speeds and significant extreme wave heights for six places along the Indian coast using 33 years of forecast data. Huang et al. [7] developed non-stationary extreme value models to estimate the non-stationary extreme wind speed quantiles with different mean recurrence intervals (MRIs) while taking climate change into account. These were then compared to the corresponding stationary ones with different MRIs for the Chinese city of Hangzhou. De Leo M., et al. [3] suggested a way to evaluate the importance of the non-stationary model's findings. The results demonstrate that only when all of the indicators taken into consideration are consistent in pointing to the existence of a trend does the non-stationary analysis outperform the stationary approach.

Moreover, Lornezhad, E., Ebrahimi, H., & Rabieifar, H. R. [12] used the Mann-Kendall method to assess the trend of precipitation change in western Iran. In other words, there was a drop in irrigation in the stations reviewed, as evidenced by the study's annual scale results, which showed that each station had a significant negative trend at the 5% level. Tosunoglu, F. et al. [21] evaluated the potential of a non-stationary framework for modeling seasonal precipitation series utilizing the well-known method for modeling hydro-meteorological variables in non-stationary settings, Generalized Additive Models for Location, Scale, and Shape (GAMLSS). 95 stations' seasonal precipitation series from 1970–2021 throughout Turkey were taken into consideration. Ustaoglu, B. et al. [22] predicted daily mean, maximum, and lowest temperature time series using three different ANL techniques. Kim, C., & Suh, M. S. [9] explored the possibility of calibrating one-month surface air temperature forecasts for South Korea using Bayesian model averaging. Zhu, S. et al. [25] employed sub-seasonal forecast of surface air temperature using super-ensemble approaches: experiments in northeast Asia for 2018.

Wang, Y. et al. [24] detected the non-stationary changes of precipitation on the Inner Mongolia section of the Yellow River basin, which is considered a key ecological barrier in northern China. Tan, X. & Gan, T. [20] used the non-stationary generalized extreme value distribution (GEV), Poisson distribution, and generalized Pareto (GP) distribution to examine long-term precipitation data from 463 Canadian gauging stations. Piyoosh, A. K. & Ghosh, S. K. [17] used the corrected and unbiased trend-free-pre-whitening ($TFPWcu$) approach to investigate how autocorrelation affects step and monotonic trends in seasonal and yearly rainfall. NCDC data for years 1901–2012 and its subperiods are subjected to the Mann–Kendall (MK) and six modified Mann–Kendall (MMK) test techniques for monotonic trends.

This study aimed to evaluate the Mann-Kendall time series test model and the generalized additive model(GAM) in the simulation of nonstationary extreme values. In addition, the study used the monthly mean temperature data obtained from the Nigerian Metrological Agency (NiMet) for the Northeastern Region of Nigeria over a 41-year period with the objective of comparing the performance of the Mann Kendall test model and the generalized additive model (GAM) technique.

2. METHODOLOGY

Time series analysis is a very useful technique for forecasting series dataset. Generally, most of the hydrological dataset contain both linear and nonlinear patterns. Therefore, this study investigated the forecasting/predicting performance of the Mann-Kendall test and the Generalized Additive Model.

2.1. *Mann–Kendall Test Method*

The popular nonparametric test known as the Mann-Kendall test (MK) was developed by Mann in 1945 and then improved and improved by Kendall in 1975. When data from multiple sources are used in a single study, the test is usually recommended (Nourani, V., Danandeh, A., & Narges, M. [16]). The main advantage of the method is that the test does not require the data to follow any certain statistical distribution, nor does it require that the data be normally distributed (Nourani, V., et al. [15]).

For a given time series of n data points, the Mann-Kendall test statistic (S) is the sum of positive differences minus negative differences, where X_j is the data point at time j ([16]). The statistic S is calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(X_j - X_i) \tag{1}$$

where sgn(·) in the eq(1) is the sign function defined as:

$$\operatorname{sgn}(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x = 0 \\ -1, & \text{if } x < 0 \end{cases} \tag{2}$$

The magnitude of S represents the strength of the trend in the data. An upward trend is indicated by a very high positive value of S, and a downward trend is indicated by a very low negative value (Lornezhad, E., Ebrahimi, H., & Rabieifar, H. R. [12]). As Mann (1945) and Kendall (1975) have shown, S strongly resembles a normal distribution when there are more than eight observations. The mean (μ_S) and standard deviation (σ_S) of S are determined by the following relationships:

$$\mu_S = 0 \tag{3}$$

$$\sigma_S = \sqrt{\frac{n(n-1)(2n+5) - \sum_{i=1}^{p} t_i(t_i-1)(2t_i+5)}{18}} \tag{4}$$

where t_i is the number of identical data points in the i-th category. The standardized Mann-Kendall test statistic (Z) is given by:

$$Z = \begin{cases} \frac{S-1}{\sigma_S}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sigma_S}, & \text{if } S < 0 \end{cases} \tag{5}$$

The statistic Z follows a standard normal distribution with a mean of 0 and a variance of 1 ([16]).

2.2. *Generalized Additive Models (GAMs)*

Generalized Additive Models (GAMs) provide an extension to the generalized linear model (GLM) (Hastie, T., & Tibshirani, R. [6]). GAMs are a novel class of models used by the statistical community to model observable data Hastie, T., & Tibshirani, R. [6];Hastie, T., & Tibshirani, R. [6]; Li, X., Lord, D., & Zhang, Y. [10]. Unlike GLMs, GAMs incorporate smooth functions of predictor variables into the linear predictor (McKeown, G. J., & Sneddon, I. [13]). The structure of a GAM is given by:

$$y_t = \beta_0 + \sum_{j=1}^{m} s_j(y_{t-j}) + \epsilon_t \tag{6}$$

where: - s_j is the weight of j-th additive function, - β_0 is a constant, - m is the number of lags, - ϵ_t is the error term at time t.

2.3. *Forecast Evaluation Measures*

In order to assess the effectiveness of the suggested model and produce reliable forecasting results, a number of criteria have been taken into account, guaranteeing that the optimal model is selected in the end. The generalization error is estimated using the MSE, RMSE, MAE, and MAPE performance indices.

3. Results and Discussion

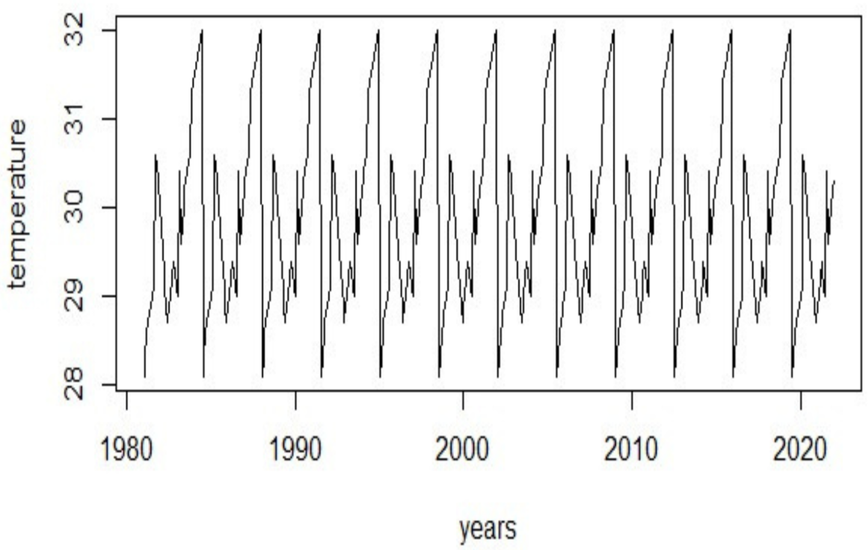

Figure 1.: Time Plot for the Temperature series.

The series plot in figure 1 exhibited a pattern of seasonality pattern at that level and a random walk that indicated cycles in the data. Determining if there is a general trend in the data across time and verifying seasonality are consequently crucial for comprehending the variable's long-term behavior.

Table 1.: Descriptive Statistics of the time series data.

Descriptive Statistics of the Time Series Data			
Mean	31.09225	Skewness	-0.13348
Median	31.70000	Kurtosis	-1.31176
Mode	35.70000	Sum	15639.4
Maximum	38.70000	Sample Variance	19.02446
Minimum	22.70000	Observations	503
Standard Deviation	0.194479	Confidence Level (95.0%)	0.382093

The descriptive statistics for the time series data taken into account for this investigation are shown in Table 1. According to the data, the mean is 31.09225, with a standard deviation of 0.194479. This tiny standard deviation suggests that the data points are very close to the mean and that there was little variability. The distribution has a maximum temperature of 38.70 ° C and a low temperature of 22.70 ° C.

According to the values for skewness and kurtosis, the data had fewer extreme values (outliers) than a normally distributed distribution. With a skewness value of -0.13348, the distribution was skewed to the left, indicating that the data were more dispersed toward the lower end of the range. With a measured kurtosis of -1.3176, the distribution was less peaked and had thinner tails. The distribution was therefore asymmetric because of its *platykurtic* nature.

Figure 2.: Histogram: Normality Test Plot.

As seen in Figure 2, a histogram plot and a normality test were performed on the data set. The results verified that the distribution was less peaked and had thinner tails than a normally distributed distribution.

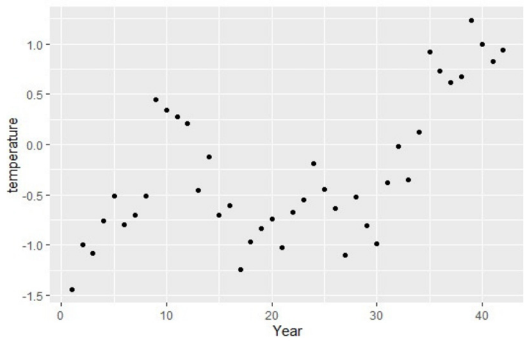

Figure 3.: Scatter plot of the annual series.

Figure 3 shows the scatter plot of the annual series. The behavior of the time series was explained by the scatterplot in Figure 3. The plot revealed that the series was nonlinear and that there were outliers in the data, which affects the accuracy of the prediction because outliers can skew and distort the relationships and patterns in the data. Consequently, it is often advised to deal with outliers before performing a forecasting analysis.

In this work, the stationarity or nonstationarity of the dataset was confirmed by using the Augmented Dickey-Fuller test (ADF) to check for the presence of the unit root in dataset.

Table 2.: Augmented Dickey-Fuller Test

Augmented Dickey-Fuller Test (Test for Stationarity)	
Dickey-Fuller (Test statistic)	-1.489
Lag order	3.00
p-value	0.775

Table 2 shows that the p-value is 0.775, the lag order is 3, and the ADF test statistics is -1.489. Therefore, the null hypothesis cannot be categorically rejected because the p-value is higher than the significant level (i.e., 0.775 ¿ 0.05). This suggests that the time-series data were not stationary. In other words, its variance is not constant over time and it exhibits some time-dependent structure. As a result, the time series data must be transformed in order to make it stationary. We investigated the possibility of serial correlation between the data set before performing the Mann-Kendall test to the time-series data.

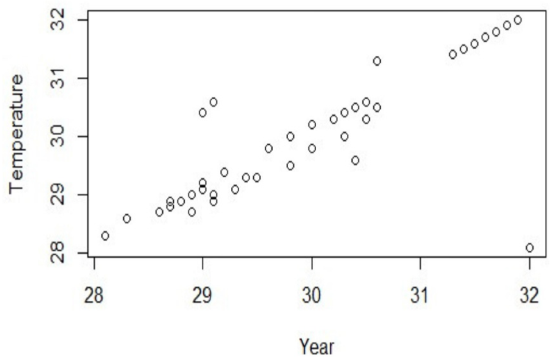

Figure 4.: Scatter plot of the temperature series.

Figure 4 shows the association between the variables in a scatter plot. Given that both variables' values rise in tandem, the plot demonstrated a positive association. The plot also suggested a substantial link, which also showed the direction and strength of the correlation.

To increase the prediction accuracy, the temporal structure of the time series was precisely captured using the ACF and PACF plot. Taking into account seasonal components, the residual ACF plot in Figure 5 displayed correlation coefficients at different lags. The notable increases in this graphic occurred around lag 12, indicating a seasonal pattern with an annual cycle. When intermediate lags, including seasonal lags, were controlled, the residual PACF plot in Figure 6 also displayed a partial correlation coefficient at different lags. This suggested that partial autocorrelation and seasonal autocorrelation were present.

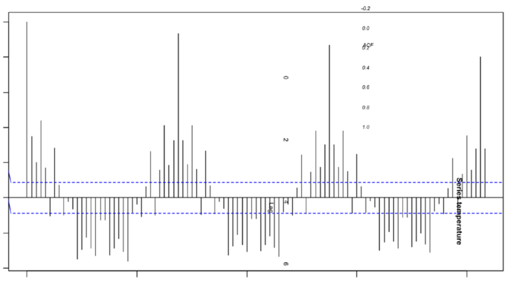

Figure 5.: Residual ACF Plot.

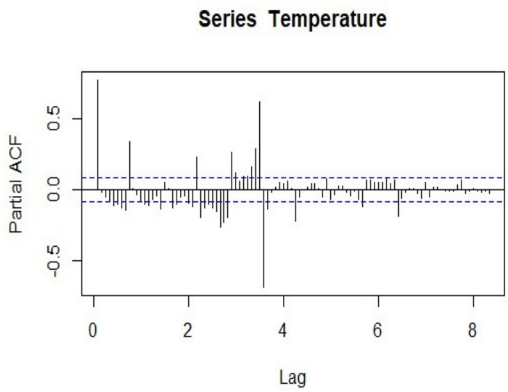

Figure 6.: Residual PACF Plot.

The time series data show notable connections in both the ACF and PACF plots in Figures 5 and 6. For stationarity, the seasonal influence must be removed. By taking the first-order difference, we were able to eliminate the seasonal effect of stationarity.

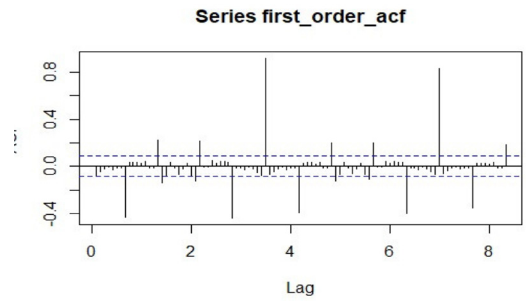

Figure 7.: First Order Derivatives of Residual ACF

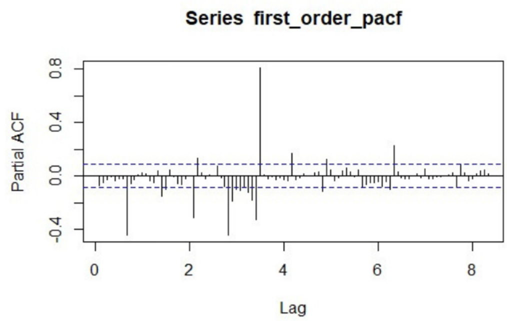

Figure 8.: First Order Derivative of Residual PACF.

The seasonal effect of the series was avoided by taking the first-order difference for stationarity. After reviewing the plots of autocorrelation and partial autocorrelation created by the R software, it was decided that these statistical measures seem to be significant for this series.

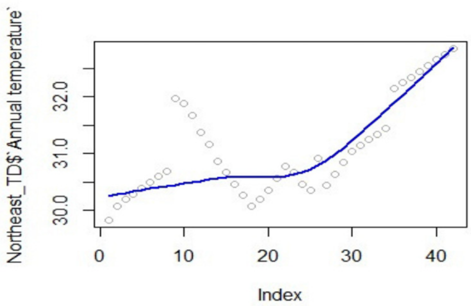

Figure 9.: Plot of the Mann-Kendall trend test.

The graphical representation of the Mann-Kendall trend test in Figure 9 revealed the underlying upward trend present in the data more clearly. The behavior of the series indicated an increased trend in the yearly temperature over the period of interest, as shown by the time series plot in Figure 9. This was used to describe a steady increase in average temperatures over time, typically on a regional or global level.

Table 3.: Mann-Kendall Test for the temperature data.

Mann-Kendall Test for the temperature data	
Tau (Kendall tau statistic)	0.536672
p-value	$6.152e-07$
S (Kendall score)	461.000000
Var (variance of Kendall score)	8510.333333
Z	4.9864000
N	42

According to the Mann-Kendall test in Table 3, the equivalent 2-sided p-value was 0.0000006152, and the test statistics were 4.9864. Given that the p-value was below the significance level (p-value = 0.0000006152 ¡ 0.05), our data meets the p-value requirements. The p-value for the Mann-Kendall test was statistically significant, suggesting a statistically significant upward trend in the yearly mean temperature dataset. The test's null hypothesis is thus rejected, and we draw the conclusion that the data show a trend. With a Sen's slope of 0.05625, the dataset is showing a positive trend.

In order to create a better model, we looked at how the Generalized Additive Model (GAM) refers to the added material model as a blended impacts model because of the significant equality of subjective impacts and splines, and how Linear Mixed Effect fits the model, which takes into account the relationship frameworks of the residuals. To begin, we extracted the fitted values from the time series data in order to model and capture the nonlinear relationship and lessen the impact of outliers from the dataset. This was done using the R software ([19].

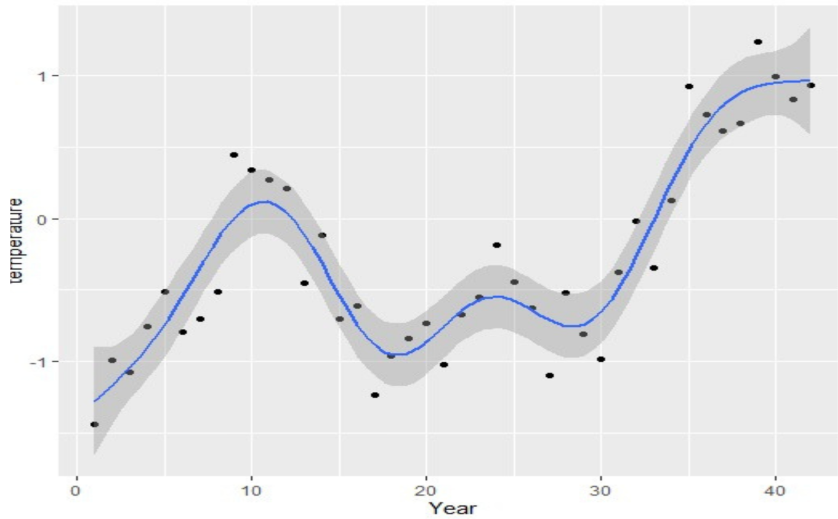

Figure 10.: Plot of the fitted values using mgcv package

Figure 10 shows how Generalized Additive Model was able to capture nonlinearity in time series data, which decreased the impact of outliers in a time series data. In order to evaluate the performance of the Generalized Additive Model and determine the accuracy of the model fit, a diagnostic residual plot was performed in this study. We examine the patterns of the model residuals to check for systematic deviations from the GAM assumptions.

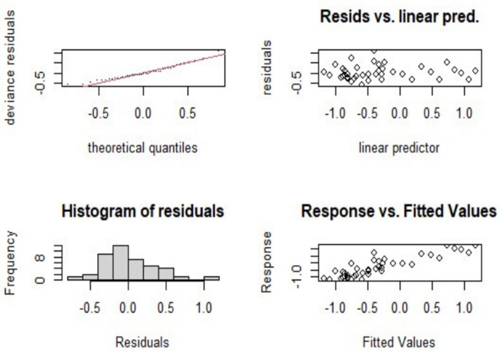

Figure 11.: Residuals Diagnostics checks of the fitted values

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 had sufficiently captured the variability in the data. There was no curved pattern in the residuals' form with regard to the fitted values, indicating that the model accurately represented the nonlinear connection. The majority of the outliers are well inside the predicted range of the residuals. The residual plot histogram showed that the data are independent and distributed regularly. This demonstrated that the dataset meets the normality condition for errors.

As indicated in Table 4, we were able to determine the significance of the smooth term and the variance explained using the summary of the model object.

Table 4.: Approximate significance of smooth terms:

smooth terms	Estimate	R-sq.(adj)	Standard error	T value	p-value
Intercept	-0.31709	0.739	0.05767	-5.498	$3.29e-06$ ***

According to Table 4, the p-value was $3.29e-06 < 0.05$. This demonstrated that the smooth term was statistically significant and that the model's fit to the data was enhanced by including the nonlinearity and flexibility it represents. However, adding the smooth term to the GAM greatly improves the fit of the model to the data. It captures a large non-linear relationship between the response and the predictor variable that the smooth term represents.

Table 5.: Comparison of the Trend Test Accuracy.

Models	Selected model's test	Test statistics	P-value
Model 1	Mann Kendall Test	0.53667	6.152e-07***
Model 2	Generalized Additive Model	6.99300	3.29e-06 ***

Table 5 gives a comparison of the trend test accuracy between Mann-Kendall's test and Generalized Additive Models (GAM). Mann-Kendall test has a p-value $6.152e-07$ while GAM has a p-value $3.29e-06$. From the result it has shown that the Mann-Kendall test is more capable in trend detection than the Generalized Additive Model.

Table 6.: Performance accuracy of the Individual Models

Models	Selected model's Test	MSE	RMSE	MAE	MAPE
Model 1	Mann Kendall Test	0.53489	0.286108	1.59806	0.65398
Model 2	Generalized Additive Model	0.48553	0.235743	1.40240	0.49196

Table 6 summarizes the forecasting effects of the aforementioned models. The table also showed that the generalized additive model outperformed the Mann-Kendall test. The MSE, RMSE, MAE and MAPE values obtained by the generalized additive model were slightly lower than those obtained by the Mann-Kendall test.

4. Conclusion

The Mann-Kendall test is a nonparametric statistical method that is used to find patterns in the data over time. Conversely, Generalized Additive Models (GAM) is a flexible regression framework that is used for modeling of nonlinear trends in time series data. GAMs are used to capture complex relationships between the response variable and the predictor variables and provide estimates of trends, confidence intervals, and other model diagnostics.

Well-known statistical measures such as MSE, RMSE, MAE, and MAPE were employed to evaluate and compare the expected performance of the models. From the result of the trend test accuracy between Mann-Kendall's test and Generalized Additive Models (GAM), it has shown that the Mann-Kendall's test is good in trend detection but unable to capture nonlinear trend. Principal results with strong evidence from the plots showed that the Generalized Additive Model (GAM) outperforms the Mann Kendall test (MK) models both in capturing nonlinear relationship and modeling the time series trend.

This paper suggested Generalized Additive Models (GAM) as an alternative to those using the Mann-Kendall test to capture nonlinearity and detect trend in time-series data. According to the analysis results, once the time series data included any trend, the MK test models performed well and failed if there was nonlinearity in the series. The Generalized Additive Models (GAM) seemed to be better than the Mann-Kendall test for the time-series data with nonlinearity. These results can be applied to the corresponding real data, and some related business implications seem to be available.

In general, generalized additive models (GAM) outperform a Mann-Kendall test model. Generalized additive models (GAM) achieved the best output outcomes, according to the results of the analysis. The findings implied that the Generalized Additive Models (GAM) were viable, appropriate, and trustworthy techniques to predict the time series dataset. This work added to the body of knowledge by offering an autonomous forecasting technique that reduces time series prediction mistakes.

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