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Study of Atmospheric Parameters Variation using Time Series Multiplicative Decomposition Model for Accurate Forecasting

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ABSTRACT
In this study, the variations in selected atmospheric parameters (rainfall, temperature, relative humidity, and wind speed) were investigated via a time series multiplicative decomposition model to enhanceaccurate weather forecasting. The time series multiplicative decomposition model application in atmospheric studies provides a sophisticated tool to better understand, model, and predict complex weather and environmental phenomena, offering significant improvements in accuracy over simpler forecasting methods. In this study, the selected atmospheric parameters were analysed over several years to capture both short-term fluctuations and long-term trends, with a focus on improving the forecasting accuracy. The findings highlight significant variability in multiplicative model performance across the different atmospheric parameters studied. The results show that rainfall exhibited extremely poor accuracy, with a high MAPE of 275.068, indicating significant forecasting errors with the model and suggesting a need for model enhancement. Conversely, the model demonstrated strong predictive performance for temperature, with a low MAPE value of 7.65%, indicating a reliable forecast with only occasional larger deviations, as reflected by the moderate MSD value. The relative humidity model showed relatively good accuracy of forecasts, with a MAPE value of 5.11%, although the high MSD suggested occasional outliers. The result of the wind speed model, however, showed an exceptionally high MAPE value of 93.38%, indicating a high forecast error, despite lower MAD and MSD values. These results underscore the importance of multiplicative model refinement, particularly for rainfall and wind speed, to improve prediction accuracy. The findings of this study provide insights into the strengths and weaknesses of current forecasting models for atmospheric parameters, guiding future improvements in predictive modelling. Similarly, it will serve as a foundation for more accurate and reliable forecasting techniques, which can be applied in climate monitoring, agricultural planning, disaster management and control, particularly in regions experiencing variable weather patterns.

Keywords:
Atmospheric parameters,
Time series,
Multiplicative decomposition model,
Accurate forecasting.

INTRODUCTION

Variations in atmospheric parameters, including rainfall, temperature, relative humidity, and wind speed, significantly influence weather patterns, climate modelling, and disaster preparedness. Atmospheric parameters, such as rainfall, temperature, relative humidity, and wind speed, are critical components in the study of the Earth's climate system. According to Karabulut et al. (2008), the climate of the Earth has changed across spatial and temporal scales over the planet, and climate change is a long-term continuous change (increase or decrease) to average weather conditions (e.g., average temperature). Therefore, climate change has the ability to influence all naturalenvironment, thereby becoming a threat to human life and survival socially, politically, and economically (Oluwafemi *et al.*, 2010). According to Ahmad *et al.* (2017), temperature among all other meteorological parameters, plays a vital role in identifying and evaluating climatic variability due to urbanization and industrialization. Okoro and Onugwu (2023), studied the rainfall distribution pattern changes and their relationship with atmospheric parameters at Enugu and Kano states using regression model. Rehman and Hadhrami (2012) studied long-term temperature variability via linear trends and anomalies on a yearly basis by using daily time series datasets collected from 1970-2006 in Jeddah. Karabulut *et al.* (2008) applied linear regression analysis to detect trends in temperature variation. Research carried out by Groisman *et al.* (2004) revealed significant variations in the distribution of precipitation across half of the global land area via linear regression. Kaushik and Singh (2008) employed a seasonal autoregressive integrated moving average (SARIMA) model to forecast the temperature and rainfall of the next five years by analysing data from the last 12 years (1994–2006) at Mirzapur, Uttar Pradesh (India).The mitigation of the hazards and impacts of extreme weather events, ensuring effective management of resources such as water and agriculture and improving disaster preparedness can essentially be achieved by accurate forecasting of these parameters. However, significant challenges are presented by the atmosphere because of its dynamic and complex nature driven by natural variability and anthropogenic influences, which hinders the accurate forecasting of these parameters.

According to Box *et al.* (2008), time series can be perceived as an ordered sequence of values at equally spaced time intervals. A time series may be in the form of a time-ordered sequence of events taken at regular intervals, including hourly, daily, weekly, monthly, quarterly and annually for a particular geographic location. As reported by Stevenson (2012), time series forecasting is based on the perception that past data can be used to estimate future data of a series. Time series analysis comprises methods for analysing time series data to extract meaningful periodic statistics and other characteristics of the data (Sobu and Wu, 2012; Kang *et al.*, 2011; Mori and Takahashi, 2012). Time series analysis has long been employed as a useful tool for studying the periodic interactions of meteorological parameters for modelling and forecasting atmospheric phenomena. The origin of time series analysis was traced to Box and Jenkins (1970), who laid the foundation using their seminal work on autoregressive, integrated moving average (ARIMA) models, which are widely employed to model observations related to linear time series. Hyndman and Athanasopoulos (2018), more recently, have expanded this approach by integrating exponential smoothing state–space models that can be used to predict seasonal and non-seasonal data.

The emergence of time series analysis stands out as a powerful tool that can be used in atmospheric science to study variations in atmospheric parameters over a given time interval. The decomposition method, among other techniques in time series analysis, stands out as a robust approach for the identification of patterns, trends, and seasonality within atmospheric datasets. The concept of time series decomposition hinges on the breakdown of a series into its fundamental components, which include trend, seasonal, and residual components, thereby permitting researchers to uncover underlying patterns to help model future behaviour different parameters more effectively. The multiplicative decomposition model is a type of time series decomposition method that assumes that the observed data of the time series are the product of its components. The model is appropriate for the analysis of datasets where the seasonal variation in the data value is proportional to the trend, and it is useful for investigating parameters such as rainfall, temperature, and relative humidity. A study carried out by Golyandina *et al.* (2018) demonstrated the application of a multiplicative decomposition model in analysing atmospheric time series involving exponential or proportional seasonal variations. The multiplicative decomposition model has been particularly effective in tropical regions, where fluctuations in atmospheric parameters such as rainfall and temperature are presumably dependent on large-scale climatic phenomena such as the El Niño–Southern Oscillation (ENSO) (Golyandina *et al.*, 2018).

Therefore, the motivation for this study stems from the increasing demand for accurate forecasting of the variation in weather situation reports to address rising global environmental challenges including climate change, hazard, disaster risk monitoring, and reduction and control and to enhance sustainable development. The traditional forecasting models most often fall short in capturing the complexity of atmospheric systems and interactions, leading to uncertainties in forecasting the environmental impacts. By incorporating a time series multiplicative decomposition model, this study aims to increase the forecasting accuracy by providing a clearer understanding of the temporal dynamics of atmospheric parameters. The findings of this study will contribute to improving the monitoring approach, offer early warning system signals, support disaster management and control strategies, and inform policy decisions aimed at climate change effect control adaptation and resilience. By leveraging the multiplicative decomposition model, this study aims to provide a systematic framework for predicting and analysing atmospheric parameter variations, ultimately contributing to a more comprehensive understanding of atmospheric dynamics and their implications for human and environmental systems.

MATERIALS AND METHODS

Study Area

The Imo State is located in southeastern Nigeria and is one of the 36 states of the country. Created in 1976 from the former East Central State, Imo is known for its rich cultural heritage, economic activities, and natural resources. The Imo State shares borders with Anambra State to the north, Rivers State to the south and west and Abia State to the east (Encyclopedia Britannica, 2021). Imo State lies approximately between latitudes 4°45'N and 7°15'N and longitudes 6°50'E and 7°25'E. The state falls within the tropical rainforest zone and is characterized by heavy rainfall during the wet season (May–October), high temperatures during the dry season (November–April), and high humidity, which significantly influences its weather conditions and increases the susceptibility of the state to climate-related hazards and disasters such as flooding and erosion.

Collection, computation and analysis of data

The daily data of the atmospheric parameters of Imo State from 1983-2013 used in this work, which consists of a satellite (Reanalysis-Interim) dataset, were obtained from the European Centre for Medium-Range Weather Forecasting (ECMWF), which is jointly managed by the National Center for Atmospheric Research data support section. After data collection, data downscaling and conversion were carried out using Panoply and Ferret software packages sourced from the Goddard Institute for Space Studies (GISS) and the National Oceanic and Atmospheric Administration (NOAA), respectively. Thereafter, statistical computation and analysis were performed via an Excel spreadsheet and the Minitab 19 software package.

Methods

In the time series multiplicative decomposition model employed for this study, the seasonal period m of the datasets was used for computation. The multiplicative decomposition model assumes that the actual data of the time series are the product of its components. That is:

$Y(t) = T(t) \times S(t) \times R(t) Y(t)$

$= \mathrm{T(t)} \times \mathrm{S(t)} \times \mathrm{R(t)} \mathrm{Y(t)} = \mathrm{T(t)} \times \mathrm{S(t)} \times \mathrm{R(t)}$ (1)

where

Y(t)Y(t)Y(t) = the observed data,

T(t)T(t)T(t) = the trend,

S(t)S(t)S(t)=the seasonal component,

R(t)R(t)R(t) =the residual component.

For multiplicative decomposition seasonality, the mvalues that form the seasonal components are called the seasonal indices in most cases. If mis an even number, then for time series multiplicative decomposition, compute the trend-cycle component $\hat{T}_t$via a 2×m-MA. If mis an odd number, the trend-cycle component $\hat{T}_t$ is computed viam-MA.

Error metrics

The mean absolute percentage error (MAPE):The MAPE measures the accuracy of the prediction model as a percentage (%). It was calculated as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{O_t - F_t}{O_t}\right| \quad (2)$$

where O_t is the observed value and F_t denotes the forecasted value.

Mean absolute deviation (MAD): This error parameter is used to measure the accuracy of the fitted time series datasets. It expresses accuracy in the same units as the data do, which helps to measure the accuracy of the forecast. It is given as:

$$MAD = \sum_{t=1}^{n}\left|\frac{y_t - \overline{y_t}}{n}\right| \quad (3)$$

where$y_t$represents the actual value, $\overline{y_t}$represents the forecast value, and n represents the number of forecasts.

The mean square deviation (MSD): This is a measure used for evaluating forecast accuracy. The error was calculated by squaring the individual forecast deviation (error) for each period and then finding the average or mean value of the sum of squared errors. The forecast error is the actual observation for a period minus the forecast for that period Okoro (2024). The mean squared error is used because, by squaring the error values, the resulting values are all positive.It is given as:

$$MSD = \frac{1}{n}\sum_{t=1}^{n}\left(x_{obs,t} - x_{pred,t}\right)^2 \quad (4)$$

where $\mathrm{x_{obs,i}}$ = observed varaiable,and$\mathrm{x_{pred,i}}$ = predicted variable.

RESULTS AND DISCUSSION

Figs. 1, 2, 3 and 4 show likely patterns of variation in actual rainfall, temperature, relative humidity and wind speed data obtained via the time series multiplicative decomposition model for the study area. The plots contain the actual data, the fits, the trend lines and the forecasts.

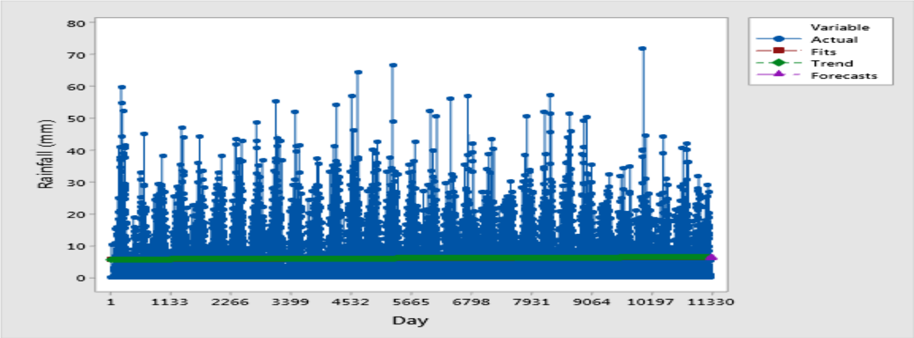

Figure 1: Time series multiplicative decomposition plot for rainfall (mm)

Fig. 1(multiplicative model plot) shows that the fits of the plot do not closely follow the trend of the actual data and therefore suggest that the model does not fit the data accurately and implies that the model underpredicted the dataset of the series. However, the trend component of the plot shows the overall up- and downwards movement in the rainfall data variation over time, which was observed to be predominantly greater in the middle of the plot, suggesting that rainfall in the study area does not maintain a constant pattern during different periods and seasons of the year, possibly due to the geographical location of the study area.

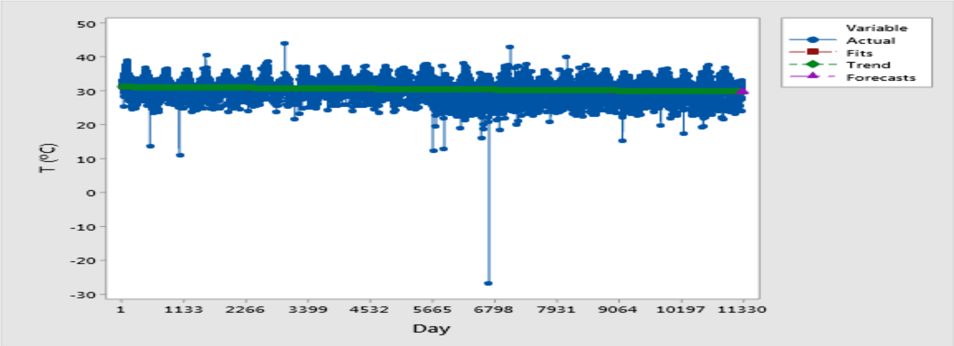

Figure 2: Time series multiplicative decomposition plot for temp (°C)

Fig. 2 shows that the trend of the plots closely fits the data and therefore means that the model actually predicts the data. Overall, there wereupwards and downwards movements in the trend component of the variation in temperature data over time, suggesting that the temperature in the study area does not have a definite pattern during different periods of the year. It is solely dependent on the weather conditions over a given period of time

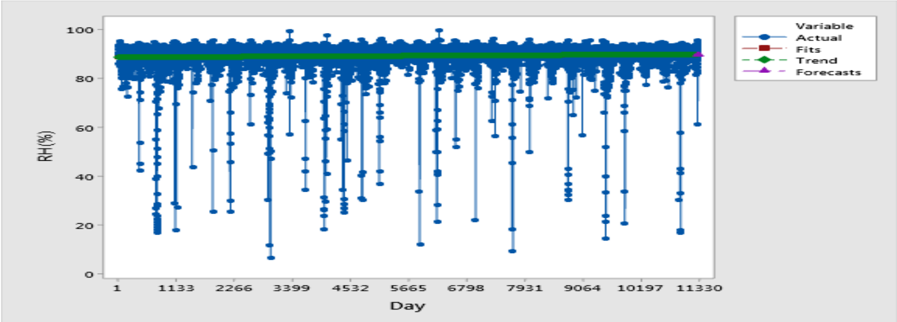

Figure 3: Time series multiplicative decomposition plot for RH (%)

Fig. 3 shows that the trend of the plots fits the data closely, which means that the model accurately predicts the relative humidity data. Overall, there were upwards and downwards movements in the trend component of the variation in relative humidity data over time, which represents the fluctuation pattern at different periods of the year for the study area.

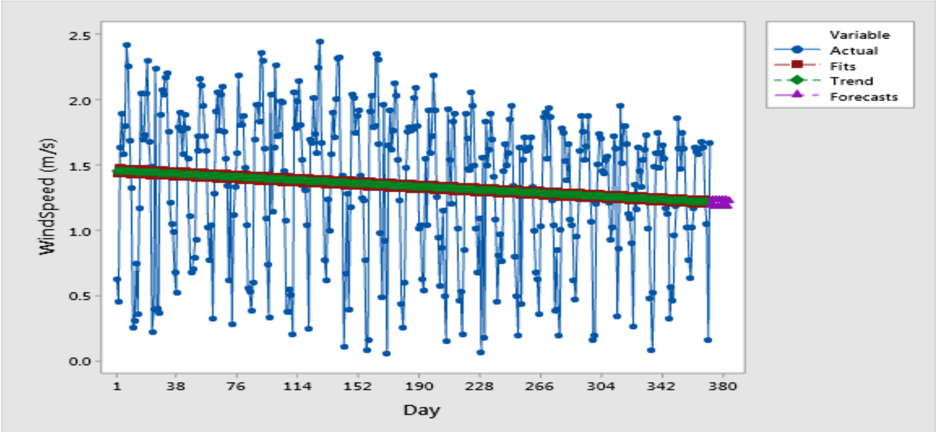

Figure 4: Time seriesmultiplicative decomposition plot for the wind speed (m/s)

Fig. 4 shows that the trend of the plots fits the data closely and thus suggests that the models have the potential to forecast the data accurately. Overall, there were upwards and downwards movements in the trend component of the variation in the wind speed data over a specific period of time.

Table 1: Error indices

Parameter	MAPE	MAD	MSD
Rainfall	275.068	5.963	63.123
Temperature	7.65466	2.25300	8.16855
RH	5.1126	3.2397	43.8606
Wind speed	93.3776	0.4914	0.3356

Rainfall error indices

Table 1 presents the common error metrics used to evaluate the accuracy of the time series multiplicative forecasting model for the different atmospheric parameters. Rainfall has a mean absolute percentage error (MAPE) of 275.068. This value is extremely high, indicating that the forecasted rainfall values are on average 275% greater than the actual value. This suggests a poor fit of the model for rainfall data. This could be due to extreme fluctuations in rainfall or a mismatch between the model and the data pattern. The mean absolute deviation (MAD) value for rainfall is 5.963. This indicates that the average deviation between the forecasted and actual rainfall data is approximately 5.963 mm. However, due to the large MAPE, this suggests that there might be very large outliers or highly variable rainfall events. For the mean squared deviation (MSD), the value for rainfall is 63.123. This is another measure of error, and a high value suggests significant variance in the errors. A high MSD often correlates with large deviations from the true values, further indicating poor prediction accuracy. This result suggests that the multiplicative model fails to capture the complex variations and extremes in rainfall variation patterns.

Temperature error indices

The error metricMAPE of 7.65% obtained for temperature, as shown in Table 1, is relatively low and thus indicates that the forecasted temperature is, on average, but only deviates by approximately 7.65% from the actual data values, which suggests good forecasting accuracy of temperature variation by the model in the study area. For the MAD 2.25300 error metric, the average absolute deviation of the forecasted value from the actual value is 2.253 °C. This result further confirms that the model is good at forecasting temperature variations in the study area. For the error metrics, an MSD of 8.16855 indicates a moderately high value compared with the MAD, indicating that while most forecasts are close to the actual temperature, there are some larger deviations. This result therefore suggests that there are occasional outliers or large deviations in the data values, but overall, the model still performs well.

Relative humidity error indices

The model error metric MAPE value of 5.11% for relative humidity is relatively low and thus implies a good fit for the data. This result suggests that the forecast for relative humidity is quite accurate and therefore underscores the models' ability to predict relative humidity within the study area with minimal error. The mean absolute deviation (MAD) of 3.24% indicates that the model's errors are relatively small in terms of absolute percentage deviations, which reinforces the accuracy of the forecast. The high mean squared deviation (MSD) of 43.86 shows that whereas most of the relative humidity values are forecasted fairly accurately, there are some significant outliers or large deviations of the forecasted values from the actual values.

Wind speed error indices

For the wind speed, the extremely high MAPE of 93.3776suggests that the wind speed model is very inaccurate and that the forecasted values are often incorrectly greater than 93%. This could be caused by the inability of the model to capture the underlying variation patterns in wind speed, possibly due to nonlinear relationships or high variability in the study area. Despite the high MAPE, the MAD value of 0.4914is relatively low, which implies that the predicted values are not dramatically different from the actual values; rather, the large MAPE value suggests that large errors or outliers skew the results. The MSD value of 0.3356is also quite low, which shows that the forecast errors are fairly small on average. However, the large MAPE value still suggests that some extreme values are poorly forecasted; therefore, the model is deemed unfit in this context.

The findings from this study confirmed that the multiplicative time series decomposition model is more effective in forecasting some atmospheric parameters such as temperature and relative humidity with minimal prediction error than rainfall and wind speed. The model successfully identified seasonal trends and minimized residual errors, outperforming traditional models in terms of accuracy. These results suggest that time series decomposition methods, particularly the multiplicative model, should be considered as a standard tool in atmospheric forecasting. These findings are in agreement with a research carried out by Monday *et al.* (2013) who revealed that the forecast error variance decomposition can be used to interpret the variance model. The low MAPE of 7.65466 obtained in this study is in agreement with the MAPE of 6.71888 and 7.07229 respectively obtained by Adenomon and Ojehomon (2014) in their study on a comparison of decomposition time series method and winters' seasonal exponential smoothing in forecasting seasonal temperature in Niger state, Nigeria. The result of their research showed that the application of decomposition time series model in forecasting seasonal temperature in Niger State, Nigeria outperforms the winters' seasonal exponential smoothing method. The improved accuracy of forecasting has significant implications for sectors that depend on reliable weather data, such as agriculture, water management, and disaster preparedness. Accurate forecasts of atmospheric parameters such as rainfall and temperature can help farmers optimize planting schedules and reduce losses due to extreme weather events.

CONCLUSION

From the results, it is obvious that the model seems to perform poorly for the forecasting of rainfall, with a very high MAPE and significant errors (both MAD and MSD), which may be due to high variability or extreme weather events in the study area. For temperature forecasting, the model performs relatively well, with low MAPE and MAD values, indicating that the prediction is generally accurate. Similar to the results obtained for temperature, the model is fairly accurate in forecasting relative humidity, with a small MAPE and MAD, but a high MSD suggests occasional outliers or large forecast errors. The extremely high MAPE for the wind speed indicates significant errors with the model accuracy, although the values of MAD and MSD obtained suggest that the errors might not be uniformly distributed or the same across the data, thus improving the accuracy of the forecasting models. Conclusively, while multiplicative models for temperature and relative humidity show relatively good accuracy measures, the models for rainfall and wind speed need substantial refinement. The high error indices obtained for these parameters suggest that further investigations and possibly alternative forecasting models should be explored to improve the accuracy of forecasts for these parameters.

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