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Forecasting the Rainfall of Anambra State using Timeseries Model

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ABSTRACT

This study employed time series analysis to forecast rainfall data obtained from Anambra State obtained from the Nigerian Meteorological Agency. Using SPSS's Time Series Expert Modeler, a simple seasonal exponential smoothing model was identified as the most suitable for the dataset. The model adequately explained variations in rainfall and passes validation tests, including the Ljung-Box test. A 12–month forecast from September 2023 to August 2024 was conducted, and the results are discussed. While the Time Series Expert Modeler may not always provide optimal models, it proves effective in this analysis. Manual model exploration remains valuable if the automated approach fails to meet criteria.

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INTRODUCTION

Water is an indicator of life, a lack or low–supply of which increases the risk of disease infections, poor industrialization, poor personal hygiene as well as community hygiene, low–quality food production, conflicts, human rights abuses, and poverty. Unsafe water and poor sanitation have been attributed to cause over a million deaths, with 90% of the deaths occurring in children under the age of five in developing countries (WHO, 2019).

Integrating data from various sources, including meteorological stations, satellites, and climate models, may encounter challenges related to data inconsistencies. Differing measurement techniques and calibration methods can lead to discrepancies that impact the accuracy of the models, (Okoro et al, 2022).

According to Olawuyi et al., (2018) and Eze et al., (2020), Anambra State features a tropical climate strongly affected by the West African Monsoon, characterized by distinct wet and dry seasons. The elevation, proximity to the Niger River, and regional weather patterns contribute to the unique climatic conditions of the State. This section explores these factors in detail, providing insights into the complexity of rainfall variability within the region.

Nwokolo et al., (2019) noted that Anambra State is prone to extreme weather conditions such as intense storms and flooding. Modeling such events requires specialized techniques and data, and the unpredictability of extreme conditions adds a layer of complexity to the development of accurate models.

Oguntunde et al. (2016) noted that Anambra State is undergoing rapid urbanization and changes in land use due to rural–urban migration. It is important to study and consider the impacts of these changes on local climate patterns and rainfall in models. Integrating land–use change scenarios into modeling efforts requires a nuanced understanding of socio-economic trends.

Despite its importance, accurate modeling of rainfall in Anambra State poses many challenges. Existing models often fall short in capturing the complexities of local climate dynamics, hindering the development of precise predictive tools for effective planning and resource management (Nwokolo et al., 2019).

OBJECTIVES

a. To obtain the best timeseries model using expert modeler.

b. To obtain a 12–month forecast using the best model

The research objectives were achieved using monthly rainfall data of Anambra State from January 2020 to August 2023. The data were sourced from Nigerian Metrological Agency (NIMET).

METHODOLOGY

TIME SERIES

This is a sequence of data points measured or recorded at successive points in time. It is a powerful tool for understanding and analyzing phenomena that evolve over time. Time series data can be found in various fields, such as finance, economics, weather forecasting, signal processing, and more. Understanding the patterns, trends, and underlying structures in time series data is crucial for making predictions and informed decisions.

KEY COMPONENTS OF TIME SERIES

Trend: The long–term movement or direction in the data. Trends can be upward, downward, or stable.

Seasonality: Regular, repeating patterns that occur at consistent intervals. For example, retail sales often exhibit seasonality with higher sales during holidays.

Cyclic Patterns: Repeating but not necessarily regular patterns that occur over a more extended period than seasonality. Unlike seasonality, cycles don't have fixed periods.

Random Noise: Unpredictable and irregular fluctuations that cannot be attributed to any specific pattern.

Common Formulas and Techniques in Time Series Analysis:

Moving Average (MA): The moving average smoothens out short–term fluctuations, making underlying trends more apparent. The formula is given by

$$MA_t = \frac{X_{t-1} + X_{t-2} + \ldots + X_{t-n}}{n} \qquad (1)$$

Exponential Smoothing (ETS): Exponential smoothing assigns exponentially decreasing weights to past observations, giving more emphasis to recent data. The formula is given by

$$F_{t+1} = \alpha + X_t + (1-\alpha)F_t \qquad (2)$$

Autoregressive Integrated Moving Average (ARIMA): ARIMA models are represented as ARIMA (p, d, q), where p is the differencing order, d and q are the moving average order. ARIMA models are effective for capturing different components of time series data.

Seasonal Decomposition of Time Series (STL): STL decomposes time series into components like trend, seasonality, and remainder to better understand underlying patterns.

Fourier Transform for Seasonality: Formula: Fourier transform can be applied to identify and analyze periodicities in time series data, especially for seasonality.

Time Series Cross Validation: Techniques like k-fold cross-validation are used to assess the performance of time series models.

Autoregressive (AR) Model: An autoregressive model expresses the current value as a linear combination of past values. The formula is

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \varepsilon_t \qquad (3)$$

Moving Average (MA) Model: A moving average model represents the current value as a linear combination of past forecast errors.

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \qquad (4)$$

EXPERT MODELER IN SPSS

An expert modeler, often referred to as a skilled data scientist or analyst, possesses advanced knowledge and experience in constructing sophisticated models to analyze data and make predictions. Expert modelers not only understand the theoretical underpinnings of various modeling techniques but also have practical expertise in selecting, implementing, and fine–tuning models based on the characteristics of the data and the goals of the analysis.

EXPONENTIAL SMOOTHENING

Exponential smoothing methods are popular techniques in time series forecasting, particularly when the data does not exhibit significant trend, cyclicality, or seasonality. These methods are effective for short-range forecasts and aim to smooth out random fluctuations in the time series data. Let's delve into the details of moving averages, weighted moving averages, and exponential smoothing:

Concept: Exponential smoothing is a special weighted average method where the weight for the most recent observation is explicitly selected, and weights for older observations are automatically computed.

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t \tag{5}$$

is forecast for the next period.
is actual observation at time.
is forecast for the current period.
Smoothing parameter .
The smoothing parameter determines the weight given to the most recent observation. Smaller values give more weight to older observations.

LJUNG BOX TEST

The Ljung–Box test is applied in the context of autoregressive integrated moving average (ARIMA) models and other time series models. While not as commonly used as with ARIMA models, you can still conduct the Ljung–Box test on the residuals of an exponential smoothing model to check for autocorrelation. However, the interpretation might be less straightforward compared to its application in ARIMA models,

Here's a general guide on how to conduct a Ljung–Box test for residuals in SPSS after fitting an exponential smoothing model:

Fit Exponential Smoothing Model: Use the appropriate function or module in SPSS to fit your exponential smoothing model.

Save Residuals: Extract the residuals from the fitted model.

Run Ljung-Box Test: Use the Ljung-Box Q test in SPSS, specifying the saved residuals and the desired lag values.

Interpret Results: Examine the p-value associated with the Ljung-Box test. If the p–value is below your chosen significance level, it may indicate the presence of autocorrelation in the residuals.

Model and Parameter Estimation/Model Validation

Table 1 and 2 shows the estimated parameters of the selected models for monthly rainfall in Awka and the forecasted values for 16months respectively. The model is obtained using the Expert modeler in SPSS software.

Table 1: Model and Parameter estimation Using Expert Modeler

(Monthly Rainfall)
Simple Seasonal Exponential
R-Square: 0.612, RMSE: 120.532, MAPE: 3498.912
Ljung-Box Q (18)
Statistics:25.698 Df:16 P-value:0.058
Parameter:
Alpha(level): 0.100 Delta(Season):8.668E-5
S.E: 0.121, t=.826, P-value:0.414 S.E:.217, t=.000, P-value:1.00
Normalized BIC=9.756

FINDINGS AND DISCUSSIONS

From table 1 above, we observe that using expert modeler to determine the appropriate model for modelling monthly rainfall, the best model selected is the simple seasonal exponential smoothing with R–square value of 0.612, which indicate that 61.2% of the variation in the dependent variable can be explained by the model indicating a more that average performance of the model and investigating the validation of the models using the Ljung–Box test, the p–value of the test is 0.058 which is greater than the level of significance value 0.05, indicating that the residuals are independently distributed which signifies that the model is valid. Therefore, the model selected by the expert modeler can be used to model monthly rainfall in Anambra State. The parameter alpha(level) and Delta(seasonal) estimated are also significant with a p–value of 0.414 and 1.000 respectively, which are both greater than the level of significance 0.05.

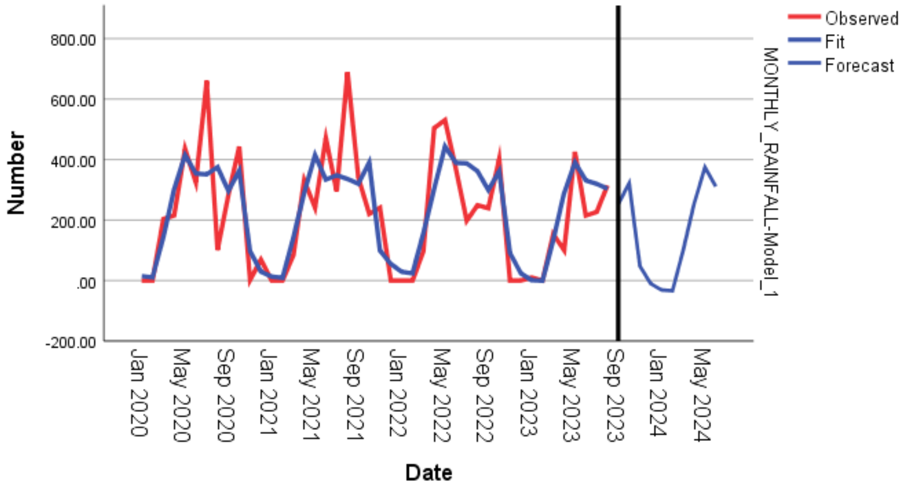

Figure 1: The Observed, the Fit, and the Forecast Plot for Monthly Rainfall in Anambra State

From fig.1 we observe an almost the same plot for the observed, fit, and forecast values from January 2020 to September 2024.

Forecasting

Using the appropriate models obtained, we made a 12–month forecast, from September 2023 to December 2024, for the monthly rainfall. The table below shows the result of the forecast.

Table 2: Observed rainfall of Anambra State from Jan. 2020 to Aug. 2023

Month	**2020**	**2021**	**2022**	**2023**
JAN	0	0	0.1	9.8
FEB	0	0	0	0
MAR	203.5	83.7	97	153.7
APRIL	215.5	331.2	504.4	100.5
MAY	435.5	241	530.5	425.5
JUNE	324.9	470.2	369.9	215.1
JULY	660.6	295.8	198.2	226.5
AUG	100.8	688.9	249.2	314.9
SEPT	282.5	340.3	239.6	Nil
OCT	443.1	220.5	401.6	Nil
NOV	2.1	240.7	0.1	Nil
DEC	69	0	0	Nil

Table 3: Forecast of 12month (Sept.2023 to Dec.2024)

S/N	**Months/Years**	**Rainfall**
1	SEP 2023	253.8
2	OCT 2023	321.4
3	NOV 2023	47.3
4	DEC 2023	-10.7
5	JAN 2024	-31.2
6	FEB 2024	-33.7
7	MAR 2024	100.8
8	APR 2024	254.2
9	MAY 2024	374.5
10	JUN 2024	311.4
11	JUL 2024	311.6
12	AUG 2024	304.8

FINDINGS AND DISCUSSIONS

From table 3, we observed that the model forecast for September 2023 had a 19.4% drop from the August 2023 observed value, a percent increase of 21.033% was observed from September 2023 to October 2023, a drastic drop of 85.28% was observed from October 2023 to November 2023, the drastic drop exceeded into the negative at an average reduction 112.69%, an average percentage increase of 75.30% in rainfall is to be expected from March 2024 to May 2024, and finally an average percentage decrease of 16.85% to be expected by June 2024, then a percentage increase of 0.06% in the month of July, and finally a percentage drop of 2.18% by August is to be expected.

CONCLUSION

From the result, the simple season exponential smoothing model was selected as the best model for fitting the rainfall data on Awka. The model performed averagely well in explaining the variations in dependent variable, it also passed the model validation test which was carried out using the Ljung-Box test, and also the model has significant parameters, the alpha(level) and the Delta(seasonal).

The model was then used to carry out a 12–month forecast from September 2023 to August 2024, and a study and discussion was made on the forecast obtained.

Though the Time Series Expert Modeler has not been proven to be always effective and efficient when it comes to the selection of best model for forecasting a time series data. In some reviewed articles or studies, it may either select models that may be able to explain the variations in the dependent variable to a large extent, but may have models that not valid, or insignificant parameters. But this is not always the case, as for this analysis it selected a model that could explain the variations in the dependent variable, passed the model validation test, and all parameters in the model were significant. So, the Time Series Expert Modeler can be used to cub the time constraint of having to discover best models manually. We could try it and if it doesn't give it doesn't provide a model that satisfies the performance test, validation test, and parameters significance, we could then find the best model manually.

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