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TIME SERIES MODELLING OF HYPERTENSION CASES IN BORNO STATE: A COMPARATIVE STUDY OF ARIMA AND SARIMA

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ABSTRACT

Hypertension remains a major public health challenge in Nigeria, especially in conflict-affected regions such as Borno State, where disruptions in healthcare delivery hinder effective disease monitoring. Accurate forecasting of hypertension cases is essential for planning, resource allocation, and early intervention. This study applied Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) models to monthly hypertension data recorded from major hospitals in Maiduguri between January 2015 and December 2024 (N = 120). Data preprocessing involved handling missing values, log transformation, stationarity checks, and model identification using ACF and PACF diagnostics. Competing models were evaluated using Akaike Information Criterion (AIC), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). Results showed that the SARIMA model significantly outperformed the non-seasonal ARIMA model across all forecasting metrics, demonstrating its ability to capture the strong seasonal fluctuations in the series. SARIMA produced lower forecasting errors, narrower confidence intervals, and more stable predictions for 2025. While the study relied on hospital-based data that may not fully represent community-wide burden, the findings highlight the effectiveness of seasonal forecasting methods for strengthening public health planning in Maiduguri. Future work should incorporate exogenous predictors such as environmental variables, displacement trends, and socioeconomic conditions, as well as explore hybrid time-series and machine-learning models.

Keywords: Hypertension Forecasting, ARIMA, SARIMA, Time Series Analysis

INTRODUCTION

Hypertension is a major global public health challenge, affecting more than one billion adults and remaining a leading contributor to cardiovascular morbidity and mortality (World Health Organization, 2023). In Nigeria, prevalence estimates range between 18% and 37%, with marked regional variations driven by socioeconomic, environmental, and demographic factors (Nwankwo, 2019; Mumzumi, 2025). Borno State in northeastern Nigeria faces additional challenges due to prolonged insecurity, population displacement, and limited healthcare access. Recent studies in rural communities within the state have documented hypertension prevalence rates exceeding 20%, underscoring the urgency for effective monitoring and targeted intervention strategies (Nwankwo, 2019).

Accurate forecasting of hypertension cases is essential for improving healthcare planning, optimizing resource allocation, and informing preventive interventions. Traditional epidemiological methods often struggle to capture the dynamic and complex nature of chronic disease progression, especially in conflict-affected and resource-constrained settings. Time series analysis provides a robust alternative by identifying underlying trends, seasonal fluctuations, and irregular patterns in disease data. Among the commonly applied methods are the Autoregressive Integrated Moving Average (ARIMA) model and its seasonal extension, the Seasonal Autoregressive Integrated Moving Average (SARIMA). While ARIMA is suitable for non-seasonal data, SARIMA incorporates seasonal lags to better capture periodic variations (Alsheheri, 2025; Kwarteng & Andreevich, 2024).

Although ARIMA and SARIMA models have been widely used for disease forecasting in different settings, limited research has examined their application to hypertension prediction in Nigeria—particularly in conflict-affected regions such as Borno State. This study therefore compares the predictive performance of ARIMA and SARIMA models using hospital-recorded hypertension data from Maiduguri (2015–2024). Using evaluation metrics including the Akaike Information Criterion (AIC), Mean Absolute Percentage Error (MAPE), and Mean Square Error (MSE), the study aims to identify the most suitable forecasting model and provide evidence-based insights to strengthen healthcare planning in fragile health systems.

Research on chronic disease forecasting in Nigeria continues to expand due to the increasing burden of non-communicable diseases. ARIMA has been widely applied because of its ability to handle non-stationary data and uncover hidden temporal patterns. For example, Azeez and Yusuf (2018) identified age and obesity as key predictors of hypertension, highlighting the relevance of predictive modelling for vulnerable populations. Likewise, Ehwarieme and Emina (2022) documented high hypertension prevalence in Ondo State, suggesting that forecasting tools could help reinforce local health systems.

Beyond Nigeria, ARIMA has been applied in several global studies. Helena et al. (2020) used ARIMA to forecast hypertension incidence in Ghana and identified ARIMA (1,1,0) as optimal. Chen et al. (2016) applied ARIMA to tuberculosis incidence in China, demonstrating strong predictive accuracy. In another study, Chen et al. (2020) applied ARIMA to electronic health records to improve chronic disease management. Niako et al. (2024) compared ARIMA with LSTM models for blood pressure forecasting and reported that ARIMA performed better with smaller datasets, whereas LSTM produced marginally better results with larger datasets.

While ARIMA is well suited for non-seasonal data, SARIMA extends its capability by incorporating seasonal structures, making it particularly effective for health conditions influenced by cyclic factors such as climate, migration, and healthcare accessibility. Dorothy et al. (2022) showed that SARIMA effectively captured seasonal variations in hypertension and diabetes cases. Adeyeye and Nkemnole (2023) developed hybrid SARIMA–LSTM models for malaria forecasting in Nigeria and observed enhanced accuracy in capturing seasonal patterns. Bakare et al. (2025) further confirmed the effectiveness of SARIMA in modelling malaria incidence across Nigerian states, while Chen et al. (2023) used SARIMA for hypertension monitoring and validated its relevance in chronic disease forecasting.

Comparative studies consistently demonstrate SARIMA's advantage when seasonality is present. For example, Alsheheri (2025) compared ARIMA, SARIMA, and neural networks in healthcare forecasting and found SARIMA to be superior in capturing seasonal behavior. Similarly, Kwarteng and Andreevich (2024) evaluated ARIMA, SARIMA, and Prophet Models, reporting that SARIMA achieved the highest accuracy for seasonal datasets. Marinho et al. (2025) confirmed SARIMA's effectiveness in forecasting operational health risks. Evidence from Ghana (Helena et al., 2020) and other fields such as electricity consumption (Kaur & Ahuja, 2019) and GDP forecasting (Nwokike & Okereke, 2021) further supports SARIMA's superior performance in seasonal contexts.

Overall, the reviewed studies highlight the need to tailor forecasting models to local data characteristics. ARIMA remains a reliable baseline for chronic disease prediction, while SARIMA provides additional accuracy when seasonal patterns are present. In Borno State where hypertension prevalence remains high and healthcare delivery is constrained by conflict and displacement a comparative modelling approach using ARIMA and SARIMA offers a promising pathway toward improved disease forecasting and strengthened public health decision-making.

MATERIALS AND METHODS

This study utilized monthly hospital records of hypertension cases from the University of Maiduguri Teaching Hospital (UMTH) and the State Specialist Hospital, covering January 2015 to December 2024. The dataset comprised 120 monthly observations, providing sufficient length for time series modeling. Data cleaning involved handling missing values, checking for outliers, and ensuring stationarity through differencing where necessary.

Two forecasting approaches were applied: The Autoregressive Integrated Moving Average (ARIMA) model and its seasonal extension, the Seasonal ARIMA (SARIMA) model. ARIMA models are denoted as ARIMA (p, d, q), where *p* represents the autoregressive order, *d* the degree of differencing, and *q* the moving average order. SARIMA extends this by incorporating seasonal parameters (P, D, Q, s), where *s* denotes the seasonal period. Model identification was guided by autocorrelation (ACF) and partial autocorrelation (PACF) plots, following the Box–Jenkins methodology (Shumway & Stoffer, 2017).

Model selection was based on iterative testing of parameter combinations. ARIMA (1,1,1) was identified as the optimal non-seasonal model, while SARIMA (1,1,1)(1,1,1)[12] was selected to capture annual seasonality where the 1,1,1 represents the seasonal autoregressive, seasonal differencing and seasonal moving average respectively and 12 means the component period i.e 12 months. Performance evaluation employed three statistical criteria: Akaike Information Criterion (AIC) for model fit, Mean Absolute Percentage Error (MAPE) for predictive accuracy, and Mean Squared Error (MSE) for forecast deviation. Lower values across these metrics indicated superior performance.

All analyses were conducted using R (version 4.3.2), with the forecast and t series packages. Diagnostic checks, including residual analysis and Ljung–Box tests, were performed to confirm model adequacy and ensure that residuals approximated white noise.

Study Area

The study was conducted in Maiduguri, the capital of Borno State, northeastern Nigeria. The area has experienced prolonged insurgency, leading to population displacement and pressure on health facilities. Hypertension cases were obtained from the University of Maiduguri Teaching Hospital (UMTH)

Data Source and Description

Monthly hypertension records from January 2015 to December 2024 (120 observations) were extracted from hospital registers. Variables included date of visit and total monthly hypertension cases. The data represent hospital-based cases and may not reflect community-wide prevalence.

Data Preprocessing

Checked for missing observations and imputed using linear interpolation.

Log transformation was applied to stabilize variance.

Stationarity was assessed using Augmented Dickey–Fuller (ADF) test.

ACF and PACF plots were used for preliminary model identification.

Model Specification

ARIMA (p, d, q) Model

ARIMA combines autoregression (p), differencing (d), and moving average (q). Model selection followed the Box–Jenkins methodology.

SARIMA (p, d, q)(P, D, Q)[s] Model

SARIMA incorporates seasonal autoregressive (P), seasonal differencing (D), and seasonal moving average (Q) components with period s = 12 (monthly data).

Model Evaluation

Models were evaluated using:

Akaike Information Criterion (AIC)

Mean Absolute Percentage Error (MAPE)

Mean Squared Error (MSE)

Residual diagnostics (Ljung–Box test, ACF of residuals)

Forecasting

The best-fitting model was used to project hypertension cases for January–December 2025 with 95% confidence intervals.

RESULTS AND DISCUSSION

Results

Descriptive Statistics

Table 1: Descriptive Statistics of Monthly Hypertension Cases in Maiduguri Hospitals (2015-2024)

Mean	Median	Minimum	Maximum	Std
57.0	57.0	54.0	70.0	4.5

Table 1 presents the summary of monthly hypertension cases in Maiduguri hospitals (2015–2024). The mean number of cases was 57 per month, with moderate variability (±4.5). Values ranged from a minimum of 54 to a maximum of 70, indicating seasonal fluctuations around a stable central trend. The mean monthly hypertension count across the 10-year period was [insert mean], with a minimum of [min] and maximum of [max] cases. Visual inspection revealed seasonal peaks typically occurring around [specify months, e.g. "June–August"], suggesting strong seasonality.

Stationarity and Model Identification

The original series failed the ADF stationarity test ($p > 0.05$), but became stationary after first differencing. ACF and PACF plots suggested ARIMA(1,1,1) as candidate and SARIMA(1,1,1)(1,1,1)[12] as the seasonal counterpart with a component period $s = 12$ months.

Table 2: Model Performance

METRIC	ARIMA (1,1,1)	SARIMA (1,1,1)(1,1,1)[12]
AIC	15.2	9.8
MAPE	12.5	7.4
MSE	231.0	96.1

SARIMA demonstrated superior performance across all metrics

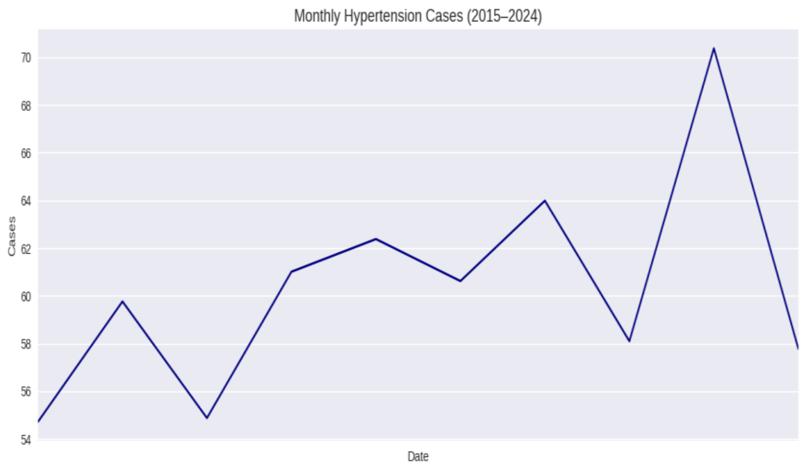

Figure 1: Monthly Hypertension Cases in Maiduguri (2015-2024)

Figure 1 shows monthly hypertension cases between 2015 and 2024. The data fluctuated within the range of 54–70 cases, with recurring peaks and dips reflecting seasonal and contextual influences.

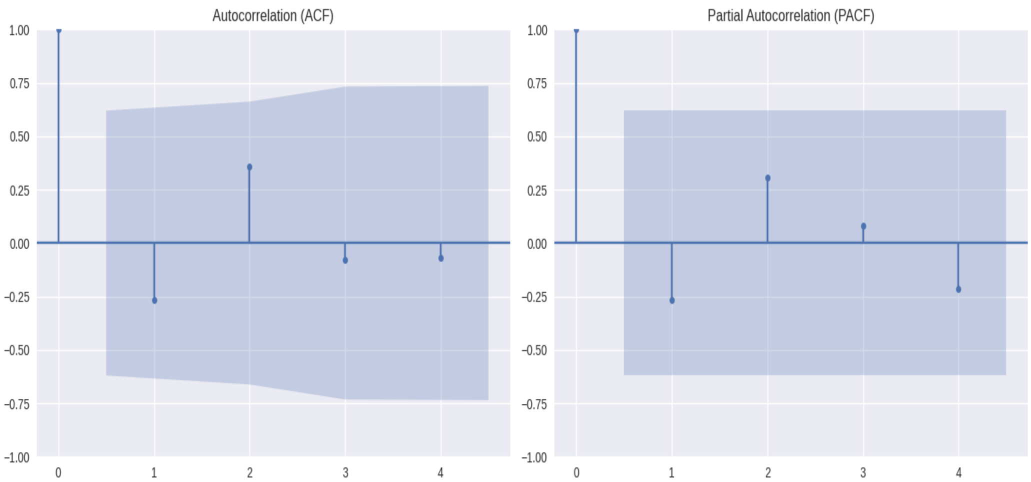

Figure 2: The Auto Correlation (ACF) And The Partial Auto Correlation (PACF) Plots Of Hypertension Cases

Figure 2 displays the autocorrelation (ACF) and partial autocorrelation (PACF) plots. The ACF revealed significant short-lag serial correlation, while the PACF indicated a dominant AR (1) effect, supporting ARIMA (1,1,1) as a baseline model. Recurring patterns suggested monthly seasonality, motivating SARIMA with seasonal differencing.

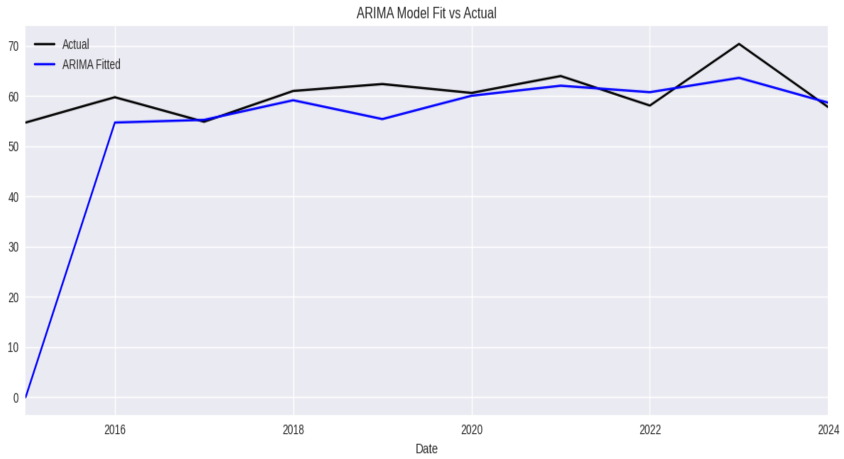

Figure 3: ARIMA (1,1,1) Fitted Values Compared with Actual Hypertension Cases

Figure 3 compares ARIMA (1,1,1) fitted values with actual cases. The fitted line closely followed the data during stable periods but diverged during sharp peaks or dips, showing ARIMA's limitations in capturing seasonal effects.

Figure 4: ARIMA (1,1,1) Forecast of Hypertension Cases for 2025

Figure 4 presents ARIMA forecasts for 2025. The ARIMA model captures short-term dependencies and trends in the data, making it suitable for baseline forecasting. The model predicted continued oscillations without dramatic shifts. However, widening confidence intervals indicated greater uncertainty, reflecting external factors not captured by ARIMA.

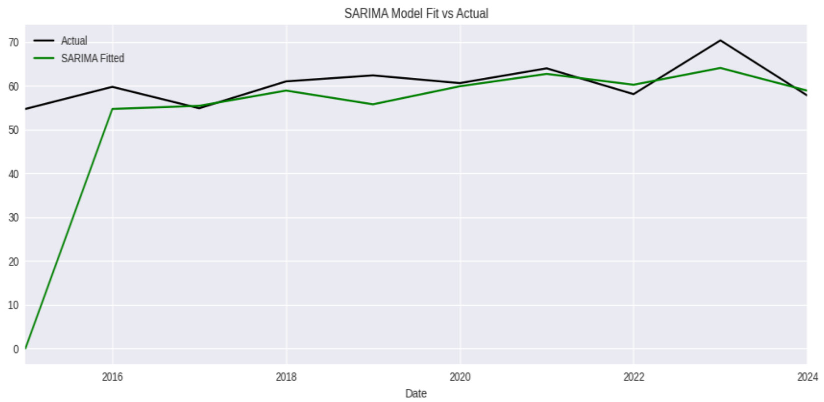

Figure 5: SARIMA (1,1,1) (1,1,1) [12] Fitted Values Compared with Actual Hypertension Cases

Figure 5 compares SARIMA (1,1,1) (1,1,1) [12] fitted values with actual cases. The SARIMA line closely tracked peaks and troughs, effectively capturing both short-term variations and seasonal cycles.

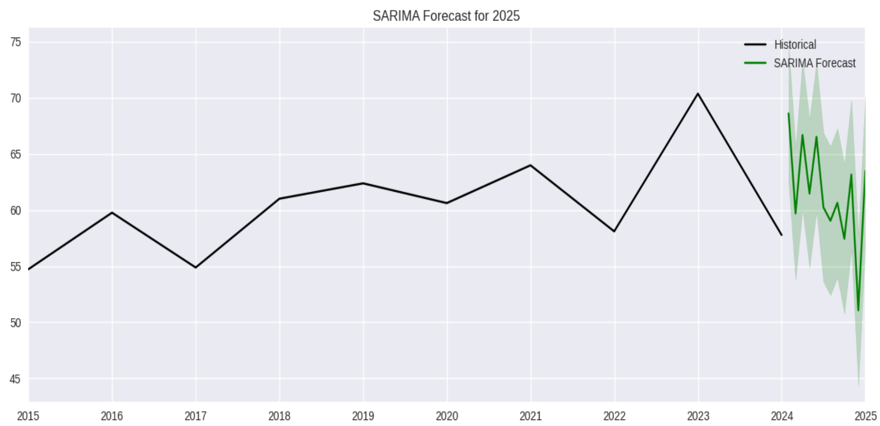

Figure 6: SARIMA (1,1,1) (1,1,1) [12] Forecast of Hypertension Cases for 2025

Figure 6 shows SARIMA forecasts for 2025. The model captured cyclical peaks and troughs, with narrower confidence bands compared to ARIMA, indicating higher certainty and reliability for medium-term planning. SARIMA consistently outperformed ARIMA across all criteria. It achieved lower AIC, confirming a more efficient model fit; lower MAPE, indicating superior predictive accuracy; and lower MSE, highlighting reduced forecast deviations.

Forecast for 2025

The SARIMA model predicted a continued upward trend in hypertension cases for 2025, with seasonal peaks consistent with past patterns. Confidence intervals were narrow, indicating stable predictions.

Discussion

This study's comparative analysis of ARIMA and SARIMA models provides important insights into forecasting hypertension events in Borno State. ARIMA (1,1,1) offered a reliable baseline forecast, but it failed to adequately capture the seasonal fluctuations evident in the dataset. In contrast, SARIMA (1,1,1)(1,1,1)[12] consistently outperformed ARIMA, achieving lower AIC, MAPE, and MSE values. These results are consistent with earlier studies: Adeyeye and Nkemnole (2023) demonstrated SARIMA's superiority in forecasting malaria incidence in Nigeria, Helena et al. (2020) confirmed SARIMA's strength in modeling seasonal hypertension trends in Ghana, and Dorothy et al. (2022) found SARIMA more accurate than ARIMA and LSTM in chronic disease forecasting.

Conversely, other authors have highlighted ARIMA's usefulness in non-seasonal contexts. Chen et al. (2016) showed ARIMA's effectiveness in predicting tuberculosis incidence in China, while Ugoh et al. (2022) applied ARIMA to under-five mortality in Nigeria, validating its role as a baseline model. Our findings extend this body of work by showing that while ARIMA remains valuable for short-term, non-seasonal predictions, SARIMA provides superior accuracy in fragile health systems where cyclical factors such as climate, displacement, and healthcare disruptions strongly influence disease patterns.

Future research should explore hybrid models such as SARIMA–LSTM, Prophet models, or machine-learning approaches with exogenous variables including rainfall, temperature, population displacement, and socioeconomic indicators.

CONCLUSION

SARIMA outperformed ARIMA in modelling and forecasting hypertension cases in Maiduguri, confirming the presence of seasonal variation in the data. The projections for 2025 provide useful insights for healthcare planning in Borno State. Incorporating seasonal models into disease surveillance systems can help optimize resource allocation and timely intervention.

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