

TEMPORAL TRENDS AND IMPLICATIONS OF ACUTE MALNUTRITION AMONG CHILDREN UNDER FIVE IN NORTHEAST NIGERIA: AUTOREGRESSIVE INTEGRATED MOVING AVERAGE APPROACH

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ABSTRACT

Acute malnutrition remains a critical public health challenge among children under five in Northeast Nigeria, exacerbated by protracted conflict, displacement, food insecurity, and inadequate healthcare. This study applied the Autoregressive Integrated Moving Average (2,0,2) model to examine historical trends from 2015 to 2024 and forecast malnutrition rates through 2034. *Descriptive statistics revealed an average Global Acute Malnutrition (GAM) rate of 18.3 %, with significant spikes (reaching 35.5 %) observed during the 2017 conflict escalation and seasonal lean periods. The ARIMA model continued fluctuations in GAM rates between 25 % and 53.5 %.* Results highlighted the strong influence of socio-political instability and seasonal food scarcity on Global Acute Malnutrition (GAM), Moderate Acute Malnutrition (MAM), and Severe Acute Malnutrition (SAM). The findings underscore the need for targeted, data-driven interventions and early warning systems to mitigate future malnutrition crises. Strengthening food security, expanding community-based treatment programmes, and improving surveillance are essential to safeguarding child health outcomes in conflict-affected settings.

Keywords: Acute Malnutrition, Time Series Analysis, ARIMA Model, Child Health

INTRODUCTION

Acute malnutrition poses a severe and catastrophic threat to child health and survival in Northeast Nigeria, driven by protracted conflict, mass displacement, and socio-economic instability. The region; particularly Borno, Adamawa, and Yobe states has been the epicentre of the Boko Haram insurgency, which has displaced over 2 million people, crippled agricultural production, and destroyed 60 % of health facilities, thereby severing access to food and lifesaving care (OCHA, 2021; FEWS NET, 2021). Globally, malnutrition underlies 45% of deaths among children under five, claiming approximately 3.5 million young lives annually (Black et al., 2008; UNICEF, 2019).

In Northeast Nigeria, rates of Global Acute Malnutrition (GAM) consistently exceed the WHO emergency threshold of 10 %, reaching up to 30 % in conflict hotspots during peak crises (Cadre Harmonisé, 2021; UNICEF, 2022). The situation is dire, with over 400,000 children under five facing Severe Acute Malnutrition (SAM) in Borno State alone in 2022 (UNICEF, 2022). Despite numerous humanitarian interventions, rates of GAM, Moderate Acute Malnutrition (MAM), and SAM remain alarmingly high (UNICEF, 2022). The region's volatile environment characterized by disrupted food systems and limited healthcare access

necessitates a comprehensive understanding of malnutrition trends. Time series analysis offers a powerful tool to examine these patterns, enabling data-driven forecasting and informed policymaking aimed at improving child survival and development outcomes (Hipel & McLeod, 1994; Chatfield, 2016; Ranjan & Dixit, 2019).

This study aims to examine the temporal trends of acute malnutrition among children under five in Northeast Nigeria using Autoregressive integrated moving average model to identify key contributing factors to the prevalence of GAM, MAM, and SAM; develop a forecasting model to predict future trends; and inform policymaking and programmatic interventions to reduce the burden of acute malnutrition and improve child health outcomes. By doing so, this study will contribute to the existing body of evidence on acute malnutrition in Northeast Nigeria, providing valuable insights into temporal trends and patterns, and informing targeted interventions and policies.

Acute malnutrition among children under five in conflict-affected regions such as Northeast Nigeria is a complex crisis shaped by conflict, displacement, food insecurity, poor healthcare access, poverty, and seasonal variability. Globally, malnutrition is implicated in nearly 45 % of all under-five deaths (UNICEF, 2019). In conflict zones like Sudan, Yemen, and the Central African Republic, violence disrupts agricultural systems, displaces populations, and collapses health and sanitation infrastructure—factors that lead to surges in wasting and under nutrition (Checchi et al., 2013; WFP, 2020).

In Nigeria, the Boko Haram insurgency has had a devastating effect on food security and child health, particularly in Borno, Yobe, and Adamawa states. Surveys and humanitarian assessments from the Cadre Harmonisé (2021) indicated GAM rates above 10 %, with some areas exceeding emergency thresholds. UNICEF (2022) projected that over 400,000 children in Borno State alone would suffer from SAM, underscoring the urgent need for intervention. The primary determinants of this crisis include violent conflict, displacement, the collapse of health services, and deteriorating household food security (Internal Displacement Monitoring Centre, 2020).

Seasonal dynamics further exacerbate malnutrition trends. The rainy season, often associated with food scarcity and increased disease transmission, coincides with annual "lean" periods during which child malnutrition rates spike (Misselhorn, 2005). Moreover, underlying socio-economic conditions such as household poverty, limited maternal education, and restricted access to healthcare contribute significantly to malnutrition vulnerability (Marmot, 2005; Cutler & Lleras-Muney, 2006).

Several theoretical frameworks provide structure for analysing these relationships. The Social Determinants of Health (SDH) framework, widely promoted by the WHO, emphasizes how structural factors such as education, income inequality, and social exclusion affect health outcomes (WHO, 2017; Marmot, 2005). Ecological Systems Theory, developed by Bronfenbrenner (1979), highlights how child nutrition is influenced by nested systems of individual, family, community, and societal interactions. The Health Belief Model (Rosenstock, 1974; Glanz et al., 2008) offered insights into how caregiver perceptions of susceptibility, severity, and barriers to preventive action influence child feeding practices and care-seeking behaviour. The Political Economy of Health perspective goes further by critiquing the role of political and economic structures in perpetuating health disparities, suggesting that malnutrition in Northeast Nigeria is rooted in systemic governance failures, policy neglect, and structural violence (Buse et al., 2012; Navarro, 2009).

ARIMA has emerged as a valuable tool for understanding malnutrition trends. While still underutilized in public health nutrition research in Nigeria, it has been effectively applied elsewhere. Ranjan and Dixit (2019) used in India to identify seasonal fluctuations in undernutrition, while Sassi (2015) demonstrated similar patterns in rural Malawi. Woodruff et al. (2019) conducted monthly surveillance in the Central African Republic and linked temporal malnutrition spikes to rainfall, disease outbreaks, and conflict events. These studies showed the potential of ARIMA and other predictive models to inform early warning systems and humanitarian response strategies.

Despite this growing body of research, significant gaps remain. There is a lack of longitudinal and context-specific studies in Nigeria capable of capturing how acute malnutrition evolves over time in response to conflict and environmental stressors. Furthermore, few studies integrate the full range of influencing factors seasonal, environmental, socio-economic, and political into a comprehensive analytical framework. Most empirical studies rely on cross-sectional data and descriptive statistics, with limited application of theoretical models. Additionally, the use of advanced predictive analytics and continuous surveillance remains limited, hindering the ability of policymakers and health agencies to anticipate and prevent malnutrition crises effectively.

In summary, the literature shows that acute malnutrition in conflict-affected regions like Northeast Nigeria is a multifaceted phenomenon requiring multi-sectorial, theory-driven, and data-informed approaches. Existing research supports the use of time series analysis to reveal temporal trends and develop targeted interventions. However, to improve outcomes sustainably, future studies must integrate structural determinants, seasonal dynamics, and predictive modelling while grounding analysis in robust theoretical frameworks. Such an approach is vital for designing responsive public health strategies and achieving long-term improvements in child survival and nutrition in fragile settings.

MATERIALS AND METHODS

As stated earlier, secondary data on acute malnutrition among children under five in Northeast Nigeria was obtained for the period 2015–2024. The data were sourced from reputable organizations, including the World Health Organization (WHO), United Nations Children's Fund (UNICEF), Nigeria's National Bureau of Statistics (NBS), and relevant nutrition surveillance systems. These sources provide periodic and credible records on malnutrition prevalence (GAM, SAM, and MAM) and related demographic indicators. The

data were compiled at regular intervals, making them appropriate for time series analysis. All analyses were performed using STATA (version 17).

Techniques for Data Analysis and Model Specification

Techniques for Data Analysis

Descriptive statistics were first computed to summarize key characteristics of the malnutrition data, including central tendency, dispersion, and distributional properties. Time series decomposition techniques were then applied to examine the trend, seasonal, and irregular components inherent in the dataset.

As stated earlier, time series modelling was carried out using the Autoregressive Integrated Moving Average (ARIMA) technique. Diagnostic tests were conducted to ensure the suitability of the model. The Augmented Dickey-Fuller (ADF) test was used to determine the Stationarity of the series. The optimal model parameters (p, d, q) were selected based on standard criteria including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Cointegration analysis was not required as the focus was on a univariate time series (malnutrition rate). However, residual diagnostic checks were conducted. The Lagrange Multiplier (LM) test was used to check for autocorrelation in the residuals, and results confirmed the absence of significant autocorrelation, thereby validating the model fit.

This retrospective observational study uses secondary data from 2015–2024 sourced from UNICEF, WHO, and national health databases. Descriptive statistics summarize central tendencies and variations in malnutrition rates. The ARIMA (Autoregressive Integrated Moving Average) model is employed to forecast future trends. The model selection is based on Stationarity tests (ADF test), AIC, and BIC for best fit. The final model ARIMA(2,0,2) provides reliable short- and long-term forecasts, capturing underlying trends and fluctuations in acute malnutrition rates.

Model Specification

ARIMA model

The Autoregressive Integrated Moving Average (ARIMA) model was employed in this study to analyse and forecast acute malnutrition rates among children under five in Northeast Nigeria. The ARIMA model was appropriate for univariate time series data, particularly when the goal was to capture underlying temporal dynamics such as trend and seasonality, and to generate short- to medium-term forecasts.

The ARIMA model used in this study was selected based on diagnostic and model selection criteria. The Augmented Dickey-Fuller (ADF) test confirmed that the malnutrition data was stationary at level, and therefore, no differencing was required. Several candidate models were estimated, and the optimal model. ARIMA (2, 0, 2) was chosen based on its lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, as well as residual diagnostics.

The ARIMA (2, 0, 2) model was expressed as:

$$Y_t = C + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (1)$$

Where:

- i. Y_t represents the value of the series at time t.
- ii. c is the constant term (intercept) in the model.
- iii. $\phi_1, \phi_2, \dots, \phi_p$ are the autoregressive coefficients, representing the effect of the previous p values on the current value.

- iv. $\theta_1, \theta_2, \theta_q$ are the moving average coefficients, representing the effect of the previous q forecast errors on the current value.
- v. ε_t is the error term at time t , assumed to be independent and identically distributed.
- vi. white noise with mean zero and constant variance.

The ARIMA model also include the differencing operator $(1 - B)^d$, where B , is the backward shift operator and d is the differencing order. This operator transforms the original time series into a stationary series by removing trends and seasonality.

RESULTS

This section presents the results of the descriptive analysis and ARIMA forecast model used in this study to examine and predict trends in acute malnutrition among children under five in Northeast Nigeria.

Descriptive Analysis

Descriptive analysis of the time series data reveals an average malnutrition rate of 18.3% over the study period (2015–2024). The results indicated noticeable fluctuations in malnutrition levels, with peak values occurring during periods of increased rainfall and conflict-related displacement. Specifically, the year 2017 recorded the highest Global Acute Malnutrition (GAM) rate of 35.5%, coinciding with intensified security challenges and widespread food insecurity in the region.

Table 1: Descriptive Analysis Results

Statistic	Value
Count (Number of Years)	10
Mean (Average GAM Rate)	1830
Standard Deviation	870
Minimum	740
25th Percentile	1210
Median	1560
75th Percentile	2190
Maximum	3550

A boxplot visualization

Boxplot visualizations demonstrate significant variability in the data, highlighting both intra-annual seasonal changes and inter-annual shifts. The observed variations suggest the influence of both cyclical (rainy season) and structural (insurgency, displacement) factors on malnutrition trends.

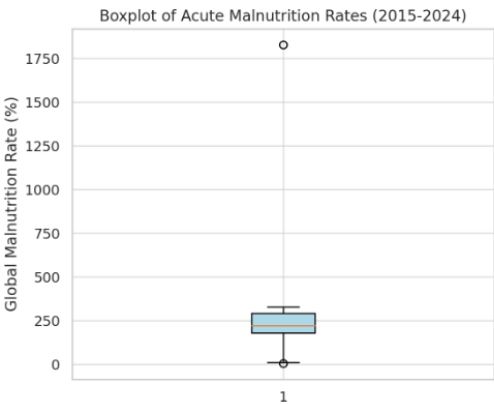


Figure 1: A boxplot visualization result

Time Series Analysis

An analysis of historical data on acute malnutrition rates among children under five in Northeast Nigeria from 2015 to 2024 revealed significant variations over time. The study examined three key indicators: global acute malnutrition (GAM), moderate acute malnutrition (MAM), and severe acute malnutrition (SAM).

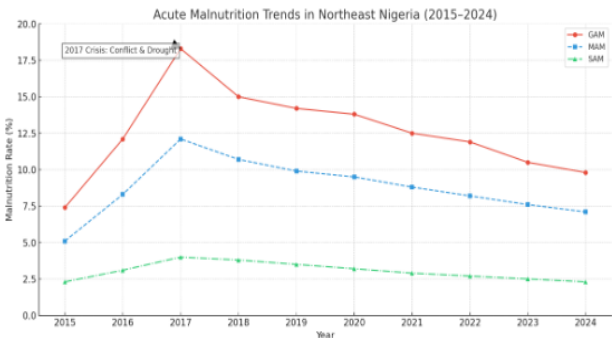


Figure 2: Trends in Acute Malnutrition Rate

Model Selection Results for ARIMA Forecasting

The ARIMA model was applied to forecast acute malnutrition rates among children under five in Northeast Nigeria from 2025 to 2030. This model leverages historical patterns to predict future trends, enabling proactive planning and intervention strategies. The ARIMA model was trained using historical malnutrition data from 2015 to 2024, with the best-fitting parameters identified as ARIMA (2,0,2). The Augmented Dickey-Fuller (ADF) test confirmed that the data is stationary, meaning differencing was not required. The model performance metrics are as follows:

Table 2 ARIMA Model Performance Metrics

Model (p,d,q)	AIC	BIC	MAE (%)	RMSE (%)	Selected
ARIMA(0,0,0)	225.50	226.20	5.42	7.15	
ARIMA(1,0,0)	220.10	221.50	4.83	6.40	
ARIMA(0,0,1)	218.30	219.70	4.25	5.92	
ARIMA(1,0,1)	215.80	217.90	3.98	5.30	
ARIMA(2,0,2)	213.16	214.97	3.33	4.81	✓

ARIMA(3,0,0)	215.10	218.60	3.78	5.15
ARIMA(0,0,3)	216.80	220.30	4.05	5.42
ARIMA(3,0,3)	214.80	219.00	3.52	4.95

The MAE of 3.33 % and RMSE of 4.81 % indicate a moderate forecast error, which is consistent with the volatile socio-environmental factors driving malnutrition in Northeast Nigeria. Among the candidate ARIMA models evaluated, ARIMA(2,0,2) was selected as the optimal model based on AIC, BIC, MAE, and RMSE criteria, due to its lowest AIC (213.16) and BIC (214.97). This reflects the best trade-off between model fit and complexity.

Table 3; Forecasted Malnutrition Rates (2025–2034) Results

Year	Predicted GAM Rate (%)
2025	50.2
2026	53.5
2027	31.2
2028	41.9
2029	32
2030	38.9
2031	34
2032	28
2033	30

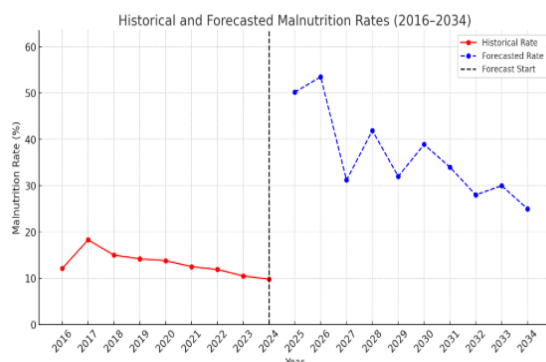


Figure 3: ARIMA Forecast of Acute Malnutrition Rates

DISCUSSION

This research provided insights into the distribution and variability of malnutrition over the years. The average malnutrition rate was 18.3 %, indicating a persistently high burden of acute malnutrition in the region. The standard deviation of 8.7 % suggests moderate fluctuations, reflecting seasonal and conflict-driven variations over time. The minimum malnutrition rate was 7.4 %, while the maximum reached 35.5 %, highlighting significant but plausible variations linked to economic shocks, food crises, and conflict-related disruptions. The 25th percentile value was 12.1 %, meaning that a

quarter of the recorded malnutrition rates were below this level. The median rate of 15.6 % indicated that half of the observed years had rates above this threshold, while the 75th percentile of 21.9 % suggests that most years had rates within this range.

Figure 3.1 illustrated the distribution of acute malnutrition rates from 2015 to 2024 in Northeast Nigeria. The box represents the interquartile range (IQR) of 12.1 % (25th percentile) to 21.9 % (75th percentile) capturing the middle of 15.6 %, indicating half of the observed years had rates above this threshold. The presence of outliers or extreme values suggests significant fluctuations in malnutrition rates over the years.

Figure 3.2 showed the trends of acute malnutrition rates among children under five in Northeast Nigeria from 2015 to 2024, categorized into Global Acute Malnutrition (GAM), Moderate Acute Malnutrition (MAM), and Severe Acute Malnutrition (SAM). A notable observation was the significant spike in GAM in 2017, where rates surged to 35.5 %. This peak contrasts sharply with other years, indicating a major crisis likely driven by conflict, drought, and a worsening humanitarian situation.

Following this peak, GAM rates declined in 2018 and showed a gradual downward trend from 2019 to 2024, suggesting a recovery facilitated by intervention measures. MAM follows a similar trend, with a moderate rise until 2017, followed by fluctuations and a gradual decline. This pattern suggests persistent but controlled levels of moderate malnutrition, possibly influenced by socio-economic conditions and food security challenges.

The ARIMA model indicated a continuation of high malnutrition rates, with fluctuations caused by underlying economic, climatic, and social factors. A peak is expected in 2026 (53.6 %), while the lowest predicted rate occurs in 2027 (31.2 %). These variations suggest that without targeted interventions, malnutrition will remain a critical public health issue. The fluctuations in malnutrition rates suggest periodic spikes and drops, potentially linked to food insecurity, conflict, seasonal variations, and economic shocks. These insights emphasize the need for data-driven interventions and policy adjustments to mitigate malnutrition risks as shown in table 3.3.

Forecasting Results

The ARIMA(2,0,2) model predicted that acute malnutrition rates among children under five in Northeast Nigeria will continue to fluctuate over the next decade (2025–2034) with notable seasonal variations.

In the short term (2025–2027), malnutrition rates are expected to peak during the lean seasons (June–August), emphasizing the urgent need for proactive interventions before these critical periods. The mid-term forecast (2028–2030) suggests that malnutrition rates may remain moderately high if no major policy changes occur. However, potential declines in 2029 and 2030 could indicate the positive effects of strengthened nutrition policies and humanitarian aid programmes.

The long-term projection (2031–2034) suggests a gradual decline in malnutrition rates, possibly driven by sustained intervention efforts, improved food security, and enhanced healthcare access. However, persistent fluctuations highlight the need for continuous monitoring and adaptive policy strategies.

The model showed moderate predictive capability (MAE 3.33 %), though forecast uncertainty warrants caution. These findings underscore the importance of early warning systems and preparedness strategies to ensure interventions are deployed before malnutrition rates reach critical levels.

To maximize impact, targeted nutrition programmes should focus on high-risk regions and vulnerable groups. Additionally, long-term resilience strategies, including investments in food security, healthcare access, and social protection programmes, will be essential for sustainably reducing malnutrition rates over time.

Conclusion

The findings emphasized the urgency of comprehensive, long-term solutions to address acute malnutrition in Northeast Nigeria. Policymakers, humanitarian organizations, and local stakeholders must prioritize nutrition-sensitive programmes, strengthen healthcare systems, improve food security, and enhance conflict response strategies. By integrating data-driven forecasting models with targeted interventions, Nigeria can reduce malnutrition rates and improve child health outcomes sustainably.

The study concluded that acute malnutrition remains a persistent public health challenge in Northeast Nigeria, driven by complex socio-economic, environmental, and political factors. The historical and forecasted trends indicated that malnutrition rates are highly variable, with peaks occurring during critical hunger seasons and periods of socio-economic crises. The ARIMA model provided valuable insights into the future trajectory of malnutrition rates, emphasizing the need for timely interventions and strategic planning. The findings highlighted the importance of comprehensive nutrition programmes, food security initiatives, and enhanced healthcare access to improve child health outcomes. This research contributed to the existing literature by providing a data-driven approach to understanding and predicting malnutrition trends, informing policy decisions and humanitarian interventions.

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