RESEARCH ARTICLE

Neonatal Mortality Forecasting in Somalia: A Comparative Time-Series Analysis of Single and Hybrid Models

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Abstract

Background

Neonatal mortality remains a critical public health concern in fragile and conflict-affected settings such as Somalia, where health system instability, environmental shocks, and limited access to maternal and newborn care contribute to persistently high mortality rates. Accurate forecasting of neonatal mortality trends is essential for evidence-based planning and monitoring progress toward Sustainable Development Goal (SDG) 3.2.

Methods

This study employed a longitudinal time-series design using annual neonatal mortality rate (NMR) data for Somalia from 1983 to 2023 obtained from the World Bank Open Data repository. Six single time-series models—ARIMA, ETS, TBATS, Theta, ARFIMA, and Neural Network Autoregression (NNAR)—along with ten hybrid model combinations were fitted and evaluated. The dataset was divided into training (1983–2015) and testing (2016–2023) subsets. Stationarity was assessed using Phillips–Perron and KPSS tests, and first-order differencing was applied. Forecast accuracy was evaluated using MAPE, sMAPE, and Theil's U statistic.

Results

Among single models, NNAR demonstrated the highest predictive

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accuracy, achieving the lowest forecast errors (MAPE = 4.84%, sMAPE ≈ 0.0467, Theil's U ≈ 2.98). The Theta model ranked second, while ARIMA and ETS showed moderate performance, and ARFIMA performed least effectively. Among hybrid models, the Theta-NNAR combination achieved the best overall performance (MAPE = 6.11%). Forecasts for 2024–2030 indicate that neonatal mortality in Somalia is likely to stabilize at approximately 35 deaths per 1,000 live births. However, prediction intervals widen over time, reflecting increasing uncertainty.

Conclusions

The findings highlight the superior performance of nonlinear models, particularly NNAR, in capturing complex mortality dynamics in fragile settings. While neonatal mortality is projected to stabilize, persistent uncertainty underscores the need for resilient, data-driven health planning. These results provide a quantitative foundation for improving neonatal health interventions and accelerating progress toward SDG 3.2 in Somalia.

Keywords
Neonatal mortality; time-series analysis; forecasting; neural network autoregression (NNAR); hybrid models; forecast accuracy; Somalia

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Introduction

Neonatal mortality (death of a live-born infant within the first 28 completed days of life) remains a core indicator of population health, maternal care quality, and overall health-system performance.[1] It is commonly expressed as the Neonatal Mortality Rate (NMR), defined as the number of neonatal deaths per 1,000 live births, and is routinely used to monitor progress in maternal and newborn health interventions and national development outcomes.[2]Despite major reductions in under-five mortality since 1990, neonatal deaths now account for a substantial share of all under-five deaths globally, reflecting slower progress in the first month of life compared to older child age groups.[3] The neonatal period is particularly vulnerable, as survival depends on continuity of care across pregnancy, delivery, and the immediate postnatal period. Preventable causes—including complications of prematurity, intrapartum events, and neonatal infections—remain leading contributors to neonatal deaths in many settings.[4,5]

Reducing neonatal mortality is central to Sustainable Development Goal (SDG) 3.2, which targets ending preventable deaths of newborns and children under five, with countries aiming to reduce NMR to at least 12 per 1,000 live births by 2030.[6] Evidence-based interventions—such as skilled birth attendance, essential newborn care, neonatal resuscitation, kangaroo mother care, and timely treatment of infections—are widely recognized as effective strategies to prevent neonatal deaths.[4] However, achieving SDG 3.2 requires more than clinical scale-up; it also requires stronger surveillance systems and predictive analytics to support resource allocation, supply planning, workforce deployment, and targeted programming in settings where health systems are weak and resources are limited.[7]

Sub-Saharan Africa continues to experience the highest neonatal mortality burden globally, with persistent inequalities driven by poverty, limited access to quality maternal and newborn services, and fragile governance systems.[2] While many countries have made progress in reducing under-five mortality, neonatal mortality decline has often been slower, partly because neonatal survival requires facility-based and timely care around birth—services that remain unevenly accessible across rural and conflict-affected areas.[8,3] In East Africa, the trajectory of neonatal survival is shaped by demographic transition, health system reforms, displacement and migration, and climatic variability that affects maternal nutrition, disease risks, and service continuity.[9,10] These interacting forces can produce non-linear or interrupted mortality transitions, highlighting the need for country-specific analyses rather than relying on regional averages alone.[2]

Somalia represents a uniquely complex environment for improving neonatal survival. Decades of conflict, institutional fragmentation, repeated droughts, and population displacement have constrained service delivery and weakened referral pathways, limiting coverage of antenatal care, skilled birth attendance, and postnatal care.[11,4] National evidence from the Somali Health and Demographic Survey (SHDS) highlights continued challenges in maternal and newborn health indicators and substantial disparities by geography and socioeconomic status.[12] Recent Somalia-focused evidence shows that neonatal mortality is strongly associated with maternal education, birth spacing, place of delivery, and access to health services, highlighting the importance of both household determinants and health system factors.[5] However, most Somalia studies are cross-sectional and determinant-focused, providing limited evidence about long-run temporal dynamics and future trajectories of neonatal mortality at the national level.

Long-horizon forecasting of neonatal mortality can support proactive policy by identifying likely future pathways, assessing whether Somalia is on track toward SDG 3.2, and guiding planning for essential newborn services, commodities, and workforce needs.[13,14] Time-series analysis offers a rigorous framework for modeling sequential health indicators and generating forecasts using historical dependence, trend structure, and stochastic variation.[9] Classical Box–Jenkins ARIMA models remain foundational for modeling autocorrelation and trend in annual health indicators, and they continue to be widely used in epidemiological forecasting due to interpretability and strong baseline performance.[15,16] Complementary approaches such as exponential smoothing/state-space models (ETS) and the Theta method have shown robust performance across diverse series, particularly when structural patterns differ across time.[17,18,19] Mortality series may exhibit persistence, gradual structural changes, and slow decay of shocks—features that motivate long-memory models such as ARFIMA, which allow fractional differencing to capture persistent dependence structures.[20] In addition, non-linear time series approaches, including neural network autoregression (NNAR) and related machine learning methods, can capture complex patterns that linear models may miss, particularly when volatility and structural shifts are present.[21] Sound time-series modeling requires careful assessment of stationarity and integration properties using complementary tests such as Phillips–Perron (unit root) and KPSS (stationarity) to support valid model selection and transformation decisions.[22,23]

Modern forecasting best practice emphasizes comparing multiple model classes rather than relying on a single preferred specification. Evidence from major forecasting competitions (e.g., M3 and M4) shows that predictive performance varies by data structure and that comparative benchmarking and combination strategies often improve reliability.[24,25] In health forecasting, evaluating competing approaches using standard metrics—such as Mean Absolute Percentage Error

(MAPE), Symmetric MAPE (sMAPE), and Theil's U—enables transparent selection of robust models suited to local data characteristics and policy needs.[26]

This study uses annual neonatal mortality rate data for Somalia (1983–2023) obtained from the World Bank Open Data indicator for NMR.[11]The availability of harmonized annual data across four decades provides an opportunity to examine Somalia's long-term neonatal mortality trajectory and generate policy-relevant forecasts. Given Somalia's fragility and exposure to recurrent shocks, identifying a robust forecasting approach is essential for strengthening evidence-based newborn health planning and monitoring progress toward SDG 3.2.[11]

Novelty and main contribution

This study presents a methodologically integrated forecasting framework for neonatal mortality in fragile and conflict-affected settings, using four decades (1983–2023) of harmonized national data from Somalia. While prior studies have largely examined cross-sectional determinants of neonatal mortality, limited evidence exists on long-run mortality dynamics, structural persistence, and forward-looking risk trajectories in health systems exposed to recurrent shocks.

The study advances the literature in four major ways. First, it develops a unified multi-model forecasting framework that integrates classical linear time-series models (ARIMA, ETS, Theta), long-memory approaches (ARFIMA), and non-linear machine learning models (NNAR) within a consistent validation architecture. This integrated design enables rigorous cross-model benchmarking under identical data and evaluation conditions, reducing methodological fragmentation common in demographic forecasting studies. The framework ensures fair model comparison through uniform data partitioning, identical forecast horizons, and standardized performance metrics.

Second, the analysis incorporates long-memory modeling—rarely applied in mortality forecasting in fragile contexts—to capture persistent dependence structures associated with conflict cycles, institutional disruptions, and climate-related shocks. This approach enhances the representation of slow-decaying structural effects that conventional short-memory models may fail to detect.

Third, the study strengthens predictive rigor through a transparent and reproducible evaluation pipeline using standardized forecast accuracy metrics (MAPE, sMAPE, and Theil's U) and out-of-sample validation. This design improves reliability, comparability, and replicability of mortality forecasting in data-constrained environments.

Fourth, beyond single-country estimation, the proposed framework provides a transferable methodological template for mortality forecasting in other fragile and low-resource settings facing similar structural volatility. The framework is adaptable to other fragile and conflict-affected states experiencing mortality volatility and data limitations. By emphasizing model interoperability and validation transparency, the study contributes a scalable evidence-generation approach for global maternal and newborn health analytics.

Collectively, these contributions extend beyond conventional single-model applications and reposition neonatal mortality forecasting as a decision-support tool for fragile health systems. The empirically validated projections provide actionable evidence for monitoring progress toward Sustainable Development Goal (SDG) 3.2, optimizing resource allocation, and strengthening anticipatory health planning under uncertainty. The proposed framework is adaptable to other fragile and conflict-affected health systems experiencing mortality volatility and data constraints.

Main objective of the paper

The primary objective of this study is to conduct a comprehensive time-series analysis and forecasting assessment of the neonatal mortality rate (NMR) in Somalia over the period 1983–2023 using harmonized annual data from the World Bank Open Data repository. Specifically, the study aims to systematically fit, validate, and benchmark multiple forecasting model families—including Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing State-Space models (ETS), the Theta method, Neural Network Autoregression (NNAR), and Autoregressive Fractionally Integrated Moving Average (ARFIMA)—within a unified and reproducible evaluation framework.[34]

Model performance will be rigorously assessed using standardized forecast accuracy metrics, including Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic, applied within a structured training–validation design. Through comparative analysis, the study seeks to identify the most robust and reliable predictive framework for modeling neonatal mortality dynamics in a fragile, high-volatility context.

Ultimately, the study aims to generate evidence-based medium-term projections that can support strategic newborn health planning, resource allocation, and progress monitoring toward Sustainable Development Goal (SDG) Target 3.2 in Somalia.

Materials and methods

Study design and data source

This study employed a longitudinal time-series research design to analyze historical trends and forecast neonatal mortality in Somalia. Time-series designs are well suited for examining temporal dynamics, structural patterns, and long-term trajectories using sequential observations recorded over extended periods.

Annual neonatal mortality rate (NMR) data for the period 1983–2023 were obtained from the World Bank Open Data repository. NMR is defined as the number of neonatal deaths per 1,000 live births. The World Bank database provides harmonized and internationally comparable mortality estimates that are widely used in demographic and public health research, ensuring data reliability and cross-country comparability.

Data preprocessing and time-series construction

Prior to model development, the neonatal mortality rate (NMR) dataset for Somalia underwent systematic quality assessment to ensure completeness, continuity, and internal consistency across the study period. The dataset was screened for missing values, outliers, and structural irregularities that could influence model estimation and forecasting accuracy. The annual time series was confirmed to be complete and consistently recorded from 1983 to 2023.

Following data validation, annual NMR observations were chronologically ordered and converted into a time-series object using R statistical software. This process preserved the temporal structure of the data and enabled the implementation of both classical and hybrid time-series models for trend analysis and forecasting.

The NMR data were retrieved from the World Bank Open Data repository, an internationally recognized source providing harmonized and comparable demographic and public health statistics[27]:.

Stationarity testing with PP and KPSS tests

Establishing stationarity is a fundamental prerequisite in time-series modeling, as it ensures that key statistical properties —such as the mean and variance—remain stable over time. Non-stationary series may lead to biased parameter estimates and unreliable forecasts. To evaluate the stationarity of the neonatal mortality rate (NMR) series for Somalia, two complementary tests were employed: the Phillips–Perron (PP) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

The Phillips–Perron (PP) test evaluates the presence of a unit root while applying non-parametric corrections for serial correlation and heteroskedasticity without requiring explicit lag-length specification. The null hypothesis (H_0) states that the series contains a unit root (non-stationary), whereas the alternative hypothesis (H_1) indicates stationarity. Rejection of H_0 implies that the series is stationary.

In contrast, the KPSS test assumes stationarity under the null hypothesis and tests against the alternative of a unit root. Employing both PP and KPSS tests provides robust inference through complementary hypotheses, thereby reducing the risk of misclassification.

When non-stationarity was detected, first-order differencing was applied to stabilize the mean and remove stochastic trends. The differenced series was subsequently re-tested to confirm stationarity prior to model estimation.

$$PP = \frac{\text{Coefficient Estimate} - 1}{\text{Standard Error}} \tag{1}$$

To complement the PP test, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test was also employed. In contrast to unit root tests such as the PP test, the KPSS test evaluates stationarity around a deterministic level or trend and adopts a reversed hypothesis framework. Specifically, the null hypothesis (H_0) assumes that the time series is level-stationary or trend-stationary, whereas the alternative hypothesis (H_1) indicates non-stationarity due to the presence of a unit root. If the KPSS test statistic exceeds the corresponding critical value, the null hypothesis is rejected, providing evidence that the series is non-stationary. The KPSS test statistic is defined as:

$$KPSS = \frac{1}{T^2} \sum_{t=1}^{T} \frac{s_t^2}{\widehat{\sigma}^2} \tag{2}$$

In this study, the PP and KPSS tests were applied jointly to the neonatal mortality rate time series for Somalia. The rationale for employing both tests lies in their complementary nature: while the PP test assesses the presence of a unit root, the KPSS test evaluates stationarity directly. Using both tests together enhances the robustness of the stationarity assessment and reduces the risk of misleading conclusions arising from the limitations of a single testing procedure. This combined approach ensures a reliable foundation for subsequent model selection and forecasting analysis.

Software and implementation environment

All statistical analyses and forecasting procedures were conducted using the R statistical computing environment, which provides advanced tools for time-series modeling, validation, and visualization. A suite of specialized R packages was employed to support different stages of the analytical workflow.

Core forecasting models—including ARIMA, ETS, TBATS, and Theta—were implemented using the forecast package. Neural network autoregression (NNAR) was performed using the nnfor package, while hybrid model combinations were developed using the forecastHybrid package. Stationarity diagnostics were conducted with the tseries package. Forecast accuracy metrics were computed using the Metrics package. Data visualization and exploratory time-series analysis were supported by plotly and TSstudio.

The study followed a structured analytical workflow. First, annual neonatal mortality rate observations were inspected for completeness and formatted as a time-series object to preserve temporal ordering. Second, stationarity was assessed using the Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, with differencing applied where necessary. Third, candidate forecasting models were specified and estimated using the training dataset. Fourth, predictive performance was evaluated using standardized forecast accuracy metrics. Finally, out-of-sample forecasts were generated based on the best-performing models.

To ensure objective model comparison, the dataset was partitioned into training (1983–2015) and testing (2016–2023) subsets. Single-model approaches—including ARIMA, ETS, TBATS, Theta, ARFIMA, and NNAR—alongside multiple hybrid configurations were estimated using the training data. Predictive accuracy was assessed using Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic. These measures enabled systematic benchmarking of competing forecasting frameworks.

The sequential stages of the computational implementation and analytical workflow are illustrated in Figure 1.

ARIMA model

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used time series forecasting technique that combines autoregressive (AR), differencing (I), and moving average (MA) components. It is effective in modeling linear temporal dependencies and stochastic patterns in mortality time series data. The general form of the ARIMA (p,d,q)model is given by:

$$\left(1-\phi_1 L-\phi_2 L^2-\cdots-\phi_p L^p\right)(1-L)^d y_t=\left(1+\theta_1 L+\theta_2 L^2+\cdots+\theta_q L^q\right)\varepsilon_t \tag{3}$$

where $y_t$represents the neonatal mortality rate at time t, Ldenotes the lag operator, $\phi_i$and $\theta_i$are the autoregressive and moving average parameters, respectively, $p$is the AR order, $d$is the degree of differencing, and $q$is the MA order. The error term $\varepsilon_t$is assumed to be white noise.

ARIMA models were estimated using the auto.arima() function from the **forecast** package in R. This function automatically selects optimal values of p, d, and $q$using the Hyndman–Khandakar algorithm, with model selection based on the Akaike Information Criterion (AIC). Diagnostic checks were conducted through standardized residual plots, residual autocorrelation (ACF) plots, and the Ljung–Box test to validate model adequacy.

ARFIMA model

The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model extends the ARIMA framework by allowing fractional differencing, thereby capturing long-range dependence or long-memory characteristics in time series data. This feature is particularly relevant for neonatal mortality rates, which may exhibit persistent temporal dependencies over long periods. The ARFIMA (p,d,q)model is expressed as:

$$\left(1-\phi_1 L-\phi_2 L^2-\cdots-\phi_p L^p\right)(1-L)^d\left(1-\theta_1 L-\theta_2 L^2-\cdots-\theta_q L^q\right)y_t=\varepsilon_t \tag{4}$$

where $d$represents the fractional differencing parameter, allowing the model to capture intermediate behavior between stationarity and non-stationarity.

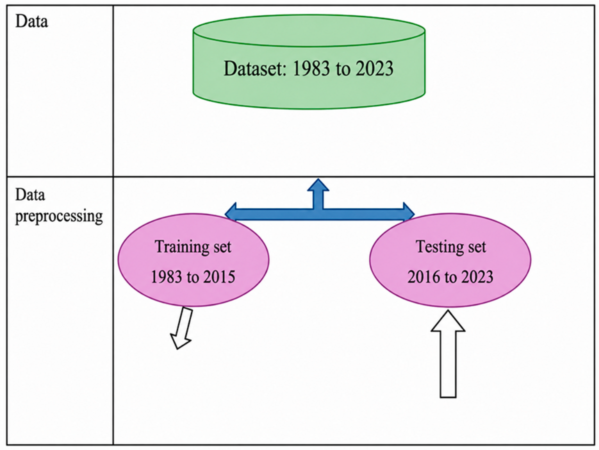

Figure 1. Workflow of time-series modelling and evaluation. Schematic diagram illustrating the modelling workflow, including dataset preparation (1983–2023), data preprocessing with training (1983–2015) and testing (2016–2023) sets, development of multiple models (ARIMA, ETS, TBATS, Theta, ARFIMA, NNAR, and hybrid models), and model evaluation using forecast accuracy metrics (MAPE, sMAPE, and Theil's U statistic).

Theta model

The Theta model, also known as the random walk with drift model, is a simple yet robust forecasting approach that has demonstrated strong empirical performance in forecasting competitions. The model assumes that future values of a time series depend on the most recent observation and a drift component. The Theta model is expressed as:

$$y_{t+1} = (1+\theta)y_t + \mu + \varepsilon_{t+1} \tag{5}$$

where $y_t$denotes the neonatal mortality rate at time t, θrepresents the slope parameter, $\mu$is the drift term, and $\varepsilon_{t+1}$is the random error term.

ETS model

The Error–Trend–Seasonal (ETS) model is a flexible state-space framework for modeling and forecasting time series data. The ETS approach accommodates different combinations of error (E), trend (T), and seasonal (S) components, which may be additive (A), multiplicative (M), or absent (N). This flexibility enables the ETS model to capture heterogeneity and nonlinear patterns in neonatal mortality trends.

The state-space representation of the ETS model is given by:

$$y_t = w(x_{t-1}) + r(x_{t-1})\varepsilon_t \tag{6}$$

$$x_t = f(x_{t-1}) + g(x_{t-1})\varepsilon_t \tag{7}$$

where $x_t$denotes the state vector, $y_t$is the observed neonatal mortality rate, and $\varepsilon_t$represents Gaussian white noise. The ETS models were implemented using the ets() function from the forecast package.

NNAR model

The Neural Network Autoregressive (NNAR) model integrates autoregressive structures with the nonlinear learning capacity of artificial neural networks. Lagged values of the neonatal mortality rate are used as inputs to a feed-forward neural network, enabling the model to capture nonlinear patterns in the data. The NNAR model can be expressed as:

$$y_t = \omega_0 + \sum_{j=1}^{Q} \omega_j \left(\omega_{0j} + \sum_{i=1}^{P} \omega_{i,j} y_{t-i} \right) + e_t \tag{8}$$

where Pdenotes the number of lagged inputs, $Q$is the number of hidden neurons, and ωrepresents connection weights. The NNAR model was fitted using the nnetar() function from the forecast package, with default parameter settings.

TBATS model

The TBATS model—incorporating Trigonometric seasonality, Box–Cox transformation, ARMA errors, Trend, and Seasonal components—is a highly flexible forecasting approach designed to handle complex trend structures and irregular patterns. TBATS models combine Fourier representations of seasonality with exponential smoothing state-space models and ARMA residuals. The measurement equation for the TBATS model is expressed as:

$$y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum s_{t-m_i}^{(i)} + d_t \tag{9}$$

where $y_t^{(\omega)}$ represents the Box–Cox transformed neonatal mortality rate, l_t is the local level, b_t denotes the trend, $s_t^{(i)}$ represents seasonal components, and d_t follows an ARMA process. The TBATS model was implemented using the tbats() function in the forecast package.

Hybrid modelling approaches

In addition to the individual time series models, this study investigates hybrid modeling approaches that combine two single forecasting techniques in order to improve predictive accuracy. Hybrid models are designed to integrate the complementary strengths of different methods, particularly their ability to capture both linear and nonlinear structures in time series data. In this study, a total of ten hybrid time series models were developed by systematically combining pairs of the single models: ARIMA, ETS, TBATS, Theta, and NNAR.

The ten pairwise hybrid models considered in this study are: ARIMA–ETS, ARIMA–TBATS, ARIMA–Theta, ARIMA–NNAR, ETS–TBATS, ETS–Theta, ETS–NNAR, TBATS–Theta, TBATS–NNAR, and Theta-NNAR. Each hybrid model combines forecasts generated by two individual models applied to the neonatal mortality rate time series for Somalia. This pairwise strategy allows the hybrid framework to capture diverse characteristics of the data, including trend persistence, nonlinear behavior, and irregular fluctuations.

All hybrid models were implemented using the hybridModel() function from the forecastHybrid package in R statistical software,[28] which enables the combination of multiple forecasting models within a unified framework. The hybrids were constructed using equal weighting, whereby each component model contributes equally to the final forecast. This weighting scheme was selected based on strong empirical evidence suggesting that simple averaging often produces robust and reliable forecasts while minimizing the risk of overfitting associated with complex weighting methods.[29]

The use of pairwise hybrid models enables the integration of linear models, such as ARIMA and ETS, with nonlinear approaches, such as NNAR and TBATS. This approach is particularly relevant for neonatal mortality rate data, which may exhibit both systematic long-term trends and irregular nonlinear dynamics due to health system instability and external shocks. Similar hybrid modeling strategies have been successfully applied in previous forecasting studies and have demonstrated superior performance compared to single models.[30]

Model evaluation

To assess the performance of the time series models, the neonatal mortality rate dataset was divided into training and validation sets. The models were estimated using the training data, and their forecasting accuracy was evaluated by comparing the predicted neonatal mortality rates with the observed values in the validation set. Forecast performance was quantified using three widely accepted accuracy measures: the Mean Absolute Percentage Error (MAPE), the Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic. These metrics provide complementary perspectives on forecast accuracy and reliability.

Selection of Best-Fitting Models: Based on the results of the model evaluation, the best-fitting time series models were identified. Models exhibiting lower values of MAPE, sMAPE, and Theil's U statistic were considered superior in terms of predictive performance. The selected models formed the basis for generating future forecasts of neonatal mortality rates in Somalia. This selection process ensured that only models with robust out-of-sample forecasting ability were retained for policy-relevant projections.

Analysis of Trends and Patterns: The fitted time series models and their corresponding forecasts were further examined to identify long-term trends and structural patterns in neonatal mortality over the historical period. This analysis provided insights into the dynamics of neonatal survival in Somalia and facilitated an understanding of how mortality trends have evolved over time. Observed patterns may reflect the combined effects of health system instability, socioeconomic conditions, environmental shocks, and conflict-related disruptions.

Implications for Policy and Intervention: The findings derived from the time series modeling and forecasting exercise provide an empirical foundation for policy formulation and intervention planning. The historical volatility and projected trends in neonatal mortality rates highlight the urgency of strengthening maternal and newborn healthcare services, improving access to skilled birth attendance, and enhancing nutrition and preventive care programs. These insights are particularly relevant for policymakers and stakeholders seeking to design targeted strategies aimed at reducing neonatal mortality and advancing progress toward Sustainable.

In summary, this study applies a comprehensive set of univariate time series models, including ARIMA, ETS, Theta, NNAR, ARFIMA, and TBATS, alongside hybrid modeling approaches, to forecast neonatal mortality rates in Somalia. Model performance was rigorously evaluated using established accuracy metrics, and historical trends were analyzed to support evidence-based decision-making. The results offer valuable insights for improving neonatal health outcomes and guiding effective public health interventions in fragile settings.

Forecast and model performance

To evaluate the predictive performance of the time-series models developed using both the full dataset and the training subset, three widely recognized forecast evaluation metrics were employed: Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic. These measures were selected due to their robustness, interpretability, and extensive use in time-series forecasting research.

MAPE was considered appropriate because the neonatal mortality rate data contained no zero values, thereby allowing meaningful percentage-based error computation. The sMAPE metric was additionally employed to address the asymmetry and scale-sensitivity limitations associated with conventional MAPE.

Theil's U statistic was applied for relative model comparison, where lower values indicate superior predictive performance among competing models.[31]

Mean absolute percentage error (MAPE)

The Mean Absolute Percentage Error (MAPE) measures the average absolute percentage deviation between the observed and forecasted values. It is a scale-independent metric that facilitates intuitive interpretation of forecast accuracy relative to the magnitude of the variable of interest, such as the neonatal mortality rate. The MAPE is defined as:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \widehat{y}_t}{y_t}\right| \times 100 \qquad (10)$$

where $y_t$denotes the observed neonatal mortality rate at time t, $\widehat{y}_t$represents the corresponding forecasted value, and $n$is the total number of observations. Lower MAPE values indicate higher forecasting accuracy.

Symmetric mean absolute percentage error (sMAPE)

The Symmetric Mean Absolute Percentage Error (sMAPE) evaluates forecast accuracy by measuring the absolute difference between the forecasted and observed values, normalized by the average magnitude of both. Unlike MAPE, sMAPE is bounded and symmetric, thereby reducing bias associated with over- or under-forecasting and improving stability when values are small. The sMAPE is computed as:

$$sMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{2|F_i - A_i|}{|F_i| + |A_i|} \times 100 \qquad (11)$$

where $F_i$and $A_i$denote the forecasted and actual neonatal mortality rates at time i, respectively. The sMAPE metric provides a balanced measure of relative forecast error and is particularly suitable for comparing model performance across different forecasting techniques.

Theil's U statistic is a widely used relative accuracy measure for comparing forecasting performance across competing models. It standardizes prediction errors and enables consistent model benchmarking within the same dataset. The statistic is computed as:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \widehat{y}_i}{y_i}\right)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \tilde{y}_i}{y_i}\right)^2}} \qquad (12)$$

where $y_i$denotes the observed value, $\hat{y}_i$is the model forecast, and $\tilde{y}_i$represents a baseline reference forecast.

Theil's U statistic was used for relative model comparison among competing forecasting models. Lower values indicate better predictive performance within the evaluated set. Thus, the statistic provides a standardized basis for benchmarking forecast accuracy.

Model performance evaluation and forecasting

The performance of the forecasting models was evaluated using annual neonatal mortality rate data for Somalia spanning 1983–2023. The dataset was partitioned into a training set (1983–2015) and a testing set (2016–2023) to facilitate both in-sample and out-of-sample evaluation. For each model, the MAPE, sMAPE, and Theil's U statistics were computed using both subsets. Models yielding lower values across these metrics were considered to demonstrate superior forecasting performance.

onsistent with findings reported in previous large-scale forecasting studies, model performance varies across data structures and evaluation settings.,[32] minimizing forecast error metrics was prioritized in selecting the most reliable models. Based on the best-performing single and hybrid models, neonatal mortality rates in Somalia were subsequently forecasted for the period 2024–2030. These forecasts provide quantitative insights into future mortality trends and support evidence-based health planning and policy formulation.

3.3 Results

3.1 Data description and overview

This study analyzes annual neonatal mortality rate (NMR) data in Somalia for the period 1983–2023, obtained from the World Bank Open Data repository. NMR is defined as the number of deaths occurring within the first 28 days of life per 1,000 live births.

The dataset comprises 41 annual observations, providing a sufficient basis for time-series analysis and forecasting. These data offer long-term insight into neonatal mortality trends in Somalia over four decades.

3.2 Descriptive statistics of neonatal mortality rate

Table 1 presents the descriptive statistics of neonatal mortality rate (NMR) in Somalia (1983–2023), summarizing its central tendency, variability, and distribution.

The mean NMR is 43.84 deaths per 1,000 live births (SD = 3.83), indicating moderate variability. The median value (44.7) and trimmed mean (44.18) are comparable, suggesting minimal influence of extreme values.

The minimum and maximum values are 34.9 and 49.7, respectively, yielding a range of 14.8. The median absolute deviation (MAD = 2.52) indicates that observations are relatively close to the median.

The distribution is slightly negatively skewed (−0.82), indicating a gradual decline over time, while the kurtosis (−0.32) suggests a relatively flat distribution with fewer extreme outliers. The standard error (0.60) indicates a reliable estimate of the mean.

Overall, these results reflect moderate dispersion and a declining trend in neonatal mortality over the study period.

The descriptive statistics of neonatal mortality rate (NMR) in Somalia from 1983 to 2023 indicate a mean value of 43.84 (SD = 3.83), reflecting moderate variability. The distribution is slightly negatively skewed (−0.82), suggesting a gradual

Table 1. Descriptive statistics of neonatal mortality rate in Somalia (1983–2023).

Variable	# of Obs. (n)	Mean	SD	Median	Trimmed Mean	MAD
Data	41	43.84	3.83	44.7	44.18	2.52
Variable	**Minimum**	**Maximum**	**Range**	**Skewness**	**Kurtosis**	**SE**
Data	34.9	49.7	14.8	−0.82	−0.32	0.60

The descriptive statistics of neonatal mortality rate (NMR) in Somalia from 1983 to 2023 indicate a mean value of 43.84 (SD = 3.83), reflecting moderate variability. The distribution is slightly negatively skewed (−0.82), suggesting a gradual decline over time, while the kurtosis (−0.32) indicates a relatively flat distribution. Overall, the results demonstrate moderate dispersion and a declining trend in NMR.

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3.3 Visual representation of the data

Figure 2 illustrates the time-series trend of neonatal mortality rate in Somalia from 1983 to 2023. The graphical pattern reveals a general declining trend over time, accompanied by short-term fluctuations.

In the early years, neonatal mortality rates were relatively high, followed by a noticeable increase in the early 1990s. Moderate variability is observed during the late 1990s and early 2000s, while a temporary rise appears around 2011. From 2012 onwards, the mortality rate shows a consistent downward trend, reaching approximately 35 deaths per 1,000 live births by 2023.

These findings indicate a long-term improvement in neonatal health outcomes, while also highlighting intermittent variations that justify the application of time-series modeling techniques.

3.4 Stationarity test results

To ensure the validity of time-series modeling, stationarity tests were conducted using the Phillips–Perron (PP) and KPSS methods. The results are presented in Table 2.

The initial results indicate that the original series is non-stationary. The PP test fails to reject the null hypothesis of a unit root, while the KPSS test rejects the null hypothesis of stationarity.

To address this, first-order differencing was applied. The automatic differencing procedure (ndiffs = 1) confirmed that one level of differencing was sufficient.

After transformation, the PP test strongly rejected the null hypothesis of a unit root, while the KPSS test failed to reject the null hypothesis of stationarity. This confirms that the first-differenced series is stationary.

Therefore, all subsequent time-series modeling and forecasting procedures were conducted using the stationary transformed data.

3.5 Time-series model fitting, evaluation, and forecasting

3.5.1 Time-series model fitting and evaluation

After applying first-order differencing to the neonatal mortality rate (NMR) series for Somalia (1983–2023), six time-series models were fitted and evaluated, including ARIMA, ETS, TBATS, Theta, NNAR, and ARFIMA.

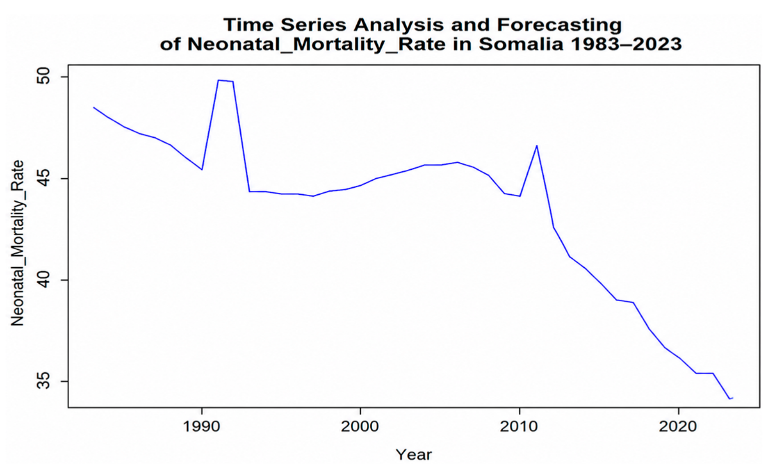

Figure 2. Time-series trend of neonatal mortality rate in Somalia (1983–2023). The figure shows the annual neonatal mortality rate over the study period, highlighting a general declining trend with fluctuations at certain periods.

Table 2. Stationarity test results for neonatal mortality rate in Somalia.

Test	Data series	Test statistic	p-value
PP	Original data	−14.162	0.2158
KPSS	Original data	0.64816	0.01826
PP	First-differenced data	−28.545	0.01
KPSS	First-differenced data	0.1232	0.10

Shows the results of the Phillips–Perron (PP) and KPSS stationarity tests. The original series is non-stationary, as indicated by the PP and KPSS results, while the first-differenced series satisfies stationarity conditions. This confirms the need for differencing prior to time-series modelling.

The automatic model selection procedure identified an ARIMA (0,1,0) specification. Diagnostic tests confirmed that the residuals approximated a white-noise process, indicating that the model was adequately specified.

Among the candidate models, the neural network autoregressive (NNAR) model demonstrated superior performance, particularly in capturing nonlinear patterns inherent in the data.

The fitted and forecasted values of the single time-series models are presented in Figure 3, which compares the observed (actual), fitted, and forecasted series across models. Overall, most models closely follow the underlying trend of neonatal mortality, although differences in predictive behaviour are evident. The NNAR model shows the closest agreement with the observed data, particularly in capturing nonlinear variations and short-term fluctuations, while ARFIMA demonstrates comparatively weaker performance.

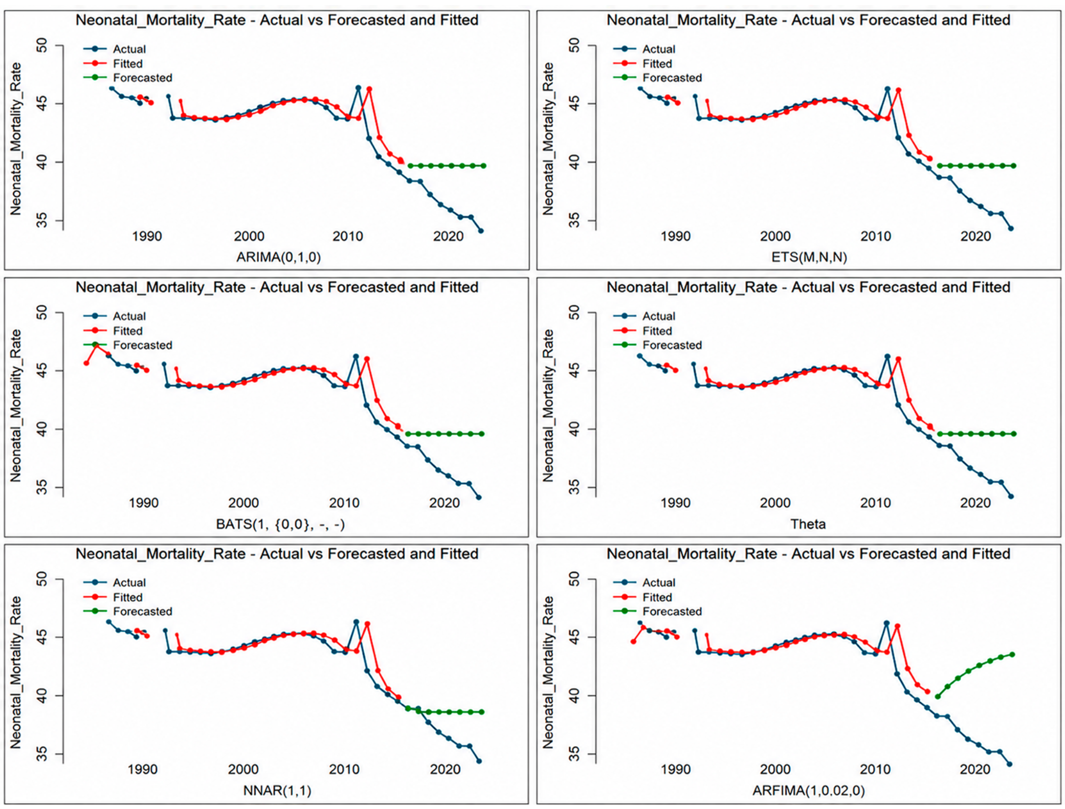

Figure 3. Actual, fitted, and forecasted values of neonatal mortality rate using single models. multi-panel plots comparing observed (actual), fitted, and forecasted values generated from single time-series models (ARIMA, ETS, TBATS, Theta, ARFIMA, and NNAR). Fitted values represent in-sample performance, while forecasts show projected trends beyond the training period.

Table 3. Forecast performance of single time-series models (test period 2016–2023).

Rank	Model	MAPE (%)	Theil's U	sMAPE
1	**NNAR**	**4.840375**	**2.977696**	**0.04666897**
2	Theta	7.547897	4.202501	0.07203163
3	ARIMA	8.262776	4.631793	0.07847013
4	ETS	8.324288	4.658558	0.07903703
5	TBATS	8.602029	4.779704	0.08159251
6	ARFIMA	16.173099	8.799707	0.14737360

This table presents a comparative evaluation of model performance based on MAPE, sMAPE, and Theil's U statistics. The NNAR model demonstrates the highest forecasting accuracy, followed by the Theta and ARIMA models, whereas ARFIMA shows the weakest predictive performance.

The comparative forecast accuracy of the single time-series models is summarized in Table 3. The NNAR model achieved the highest predictive accuracy, yielding the lowest error metrics (MAPE = 4.84%, sMAPE = 0.0467, Theil's U = 2.98). The Theta model ranked second, followed by ARIMA and ETS, which exhibited moderate and comparable performance. The TBATS model showed slightly higher errors, while ARFIMA performed least effectively, indicating limited suitability for modeling neonatal mortality dynamics in this context.

3.6 Hybrid model performance

The performance of hybrid time-series models is summarized in Table 4. Overall, hybrid approaches demonstrate improved predictive accuracy compared to single models, reflecting the advantage of integrating linear and nonlinear modeling structures.

The fitted and forecasted values of the hybrid models are illustrated in Figure 4. The results indicate that hybrid models provide smoother trajectories and better alignment with observed neonatal mortality trends. Models incorporating NNAR components show enhanced capability in capturing nonlinear dynamics and short-term variations.

Among the evaluated models, the **Theta–NNAR** hybrid achieved the best performance, with the lowest error metrics (MAPE = 6.11%, sMAPE = 0.0586, Theil's U = 3.57). This was followed by **ARIMA–NNAR** and **ETS–NNAR**, which also demonstrated strong forecasting accuracy. In contrast, hybrid models excluding NNAR components, such as **ARIMA–ETS** and **ETS–TBATS**, exhibited relatively higher errors.

These findings confirm that hybrid modeling approaches, particularly those integrating neural network components, provide superior performance in modeling complex time-series data.

Table 4. Forecast performance of hybrid time-series models.

Rank	Hybrid model	MAPE (%)	sMAPE	Theil's U
1	Theta–NNAR	6.11	0.05864	3.5721
2	ARIMA–NNAR	6.47	0.06191	3.7875
3	ETS–NNAR	6.50	0.06221	3.8009
4	NNAR–TBATS	6.64	0.06350	3.8590
5	ARIMA–Theta	7.91	0.07526	4.4171
6	ETS–Theta	7.94	0.07554	4.4305
7	Theta–TBATS	8.07	0.07683	4.4910
8	ARIMA–ETS	8.29	0.07875	4.6452
9	ARIMA–TBATS	8.43	0.08003	4.7057
10	ETS–TBATS	8.46	0.08032	4.7191

Comparison of hybrid model performance based on MAPE, sMAPE, and Theil's U statistics, showing that the Theta–NNAR model achieved the highest accuracy, followed by ARIMA–NNAR and ETS–NNAR.

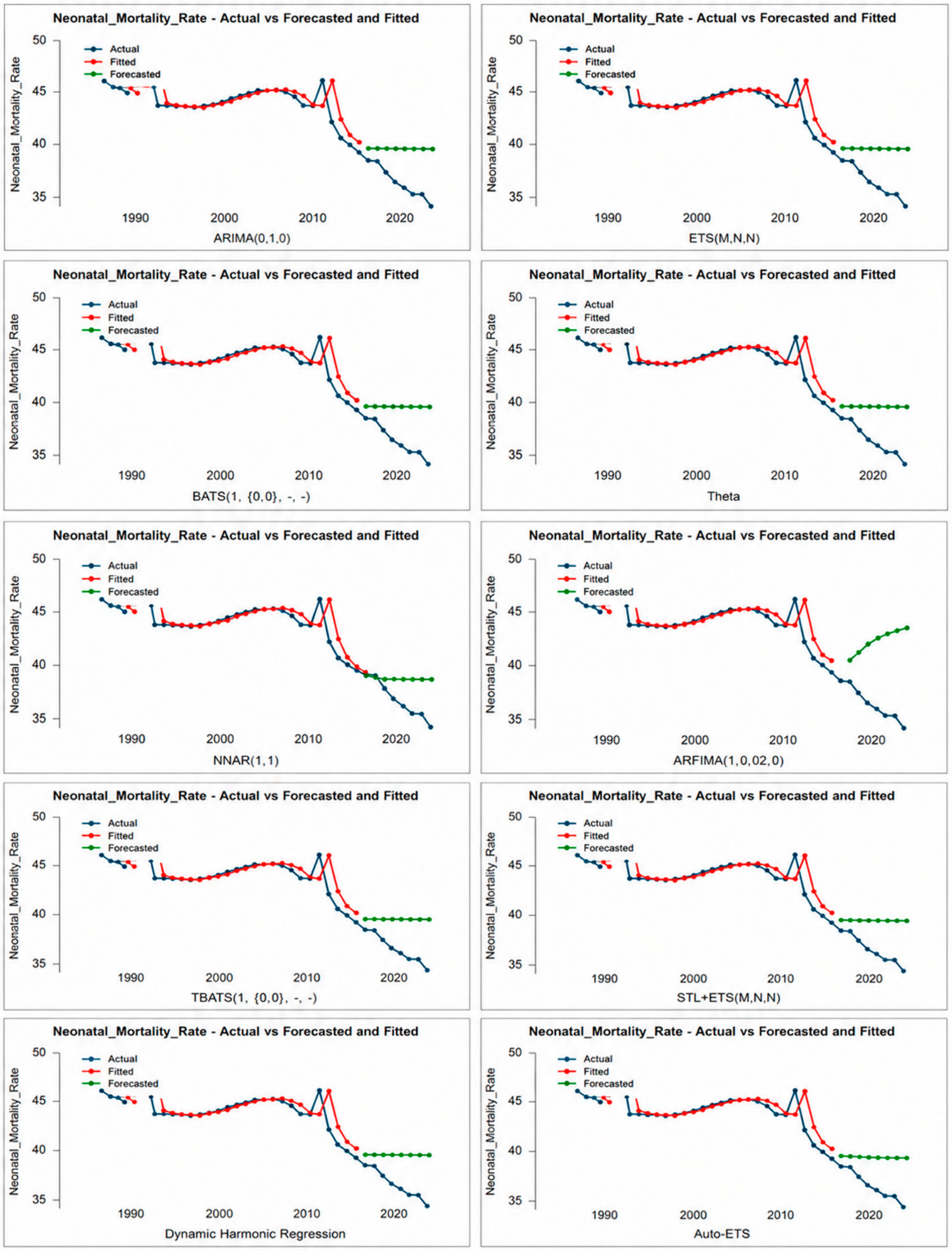

Figure 4. Actual, fitted, and forecasted values of neonatal mortality rate using hybrid models. multi-panel plots illustrating observed, fitted, and forecasted values from hybrid model combinations. The comparison demonstrates how hybrid approaches capture underlying patterns and improve forecasting performance relative to single models.

3.7 Forecasting using the NNAR model

The forecasts of neonatal mortality rates based on single time-series models are illustrated in Figure 5, which presents the projected trends alongside uncertainty intervals. Among the evaluated models, the NNAR model provided the most reliable and stable forecasts.

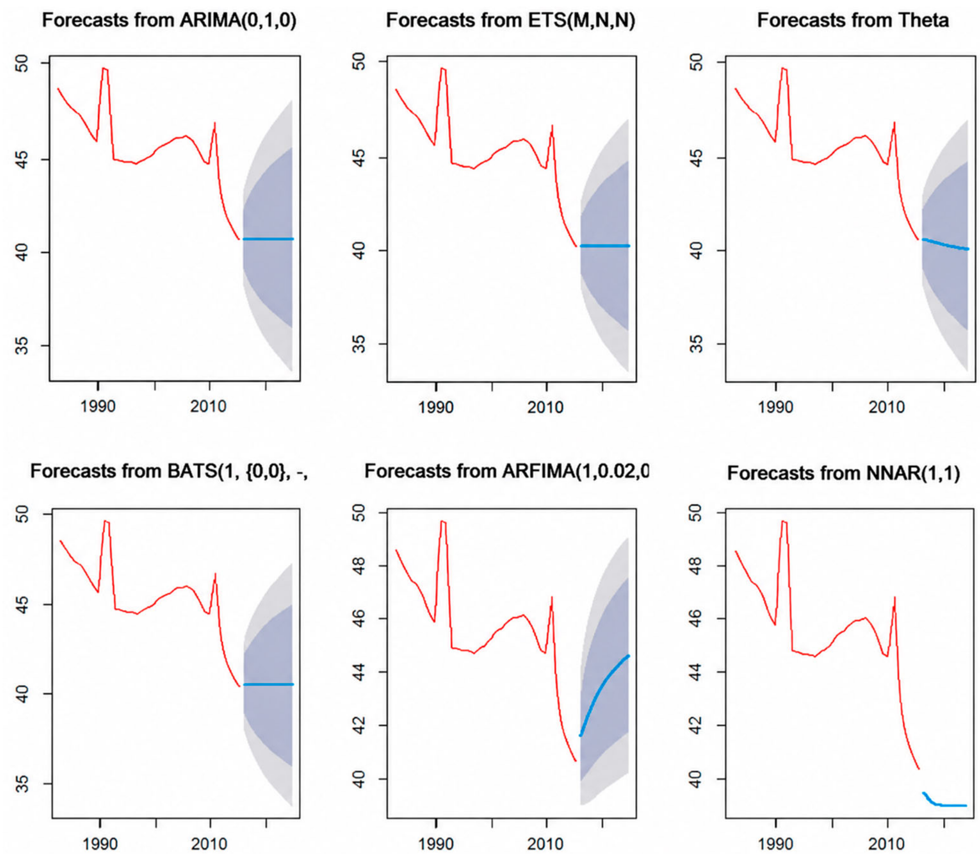

Figure 5. Forecasts of neonatal mortality rate using single models. Forecast plots from individual models showing projected neonatal mortality rates beyond the observed data. Shaded regions represent prediction intervals, indicating uncertainty in forecasts.

The forecast values generated using the NNAR model for the period 2024–2030 are presented in Table 5. The results indicate that neonatal mortality is expected to stabilize at approximately 35 deaths per 1,000 live births over the forecast horizon, with only marginal year-to-year variation.

However, the prediction intervals (80% and 95%) widen progressively over time, reflecting increasing uncertainty in longer-term forecasts. This pattern is consistent with time-series forecasting theory, where uncertainty accumulates as the prediction horizon extends.

Table 5. Forecast values of neonatal mortality rate in Somalia (2024–2030) using the NNAR model.

Year	Model	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2024	NNAR	35.18	33.62	36.74	32.74	37.47
2025	NNAR	35.29	33.80	37.07	32.89	38.00
2026	NNAR	35.34	33.91	37.09	32.97	38.15
2027	NNAR	35.35	33.87	37.19	33.03	38.21
2028	NNAR	35.36	33.97	37.24	33.18	38.42
2029	NNAR	35.37	33.87	37.33	33.06	38.36
2030	NNAR	35.37	33.85	37.22	32.80	38.27

This table presents the forecasted neonatal mortality rates along with 80% and 95% prediction intervals. The results indicate a relatively stable trend over the forecast period, while the widening intervals reflect increasing uncertainty over time.

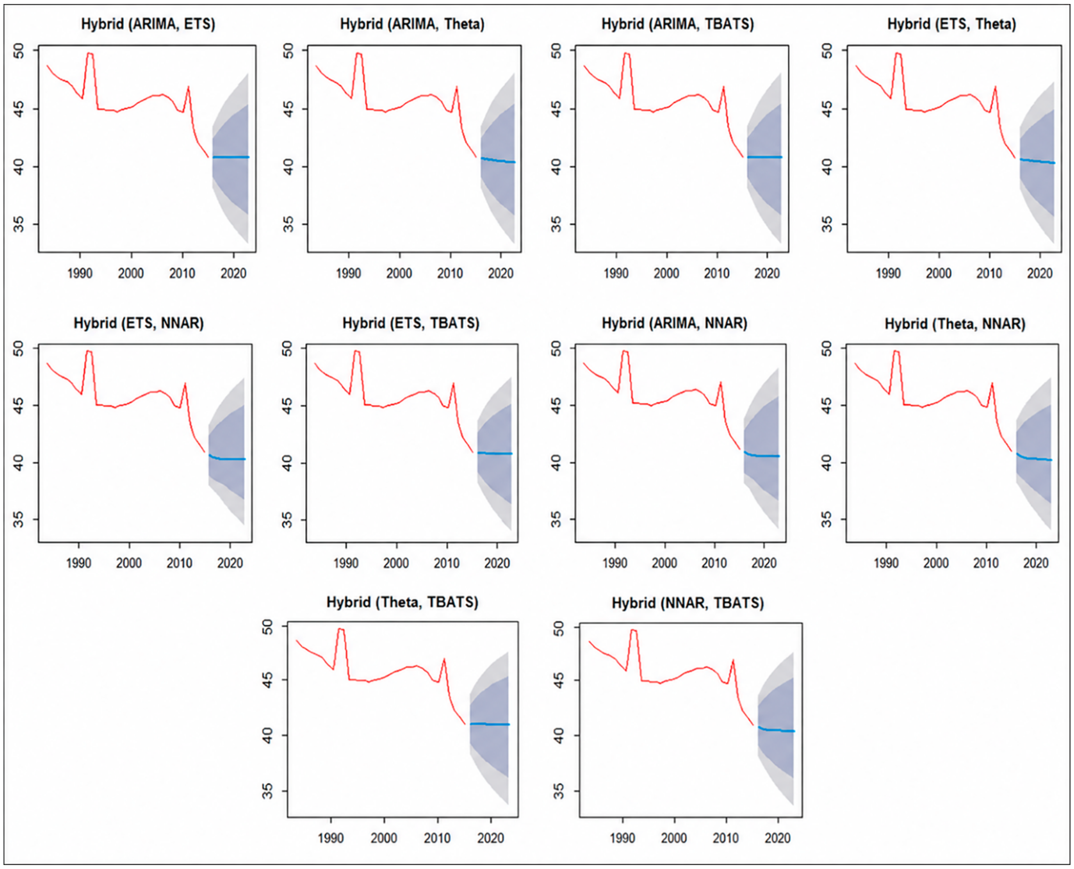

Figure 6. Forecasts of neonatal mortality rate using hybrid models. Forecast plots from hybrid models illustrating projected trends and associated uncertainty. Differences across models highlight variation in forecasting behaviour and predictive performance.

Overall, the NNAR model suggests a stabilization of neonatal mortality rates in Somalia, although the widening confidence intervals highlight the need for cautious interpretation of long-term projections.

3.8 Forecasting using the hybrid model (Theta–NNAR)

The forecasts generated from hybrid time-series models are illustrated in Figure 6, which presents projected neonatal mortality trends along with uncertainty intervals. Among the evaluated hybrid approaches, the Theta–NNAR model produced the most reliable and consistent forecasts.

Table 6. Forecast values of neonatal mortality rate in Somalia (2024–2030) using the Theta–NNAR hybrid model.

Year	Model	Point Forecast	Lower 80%	Upper 80%	Lower 95%	Upper 95%
2024	Theta–NNAR	34.97362	33.03261	36.68156	32.11610	37.46991
2025	Theta–NNAR	34.95986	32.17944	37.08661	30.88336	38.37221
2026	Theta–NNAR	34.91395	31.49308	37.49016	29.90574	39.07750
2027	Theta–NNAR	34.85514	30.89307	37.81784	29.06019	39.65072
2028	Theta–NNAR	34.79097	30.34824	38.09033	28.29904	40.13954
2029	Theta–NNAR	34.72454	29.84262	38.32362	27.59783	40.56840
2030	Theta–NNAR	34.65716	29.36670	38.52720	26.94206	40.95184

This table presents the forecasted neonatal mortality rates along with 80% and 95% prediction intervals. The results indicate a gradual decline over time, while the widening intervals reflect increasing uncertainty in long-term projections.

The forecast values for the period 2024–2030 obtained from the Theta–NNAR model are presented in Table 6. The results indicate a gradual decline in neonatal mortality, with point forecasts decreasing slightly from approximately 34.97 in 2024 to 34.66 deaths per 1,000 live births in 2030.

Compared to the NNAR model, the hybrid approach produces slightly lower estimates, suggesting a modest downward trend. However, the prediction intervals (80% and 95%) widen progressively over time, indicating increasing uncertainty associated with longer forecast horizons.

Overall, the Theta–NNAR model provides more stable and consistent forecasts by effectively capturing both linear and nonlinear patterns in the data.

Importantly, these findings suggest that hybrid modeling approaches may offer improved robustness and reliability for policy-relevant forecasting of neonatal mortality in complex and data-limited settings.

3.9 Overall model performance and forecast implications

From a methodological perspective, the results demonstrate that nonlinear and hybrid modeling approaches provide improved forecasting performance compared to traditional linear models.

This highlights the importance of model selection in time-series analysis, particularly when dealing with complex and dynamic health indicators such as neonatal mortality.

Overall, the findings suggest that neonatal mortality in Somalia is likely to stabilize during the medium-term forecast period (2024–2030). However, the increasing uncertainty reflected in widening prediction intervals underscores the need for sustained public health interventions and data-driven policy planning.

Discussion

This study presents a comprehensive time-series analysis and forecasting assessment of neonatal mortality in Somalia using annual data spanning 1983–2023. Multiple forecasting frameworks were systematically evaluated, including classical linear models (ARIMA, ETS, and Theta), long-memory modeling (ARFIMA), nonlinear machine-learning approaches (NNAR), and hybrid model combinations. The findings demonstrate that the Neural Network Autoregression (NNAR) model achieved the highest predictive accuracy among single-model approaches, exhibiting superior performance across standardized evaluation metrics (MAPE, sMAPE, and Theil's U). Among hybrid specifications, the Theta-NNAR combination produced the most reliable performance, although it performed slightly below the standalone NNAR model. Forecasts for 2024–2030 indicate a relative stabilization of neonatal mortality at approximately 35 deaths per 1,000 live births. However, progressively widening prediction intervals reflect persistent structural uncertainty associated with conflict-related disruptions, climatic shocks, and systemic health system fragility. These findings provide an empirical foundation for evidence-based neonatal health planning and long-term mortality monitoring in fragile and conflict-affected settings.

The results are consistent with prior epidemiological forecasting research, which indicates that nonlinear and machine-learning approaches often outperform traditional linear time-series models when data exhibit structural volatility and complex temporal dynamics. Previous studies have shown that neural network–based autoregressive models are particularly effective in capturing nonlinear mortality patterns that may not be adequately represented using ARIMA or exponential smoothing techniques alone. The strong performance of NNAR in this study reinforces this evidence and highlights the value of flexible modeling frameworks in shock-prone environments. Moreover, the competitive performance of hybrid models aligns with forecasting literature suggesting that combining complementary modeling approaches enhances robustness and predictive reliability. Unlike earlier Somalia-focused studies, which primarily examined determinants of neonatal or child mortality using cross-sectional designs, this research contributes long-term temporal modeling and forward-looking projections. By providing nationally aggregated forecasts across multiple decades, the study strengthens the methodological foundation for mortality forecasting and strategic planning in conflict-affected contexts.

A major strength of this study lies in its comprehensive multi-model benchmarking framework, which enables transparent comparison across diverse forecasting approaches within a unified validation design. The use of four decades of harmonized national data improves the reliability of long-term trend estimation and medium-term forecasting. Furthermore, the application of complementary stationarity diagnostics and standardized forecast accuracy metrics enhances methodological rigor, reproducibility, and comparability with global forecasting research.

Despite these strengths, several limitations should be acknowledged. Forecast accuracy relies on the assumption that historical patterns will persist, which may not hold in the presence of abrupt structural shocks such as conflict escalation, drought, displacement, or policy disruptions. The widening prediction intervals observed in this study reflect such uncertainty. Additionally, neonatal mortality estimates for Somalia may be influenced by data-quality limitations related to underreporting and weaknesses in civil registration and vital statistics systems. Finally, the univariate modeling framework does not incorporate key structural determinants—such as healthcare access, maternal education, nutrition, conflict intensity, and socioeconomic conditions—that may substantially influence mortality trajectories.

Conclusion

This study conducted a comprehensive time-series analysis of neonatal mortality in conflict-affected Somalia using annual data spanning 1983–2023. Multiple forecasting models—including ARIMA, ETS, Theta, ARFIMA, and NNAR—were systematically benchmarked using standardized forecast accuracy metrics. The findings indicate that the Neural Network Autoregression (NNAR) model outperformed other single-model approaches, while the Theta-NNAR hybrid configuration demonstrated the highest overall forecasting accuracy.

Forecasts for the period 2024–2030 suggest a relative stabilization of neonatal mortality; however, widening prediction intervals reflect persistent structural uncertainty associated with conflict, drought, and health system fragility. These projections provide important evidence for policymakers and international health organizations. By anticipating future neonatal mortality trends, strategic investments in maternal education, skilled birth attendance, neonatal care infrastructure, and nutrition programs can be prioritized to accelerate progress toward Sustainable Development Goal (SDG) 3.2.

Overall, this study contributes to the field of epidemiological forecasting in fragile, low-resource settings and provides a quantitative foundation for evidence-based planning aimed at reducing preventable neonatal deaths in Somalia.

Recommendations

Based on the empirical findings, policymakers in Somalia should prioritize data-driven neonatal health planning by integrating forecasting evidence into national maternal and newborn health strategies. Although projections indicate relative stabilization of neonatal mortality at approximately 35 deaths per 1,000 live births, widening prediction intervals highlight the need for resilience-based planning rather than reliance solely on point forecasts.

Strategic investments should focus on strengthening skilled birth attendance coverage, improving access to antenatal and postnatal care, expanding neonatal intensive care capacity, and enhancing maternal education and nutrition programs. In addition, early warning mechanisms for drought and conflict-related disruptions should be integrated into maternal and neonatal service planning to prevent mortality spikes. Institutional strengthening of health information systems and civil registration and vital statistics (CRVS) processes is also essential to improve the reliability of future forecasting and policy decision-making.

These measures are critical for accelerating progress toward Sustainable Development Goal (SDG) 3.2 within Somalia's fragile health context.

Future directions

Future research should extend the current univariate framework by incorporating multivariate time-series and machine learning approaches that integrate structural determinants such as maternal education, health expenditure, vaccination coverage, conflict intensity, and climate variability. Spatial disaggregation of neonatal mortality data would enable region-specific forecasting models to support targeted interventions across rural and urban populations.

Additionally, exploring weighted ensemble and advanced model-combination strategies may further enhance predictive robustness beyond equal-weight hybrid approaches. Integrating climate and drought projections into mortality modeling frameworks could improve preparedness in environmentally vulnerable settings such as Somalia. Finally, strengthening national data systems—including civil registration and vital statistics (CRVS)—will be essential for improving forecast precision and supporting long-term neonatal survival monitoring beyond the 2030 SDG horizon.

Ethics and consent

The study utilized publicly available secondary data obtained from the World Bank Open Data repository. As no human participants, personal data, or identifiable information were involved, ethical approval and informed consent were not required. However, the study protocol was reviewed and approved by the Internal Review Committee (IRC) of the Citycot Institute for Applied Research and Innovation (CIARI), ensuring compliance with CIARI's Research Ethics Policy and international ethical standards, including the Declaration of Helsinki and the Belmont Report.

Data availability

Underlying data

Neonatal Mortality Forecasting in Somalia: A Comparative Time-Series Analysis of Single and Hybrid Models. Zenodo: https://doi.org/10.5281/zenodo.18943224.[33]

The data underlying this study are openly available from the World Bank Open Data repository under the indicator "Mortality rate, neonatal (per 1,000 live births)" for Somalia. Annual neonatal mortality rate (NMR) data covering the period 1983–2023 were retrieved from this source and are accessible at: https://data.worldbank.org/indicator/SH.DYN.NMRT(34).

 No proprietary or restricted datasets were used.

Extended data

No extended data are associated with this study.

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