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Time Series Analysis and Forecasting of Maternal Mortality in Somalia

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Research Article

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Time Series Analysis and Forecasting of Maternal Mortality in Somalia

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Abstract

Maternal mortality remains a critical indicator of health system performance and socioeconomic development, particularly in fragile and conflict-affected settings such as Somalia. This study presents a comparative evaluation of single and hybrid time series models for forecasting the maternal mortality ratio (MMR) in Somalia. A comprehensive set of time series configurations was examined, including six single models—AutoRegressive Integrated Moving Average (ARIMA), Error–Trend–Seasonality (ETS), Trigonometric seasonality Box–Cox transformation (TBATS), Theta, AutoRegressive Fractionally Integrated Moving Average (ARFIMA), and Neural Network AutoRegression (NNAR)—as well as ten hybrid model combinations. The dataset spans from 1985 to 2023, comprising 39 annual observations, and was divided into a training set (1985–2015) and a testing set (2016–2023) to enable out-of-sample validation.

Forecasting performance was assessed using Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic. Stationarity testing indicated that the MMR series was non-stationary, necessitating first differencing prior to model estimation. Results demonstrate that the ARIMA(0,1,1) with drift model achieved the highest forecasting accuracy among single models (MAPE = 4.38%), outperforming both alternative single models and all hybrid configurations during the validation period. Although selected hybrid models, particularly ARIMA–ETS, exhibited competitive performance, none surpassed the predictive accuracy of the ARIMA model.

Forecasts for the period 2024–2030 indicate a gradual decline in maternal mortality under baseline assumptions, accompanied by wide prediction intervals reflecting historical volatility and structural uncertainty. These findings provide a quantitative framework to support evidence-based maternal health planning and strategic resource allocation in Somalia. The study contributes to the advancement of epidemiological forecasting in fragile contexts and offers actionable insights for monitoring progress toward Sustainable Development Goal (SDG) 3.1

Keywords: Maternal mortality · Hybrid models · Somalia · ARIMA · Time series forecasting · SDG 3.1 · Out-of-sample validation

1.1 Introduction

Maternal mortality remains one of the most critical indicators of health system performance, gender equity, and national development. A maternal death is defined as the death of a woman during pregnancy or within 42 days of termination of pregnancy from causes related to or aggravated by pregnancy or its management, excluding accidental or incidental causes [1]. The maternal mortality ratio (MMR), expressed per 100,000 live births, serves as a standardized measure for evaluating reproductive health systems and broader socioeconomic conditions.

Globally, reducing maternal mortality is central to Sustainable Development Goal (SDG) 3.1, which aims to reduce the global MMR to below 70 per 100,000 live births by 2030 [2]. Despite notable progress since 2000, recent reports indicate that global reductions have slowed in several regions [3]. Economic instability and health system fragility continue to hinder progress, particularly in low-income countries [4]. Large-scale global modeling studies confirm that maternal mortality remains unevenly distributed, with the majority of deaths concentrated in fragile and resource-limited settings [5]. Emerging evidence also suggests that stalled progress in maternal mortality reduction threatens SDG attainment [6].

Over the past two decades, substantial declines in maternal mortality have been observed in several regions, including East Asia and selected middle-income countries [7]. However, persistent inequalities remain between and within countries. Direct obstetric causes such as haemorrhage and hypertensive disorders remain dominant globally [8]. Advanced statistical estimation models developed for global monitoring demonstrate substantial regional variation in maternal mortality trends [7].

Measurement challenges further complicate global comparisons. Improvements in vital registration and modeling techniques have enhanced comparability across countries [9]. Nevertheless, disparities in access to high-quality maternal health services continue to drive inequitable outcomes [10].Maternal mortality therefore reflects not only clinical risk but also systemic inequities in service delivery and health financing [10].

Sub-Saharan Africa accounts for the largest share of global maternal deaths, driven by limited emergency obstetric services and high fertility rates [11]. Access to quality maternal health services remains constrained in many low-resource settings [12]. Structural barriers—including delays in seeking care, reaching facilities, and receiving treatment—remain central to maternal mortality frameworks [13].

While regional declines have occurred, they remain insufficient relative to SDG targets [14]. Recent global estimates indicate that Sub-Saharan Africa continues to bear the highest burden of maternal mortality worldwide [15]. Drivers of high maternal mortality in fragile settings include

infectious diseases, weak health systems, and conflict-related instability [16]. Global statistical modeling studies have demonstrated substantial regional variation in maternal mortality trends, with sub-Saharan Africa continuing to bear a disproportionate burden [17].

In East Africa and the broader Horn of Africa, maternal mortality trends demonstrate volatility influenced by drought, displacement, and political instability [18]. Environmental stressors, including recurrent drought and food insecurity, weaken maternal nutritional status and health service utilization [19]. In several countries of the region, maternal mortality remains closely linked to infectious disease burden and limited emergency obstetric coverage [20].

Maternal mortality remains highest in countries affected by fragility and conflict, where health system disruptions hinder sustained progress [21].Time-series forecasting methods such as ARIMA have been widely applied to analyze maternal mortality trends and to generate projections that support health policy planning and monitoring of progress toward mortality reduction targets [21]. Somalia represents one of the most fragile contexts globally for maternal health, with decades of civil conflict and recurrent humanitarian crises contributing to persistently high maternal mortality ratios [22] Maternal mortality in Somalia remains driven by preventable obstetric complications, including haemorrhage and hypertensive disorders, which are common across Sub-Saharan Africa (World Health Organization [23]. Time-series approaches such as ARIMA have been applied to maternal mortality data in African contexts to model historical trends and generate projections for health planning [24]. Socioeconomic vulnerability, high-risk fertility behaviors, and limited access to quality care further elevate maternal mortality risk in Somalia [24]. Regional disparities and fragile health governance structures contribute to fluctuations in maternal mortality over time [25]. Historical data demonstrate that fragile states experience slower declines in maternal mortality relative to global averages [14]. Given Somalia's exposure to drought, displacement, and recurrent instability, maternal mortality trends are likely to exhibit structural variability requiring advanced analytical modeling.

Maternal mortality is influenced by both direct and indirect determinants. Direct obstetric complications—including haemorrhage, sepsis, and hypertensive disorders—remain leading causes of death globally [11]. Indirect conditions such as anemia and pre-existing diseases exacerbate maternal vulnerability [26]. Socioeconomic determinants—including poverty, limited female education, and inadequate transportation infrastructure—contribute significantly to maternal risk [27].

Delayed referral and insufficient emergency response capacity are consistently linked to adverse maternal outcomes [13]. In fragile contexts, conflict and environmental shocks further weaken health system resilience [28]. These overlapping determinants illustrate the necessity of predictive planning frameworks capable of anticipating future maternal mortality burdens.

Although maternal mortality has been extensively analyzed through epidemiological and global modeling approaches [29], country-specific time series forecasting remains limited in

fragile contexts. Standard ARIMA frameworks and statistical forecasting approaches have demonstrated effectiveness in modeling mortality trends in other regions [30]. Modern forecasting methodologies emphasize model validation and comparative accuracy testing [31].

Forecast combination techniques have also been shown to improve predictive robustness relative to single-model approaches [32]. Empirical evidence supports the advantage of hybrid modeling in capturing both linear and nonlinear patterns in time series data [33]. Hybrid ARIMA–neural network models have demonstrated superior forecasting accuracy in diverse applications [34]. Recent maternal mortality forecasting research further confirms the applicability of ARIMA-based projection frameworks [35]. However, such structured forecasting applications remain underexplored for Somalia.

Novelty and Contribution

Novelty and Main Contribution

This paper introduces a novel and comprehensive approach to forecasting maternal mortality in Somalia by applying advanced time series and hybrid modeling techniques to nationally representative secondary data obtained from the World Bank. The novelty of this study lies in its systematic evaluation of a wide range of time series configurations within a fragile, conflict-affected, and data-constrained setting where robust forecasting of maternal mortality has been largely unexplored. By integrating and benchmarking both single and hybrid models—including ARIMA, ETS, NNAR, TBATS, Theta, and ARFIMA—this study advances beyond conventional descriptive and single-model analyses commonly used in maternal health research.
Furthermore, the adoption of hybrid ensemble frameworks enables the simultaneous capture of linear trends and non-linear dynamics inherent in maternal mortality data characterized by volatility and structural disruptions. This methodological contribution addresses key limitations of traditional forecasting approaches, particularly in settings exposed to recurrent shocks such as conflict, drought, and health system instability. The primary contribution of this study is the provision of the first high-resolution statistical forecasts of maternal mortality in Somalia over a defined future horizon, offering a robust quantitative foundation to support evidence-based maternal health planning, resource allocation, and progress monitoring toward Sustainable Development Goal (SDG) 3.1.

Objective and Evaluation Metrics

The primary objective of this study is to implement and compare a comprehensive set of time series forecasting models, comprising multiple single and hybrid configurations, to analyze and project maternal mortality trends in Somalia using nationally harmonized World Bank data. Model performance is evaluated using established forecasting accuracy measures, including the Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic. Through systematic comparative assessment, the study aims to identify the most robust and reliable forecasting framework suitable for a conflict-affected and resource-

constrained setting, thereby generating actionable evidence to inform maternal health policy and strategic planning in Somalia.

2.2: Materials and methods

2.1 Study Design and Data Source (Version si la mid ah Our World in Data style)

This study employed a time series research design, which falls under the category of longitudinal analytical studies. Time series designs are appropriate for examining temporal patterns, trends, and dynamics of a variable measured consistently over successive time periods.

The study relied on secondary annual maternal mortality ratio (MMR) data for Somalia, obtained from the World Bank Open Data repository (https://data.worldbank.org/indicator/SH.STA.MMRT?locations=SO).

The dataset covers the period from 1985 to 2023, comprising a total of 39 annual observations.

The World Bank maternal mortality estimates are nationally harmonized figures derived from multiple sources, including household surveys, civil registration systems, and statistical modeling by international agencies, ensuring consistency and comparability over time. Maternal mortality ratio was defined as the number of maternal deaths per 100,000 live births, and this definition was applied uniformly across the entire study period. The use of a long historical time span provides a robust basis for time series analysis and forecasting of maternal mortality trends in a fragile and conflict-affected setting such as Somalia.

Data Preprocessing

Prior to conducting the time series analysis, the maternal mortality ratio (MMR) data for Somalia underwent several preprocessing procedures to ensure its suitability for modeling and forecasting. The dataset was examined for missing values, outliers, and potential structural inconsistencies. The World Bank MMR series was verified to be complete and continuous over the study period, with no missing annual observations.

Subsequently, the data were transformed into a univariate time series object using R statistical software. This transformation enabled appropriate handling of temporal dependence and facilitated subsequent econometric and forecasting analyses. Given the long historical span of the data and its potential exposure to structural shocks, careful preprocessing was essential to preserve the integrity of the maternal mortality trend while ensuring the robustness of the modeling process.

Stationarity Testing: PP and KPSS Tests

In time series analysis, stationarity is a fundamental requirement for reliable modeling and forecasting. A stationary time series is characterized by statistical properties—such as mean and variance—that remain constant over time. To assess the stationarity properties of the maternal mortality ratio series, two complementary unit root tests were employed: the Phillips–Perron (PP) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

The Phillips–Perron (PP) test examines the presence of a unit root in a time series while applying non-parametric corrections to account for serial correlation and heteroscedasticity in the error terms. This characteristic makes the PP test particularly suitable for macro-level health indicators such as maternal mortality. The null hypothesis (H_0) of the PP test assumes that the series is non-stationary, whereas the alternative hypothesis (H_1) assumes stationarity. The PP test statistic is expressed as:

$$PP = \frac{\text{Coefficient Estimate} - 1}{\text{Standard Error}} \qquad (2)$$

To complement the PP test, the KPSS test was also applied. Unlike unit root tests, the KPSS test assumes stationarity under the null hypothesis. Specifically, the null hypothesis (H_0) states that the series is stationary around a level or deterministic trend, while the alternative hypothesis (H_1) indicates non-stationarity. A KPSS test statistic exceeding the critical value leads to rejection of

the null hypothesis, providing evidence that the series is non-stationary. The KPSS statistic is defined as:

$$KPSS = \frac{1}{T^2} \sum_{t=1}^{T} \frac{s_t^2}{\hat{\sigma}^2} \qquad (3)$$

The joint application of the PP and KPSS tests enhances the reliability of stationarity assessment by offsetting the limitations of individual methods, such as low power or size distortions. This combined approach provides robust evidence for determining whether differencing or other transformations are required prior to model estimation.

To facilitate robust model validation, the complete dataset was divided into training and testing subsets. The training dataset was used to estimate the parameters of the individual and hybrid forecasting models, while the testing dataset was reserved for out-of-sample performance evaluation. A range of time series models—including ARIMA, ETS, TBATS, Theta, ARFIMA, NNAR, and selected hybrid model configurations—were constructed using the training data.

Model performance was assessed using widely accepted forecast accuracy metrics, including the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and related scaled error measures. These metrics were used to compare the predictive accuracy of competing models and to identify the most reliable forecasting framework for maternal mortality in Somalia. Finally, forecasts of maternal mortality were generated based on the best-performing models. The overall analytical workflow ensured a transparent, replicable, and systematic approach to time series modeling and forecasting.

Software and Research Process

The R statistical software and various R packages, including psych, tseries, TSstudio, forecast, Metrics, plotly, forecastHybrid, and nnfor, were utilized for data analysis, time series

modeling, and forecasting. The process of analyzing, modeling, and forecasting the time series data followed a structured sequence of steps. These steps included: (i) examining and transforming the maternal mortality ratio (MMR) data into a time series format; (ii) assessing the stationarity of the series using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests and applying differencing techniques where necessary to achieve stationarity; (iii) identifying the final model through a systematic model development process; (iv) evaluating the performance of the developed models; and (v) generating forecasts of maternal mortality based on the selected optimal model.

The complete maternal mortality dataset was divided into separate training and testing subsets to enable out-of-sample validation. Forecasting models, including ARIMA, ETS, TBATS, Theta, ARFIMA, NNAR, and hybrid models, were constructed using the training data. To assess model performance, standard forecast accuracy measures—specifically Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic—were computed and used to compare the predictive accuracy of the competing models. Figure 1 illustrates the sequential steps of the modeling and forecasting framework.

Time Series Model Development

ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used time series forecasting approach that combines autoregressive (AR), differencing (I), and moving average (MA) components. It is effective in capturing both autoregressive and moving average patterns in non-stationary time series data. The general form of the ARIMA (p, d, q)model is expressed as:

$$(1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p)(1 - L)^d y_t = (1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q)\varepsilon_t \qquad (4)$$

where $y_t$denotes the maternal mortality ratio (MMR) at time t, $L$is the lag operator, $\phi_i$and $\theta_i$represent the autoregressive and moving average coefficients, respectively, $p$is the autoregressive order, $d$is the degree of differencing required to achieve stationarity, and $q$is the moving average order. The term $\varepsilon_t$represents a white-noise error process.

ARIMA models were estimated using the auto.arima() function from the *forecast* package in R. This function automatically selects the optimal values of p, d, and $q$based on the Akaike Information Criterion (AIC) using the Hyndman–Khandakar algorithm. The final model was selected as the one with the lowest AIC value. Model adequacy was assessed through diagnostic checks, including standardized residual plots, residual autocorrelation function (ACF) plots, and the Ljung–Box test.

ARFIMA Model

The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model extends the ARIMA framework by allowing fractional differencing, thereby enabling the modeling of long-range dependence or long-memory behavior in a time series. This feature is particularly useful for health indicators such as maternal mortality, which may exhibit persistent temporal dependence.

The ARFIMA (p, d, q)model is defined as:

$$(1 - \phi_1 L - \cdots - \phi_p L^p)(1 - L)^d (1 - \theta_1 L - \cdots - \theta_q L^q) y_t = \varepsilon_t \qquad (5)$$

where $y_t$represents the maternal mortality ratio, $d$denotes the fractional differencing parameter, and the remaining terms are defined as in the ARIMA model.

Theta Model

The Theta model is a parsimonious yet effective forecasting method that decomposes a time series into trend components and extrapolates them linearly. It can be interpreted as a random walk with drift and has demonstrated strong forecasting performance in empirical studies.

The Theta model is given by:

$$y_{t+1} = (1 + \theta)y_t + \mu + \varepsilon_{t+1} \qquad (6)$$

where $y_t$is the maternal mortality series, θrepresents the slope parameter, $\mu$is the drift term, and $\varepsilon_{t+1}$is the error term.

ETS Model

The Exponential Smoothing State Space (ETS) framework is a flexible class of models that incorporates error (E), trend (T), and seasonality (S) components. These components can be specified as additive, multiplicative, or absent, allowing the ETS framework to accommodate a wide range of time series behaviors.

The ETS state-space representation is defined as:

$$y_t = w(x_{t-1}) + r(x_{t-1})\varepsilon_t \qquad (7)$$

$$x_t = f(x_{t-1}) + g(x_{t-1})\varepsilon_t \qquad (8)$$

where $y_t$denotes the observed maternal mortality series, $x_t$represents the unobserved state vector, and $\varepsilon_t$is a Gaussian white-noise error term. The ETS models were implemented using the ets() function from the *forecast* package.

NNAR Model

The **Neural Network Autoregressive (NNAR)** model is a time series forecasting approach that utilizes artificial neural networks to capture complex patterns and non-linear relationships in the data. The NNAR model combines traditional autoregressive structures with the non-linear learning capability of neural networks, making it suitable for modeling time series that exhibit non-linear dynamics. The exact formulation of the NNAR model depends on the network architecture and selected parameters.

The NNAR model incorporates lagged values of the time series as inputs to a feed-forward neural network. The network consists of three layers—an input layer, a hidden layer, and an output layer—connected through acyclic linkages. Following Yusof and Kane (2012), the NNAR model can be expressed as:

$$y_t = \omega_0 + \sum_{j=1}^{Q} \omega_j \; g\left(\omega_{0j} + \sum\nolimits_{i=1}^{P} \omega_{i,j} \; y_{t-i}\right) + e_t \qquad (9)$$

where $y_t$denotes the output at time t, and $(y_{t-1}, \dots, y_{t-P})$represent the lagged input values. The parameters $\omega_{i,j}$and $\omega_j$are the network connection weights, Pdenotes the number of input nodes (lags), Qrepresents the number of neurons in the hidden layer, $g(\cdot)$is a non-linear activation function, and $e_t$is the error term.

For seasonal time series, the NNAR model is commonly expressed as **NNAR(**p, P, k**)** $_m$, where $p$represents the number of lagged observations from the same season, Pdenotes additional non-seasonal lags, $k$is the number of neurons in the hidden layer, and $m$indicates the frequency of the time series (e.g., $m = 1$for annual data).

In this study, the NNAR model was implemented using the **nnetar()** function from the **forecast** package in the R statistical software environment. For seasonal time series, the default value of $P$was set to 1, while the value of $p$was selected based on the optimal linear model fitted to the seasonally adjusted data. The number of hidden neurons $k$was determined automatically using the default setting $k = (p + P + 1)/2$, as recommended by Hyndman (2018).

TBATS Model

The TBATS (Trigonometric Seasonal, Box–Cox Transformation, ARMA Errors, Trend, and Seasonality) model is a flexible time series forecasting approach capable of handling complex seasonal patterns, non-linear trends, and diverse error structures. The model incorporates

trigonometric functions to capture multiple seasonal cycles, a Box–Cox transformation to address non-constant variance, ARMA components for residual modeling, and trend elements. Due to its general formulation, the exact specification of the TBATS model depends on the selected configuration and can be complex.

TBATS models combine Fourier representations of seasonality with an exponential smoothing state-space framework and a Box–Cox transformation, allowing them to accommodate multiple seasonal frequencies simultaneously. In this study, the TBATS model is represented by the following measurement equation:

$$y_t^{(\omega)} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t \qquad (10)$$

where $y_t^{(\omega)}$denotes the observation after applying the Box–Cox transformation with parameter ω, and $y_t$represents the original observation at time t. The term $\ell_t$denotes the local level, ϕrepresents the damping parameter, $b_t$is the long-run trend component, $s_{t-m_i}^{(i)}$denotes the i-th seasonal component with seasonal period m_i, and $d_t$corresponds to an ARMA(p, q) process capturing the residual dynamics.

The TBATS model was implemented using the tbats() function from the forecast package in the R statistical software environment.

Hybrid Modelling Approaches

In addition to the individual time series models, this study employed hybrid modeling approaches that combine multiple forecasting techniques in order to enhance predictive accuracy. Hybrid models are particularly useful in complex health-related time series, as they allow the integration of models that capture linear structures, non-linear dynamics, and irregular fluctuations within the data.

In this study, a targeted set of ten hybrid time-series models was developed by systematically combining selected individual techniques, namely ARIMA, ETS, TBATS, Theta, and NNAR. The hybrid models considered were: ARIMA–ETS, ARIMA–TBATS, ARIMA–Theta, ARIMA–NNAR, ARIMA–ETS–NNAR, ARIMA–Theta–NNAR, ARIMA–ETS–Theta, ARIMA–NNAR–TBATS, and ARIMA–ETS–TBATS. These hybrid configurations were selected to represent a balanced range of two- and three-model combinations while avoiding excessive model complexity. All hybrid models were implemented using the hybridModel() function available in the forecastHybrid package in the R statistical environment [36]. Hybrid forecasts were generated using an equal-weight averaging scheme, whereby each component model contributed proportionally to the final prediction. This approach was adopted in line with extensive empirical evidence indicating that simple forecast averaging frequently yields robust and stable predictive performance while mitigating the risk of overfitting associated with complex weighting algorithms [37].By combining ARIMA-based linear components with non-linear and flexible models such as NNAR, TBATS, Theta, and ETS, the hybrid approaches aim to capture both **long-term trends** and **short-term dynamics** in the maternal mortality ratio time series. The automated hybrid framework facilitates objective model construction while leveraging the complementary strengths of the individual forecasting methods. Detailed methodological foundations of hybrid forecasting and their effectiveness in time series analysis have been widely discussed in previous studies [38].

Model Evaluation

To evaluate the forecasting performance of the time series models, the dataset was divided into training and validation (testing) sets. All models were fitted using the training dataset, while their predictive accuracy was assessed by comparing the model forecasts against the observed maternal mortality ratio (MMR) values in the validation period.

Model performance was assessed using multiple accuracy measures, including the Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic. These metrics provide complementary information on forecast accuracy and allow for robust comparison across different modeling approaches. Models yielding lower values of these error measures were considered to exhibit superior predictive performance.

Based on the evaluation results, the best-fitting time series models were identified by jointly considering MAPE, sMAPE, and Theil's U statistics. This multi-criteria approach ensured that model selection was not driven by a single performance metric, thereby improving the robustness and reliability of the selected forecasting models. The models demonstrating the highest predictive accuracy were subsequently used to generate future forecasts of maternal mortality in Somalia.

The fitted models and their corresponding forecasts were further examined to assess long-term trends and short-term dynamics in maternal mortality over the historical period. This analysis provided insights into the temporal evolution of maternal mortality, including periods of accelerated decline or stagnation, which may reflect variations in health system performance, conflict intensity, or humanitarian conditions.

In summary, this study employed a comprehensive set of univariate time series models, including ARIMA, ETS, Theta, NNAR, ARFIMA, and TBATS, alongside selected hybrid modeling approaches, to forecast maternal mortality in Somalia. Model performance was systematically evaluated using standard accuracy measures, and the best-performing models formed the basis for subsequent forecasting and interpretation.

Forecast and Model Performance

Forecast performance was evaluated using three widely recognized accuracy measures: Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic [39]. Forecast performance was evaluated using established accuracy metrics, including Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Theil's U statistic [40].

Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) measures the average absolute percentage deviation between forecasted and observed values and is expressed as:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100 \qquad (11)$$

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

Symmetric Mean Absolute Percentage Error (sMAPE)

Symmetric Mean Absolute Percentage Error (sMAPE) evaluates forecasting accuracy by scaling the absolute forecast error by the average magnitude of the forecasted and observed values. The sMAPE is defined as:

$$\text{sMAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{2 \mid F_i - A_i \mid}{\mid F_i \mid + \mid A_i \mid} \times 100 \qquad (12)$$

where $F_i$denotes the forecasted value and $A_i$represents the actual observed value at time i. Unlike MAPE, sMAPE is symmetric and bounded, ensuring that over- and under-forecasts are penalized equally. This property makes sMAPE particularly suitable for comparing models across different scales and time periods.

Theil's U Statistic

Theil's U statistic is a relative measure of forecast accuracy that compares the performance of a proposed model against a naïve (random walk) benchmark. It is computed as:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - y_{t-1})^2}} \qquad (13)$$

where $y_t$represents the observed maternal mortality ratio at time t, $\hat{y}_t$denotes the forecasted value, and $y_{t-1}$is the observed value from the previous period. A Theil's U value less than one indicates that the forecasting model outperforms the naïve benchmark, while values greater than one suggest inferior performance.

The maternal mortality dataset spanning 1985–2023 was divided into two subsets: a training dataset (1985–2015) and a testing dataset (2016–2023). All single and hybrid time series models were estimated using the training data, and their forecasting accuracy was evaluated based on out-of-sample forecasts over the testing period. The error metrics (MAPE, sMAPE, and Theil's U) were computed for each model, and lower values of these metrics were used to identify superior forecasting performance, consistent with previous forecasting studies [41].

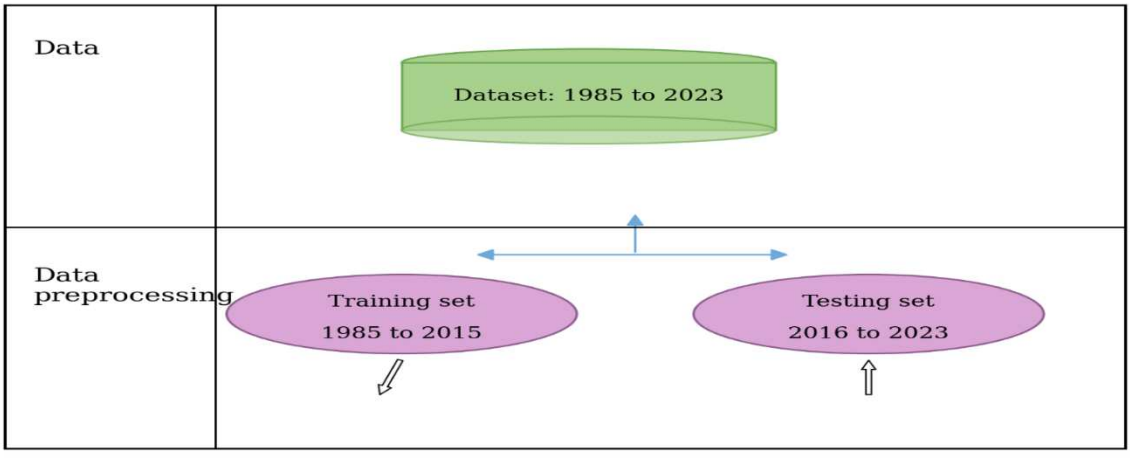


Fig. 1: Time series modelling Procedure

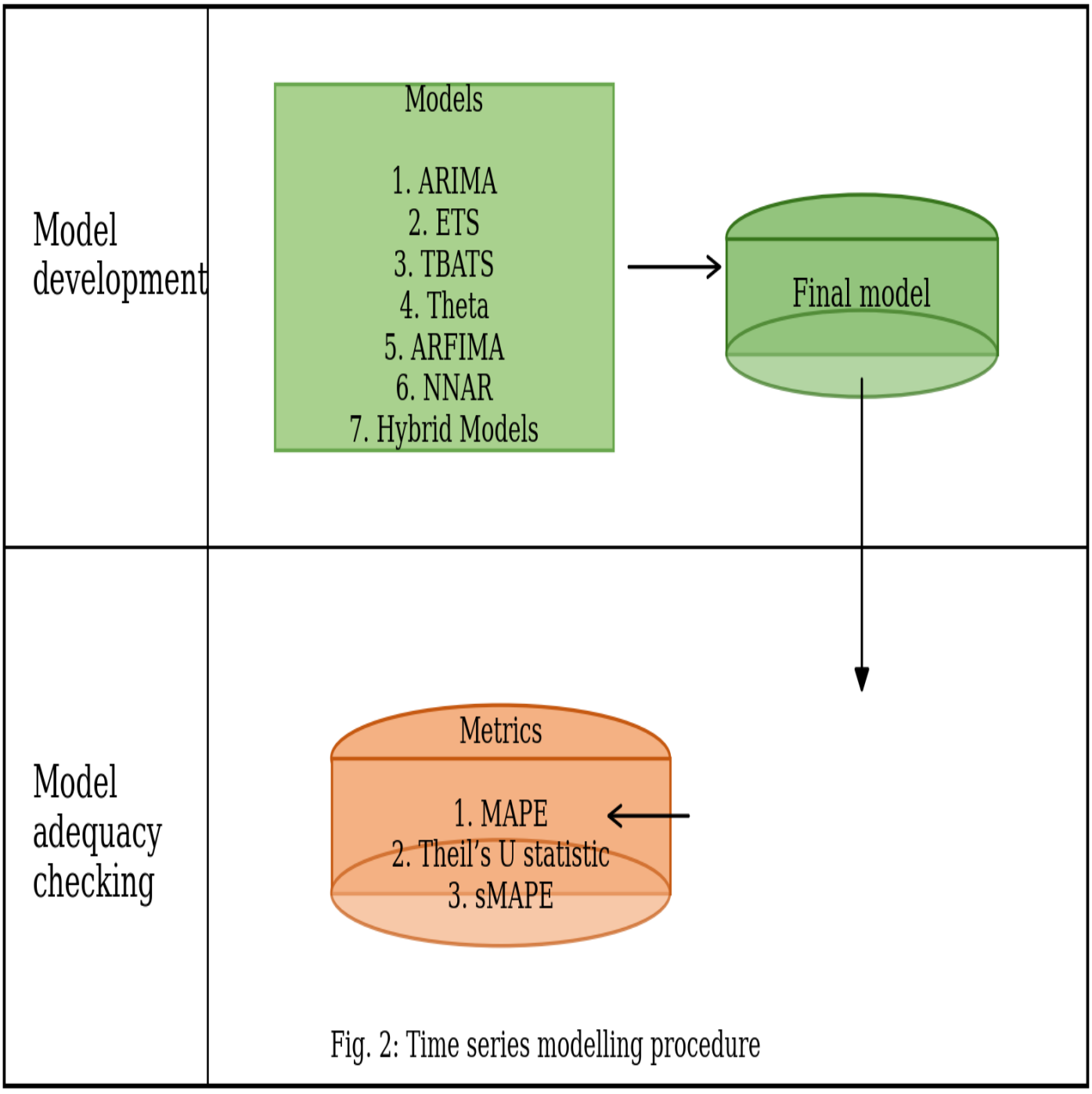


Fig. 2: Time series modelling procedure

Fig .2: time series modelling procedure

Results

Data Description

Descriptive Statistics of the Data

The descriptive statistics provide a summary of the data on the maternal mortality ratio (MMR) in Somalia from 1985 to 2023. The variable represents the annual number of maternal deaths per 100,000 live births. The data consist of 39 observations. The descriptive statistics are as follows: The descriptive statistics of maternal mortality in Somalia from 1985 to 2023 provide a summary of the data. The mean maternal mortality ratio is approximately 1,061.18, with a standard deviation of 260.13, indicating a substantial spread of data points around the mean. The median is 1,104.06, and the trimmed mean is around 1,066.62, accounting for potential outliers. The median absolute deviation is 311.29, representing the average distance between each observation and the median. The range of maternal mortality spans from 562.58 (minimum) to 1,465.31 (maximum). The data show a slight negative skewness (−0.25) and a platykurtic distribution with a kurtosis value of −1.09, indicating a flatter distribution with fewer extreme values. The standard error is approximately 41.65, estimating the standard deviation of the sample mean. Overall, these statistics provide insights into the central tendency, variability, and distribution of maternal mortality in Somalia during the specified time period.

Table 1: Descriptive statistics of maternal mortality ratio (MMR) in Somalia (1985–2023)

Variable	# of Obs. (n)	Mean	Median	Trimmed	SD	MAD
Data	39	1,061.18	1,104.06	1,066.62	260.13	311.29
Variable	Minimum	Maximum	Range	Skewness	Kurtosis	SE
	562.58	1,465.31	902.72	−0.25	−1.09	41.65

Visual Representation of the Data

Figure 2 illustrates the line graph representing the first differenced maternal mortality ratio (per 100,000 live births) in Somalia between 1985 and 2023. The data depicted in Fig. 2 indicate that changes in maternal mortality over time fluctuate around zero, suggesting the removal of long-term trends through first differencing. However, these changes are not smooth or stable across the study period. The trajectory is characterized by considerable volatility and sharp fluctuations, with pronounced positive and negative spikes, particularly during the early 1990s and around 2010–2012. These abrupt changes reflect periods of instability in maternal health outcomes, likely associated with conflict, health system disruption, and humanitarian crises. Overall, the first

differenced series highlights short-term shocks and year-to-year variability in maternal mortality rather than long-run trends.

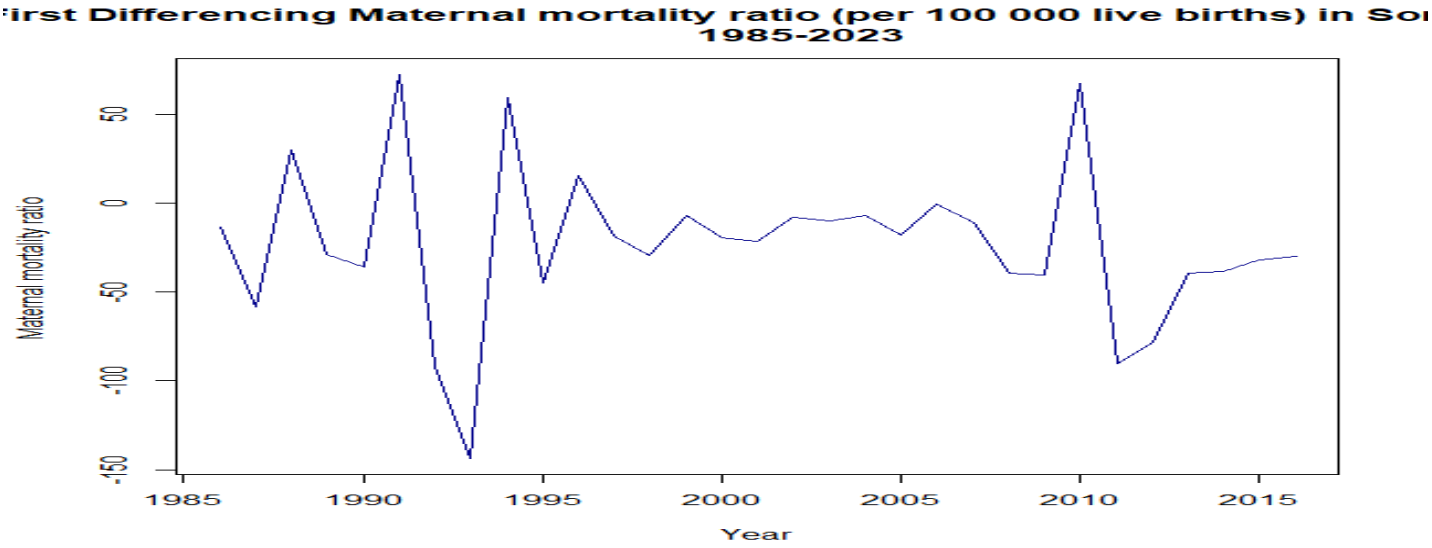


Figure 2: Time series diagram of the first differenced maternal mortality ratio (per 100,000 live births) in Somalia (1985–2023)

Table 2: Stationarity Test Results

Test	Data Series	Test Statistic	p-value
PP	Original Data	−13.455	0.2594
KPSS	Original Data	0.88069	0.01
PP	First Difference Data	−33.815	0.01
KPSS	First Difference Data	0.13757	0.10

Time Series Model Fitting, Evaluation of Model Performance, and Forecasting

After performing one differencing operation on the maternal mortality ratio (per 100,000 live births) dataset for Somalia over the period 1985–2023, a total of seven single time series models were generated and evaluated. Among these models, the ARIMA(0,1,1) with drift model was selected by the auto.arima function as the most appropriate ARIMA specification. Prior to utilizing this model for forecasting purposes, assumptions regarding the residuals were assessed. The autocorrelation function (ACF) of the residuals displayed no significant deviations from a zero-mean white noise process, supporting the adequacy of the fitted model.

In addition to ARIMA, alternative single models were estimated, including ETS, TBATS, Theta, NNAR, and ARFIMA. The ETS approach was fitted as ETS(M, A, N) (multiplicative error,

additive trend, no seasonality), while the NNAR model was also evaluated as a neural network autoregressive model. However, TBATS, Theta, and ARFIMA exhibited comparatively higher error rates and weaker performance in capturing the underlying structure of maternal mortality dynamics in Somalia.

Figure 3 illustrates the actual, fitted, and forecasted values for the single time series models. On the other hand, Figure 4 and Figure 5 present the corresponding outputs for the hybrid models. These figures provide a visual representation of the models' performance and forecasting outcomes. Table 3 presents the model performance values for the single time series models, including MAPE, sMAPE, and Theil's U, while Table 4 reports the corresponding performance values for the hybrid models.

The results in Table 3 indicate that the ARIMA model significantly outperformed the other single-technique methods, achieving the lowest error measures on the test set (MAPE = 4.38%, sMAPE = 0.0441, Theil's U = 0.652), followed closely by the ETS model. Conversely, the Theta and ARFIMA models performed poorly, producing substantially larger forecasting errors. Table 4 shows that although some hybrid combinations (e.g., ARIMA–ETS and ARIMA–NNAR) produced competitive results, none outperformed the single ARIMA model in terms of the main accuracy metrics on the test period. Consequently, the ARIMA(0,1,1) with drift model was selected as the most robust choice for projecting future maternal mortality values.

Table 5 and Table 6 present the forecasted maternal mortality ratios from the best-performing approaches for the period 2024–2030. In Figure 3, the forecasted maternal mortality ratio is represented by the forecast line, suggesting a continued decline in the point forecasts compared to earlier years. Unlike the historical data, which showed volatility and sharp movements associated with instability and shocks, the projected series follows a smoother trajectory. Overall, the forecasts indicate potential improvement in maternal mortality levels, although uncertainty remains, highlighting the importance of sustained maternal health interventions and health system strengthening.

Table 3: Forecast performance of the single time series models for maternal mortality ratio in Somalia (best results are shown in bold)

Rank	Model	MAPE (%)	Theil's U	sMAPE
1	**ARIMA**	**4.381704**	**0.6521875**	**0.0440771**
2	ETS	4.943384	0.6715971	0.0491670
3	NNAR	4.865354	0.7543908	0.0486140
4	TBATS	5.242446	0.6894973	0.0518493

Rank	Model	MAPE (%)	Theil's U	sMAPE
5	Theta	8.532397	1.1197820	0.0802483
6	ARFIMA	16.31676	2.1084560	0.1458380

Table 4: Forecast performance of the selected hybrid time series models (best results are shown in bold)

Rank	Hybrid Model	MAPE (%)	sMAPE	Theil's U
1	**ARIMA + ETS**	**6.99**	**0.07733**	**0.8368**
2	ARIMA + NNAR	12.80	0.12180	0.7652
3	ETS + NNAR	12.80	0.12180	0.7652
4	ARIMA + Theta	17.01	0.15620	0.9203
5	ETS + Theta	17.01	0.15620	0.9203
6	ARIMA + TBATS	21.66	0.18968	1.1348
7	ETS + TBATS	21.66	0.18969	1.1348
8	Theta + NNAR	27.85	0.23791	1.5578
9	NNAR + TBATS	34.57	0.28702	1.8298
10	Theta + TBATS	40.26	0.32686	2.0758

Table 5: Forecast values of the maternal mortality ratio (per 100,000 live births) in Somalia during 2024–2030 using the best fitted single model (ARIMA)

Year	Model	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2024	ARIMA	566.70	509.47	623.93	479.18	654.22
2025	ARIMA	544.38	480.02	608.73	445.95	642.80
2026	ARIMA	522.06	451.28	592.83	413.82	630.29
2027	ARIMA	499.73	423.08	576.39	382.50	616.97
2028	ARIMA	477.41	395.29	559.54	351.82	603.01

Year	Model	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2029	ARIMA	455.09	367.84	542.34	321.66	588.53
2030	ARIMA	432.77	340.68	524.86	291.93	573.61

Table 6: Forecast values of the maternal mortality ratio (per 100,000 live births) in Somalia during 2024–2030 using the best fitted hybrid model (ARIMA–ETS)

Year	Model	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2024	ARIMA–ETS	566.70	509.47	623.93	479.18	654.22
2025	ARIMA–ETS	544.38	480.02	608.73	445.95	642.80
2026	ARIMA–ETS	522.06	451.28	592.83	413.82	630.29
2027	ARIMA–ETS	499.73	423.08	576.39	382.50	616.97
2028	ARIMA–ETS	477.41	395.29	559.54	351.82	603.01
2029	ARIMA–ETS	455.09	367.84	542.34	321.66	588.53
2030	ARIMA–ETS	432.77	340.68	524.86	291.93	573.61

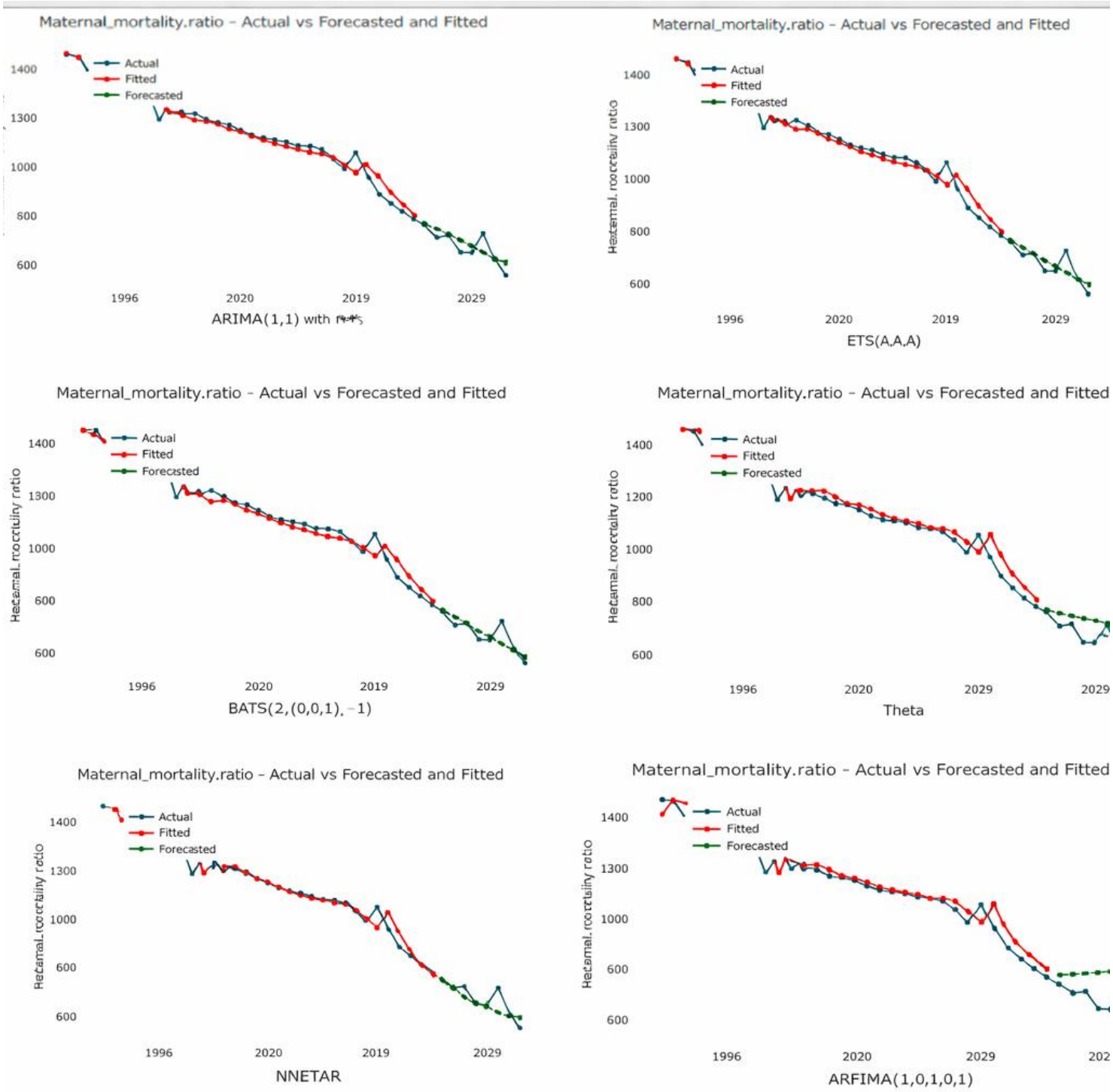


Fig. 3: Actual, fitted, and forecasted values from the ARIMA, ETS, TBATS, Theta, NNAR, and ARFIMA models. The x-axis and y-axis represent the year and the maternal mortality ratio (per 100,000 live births), respectively.

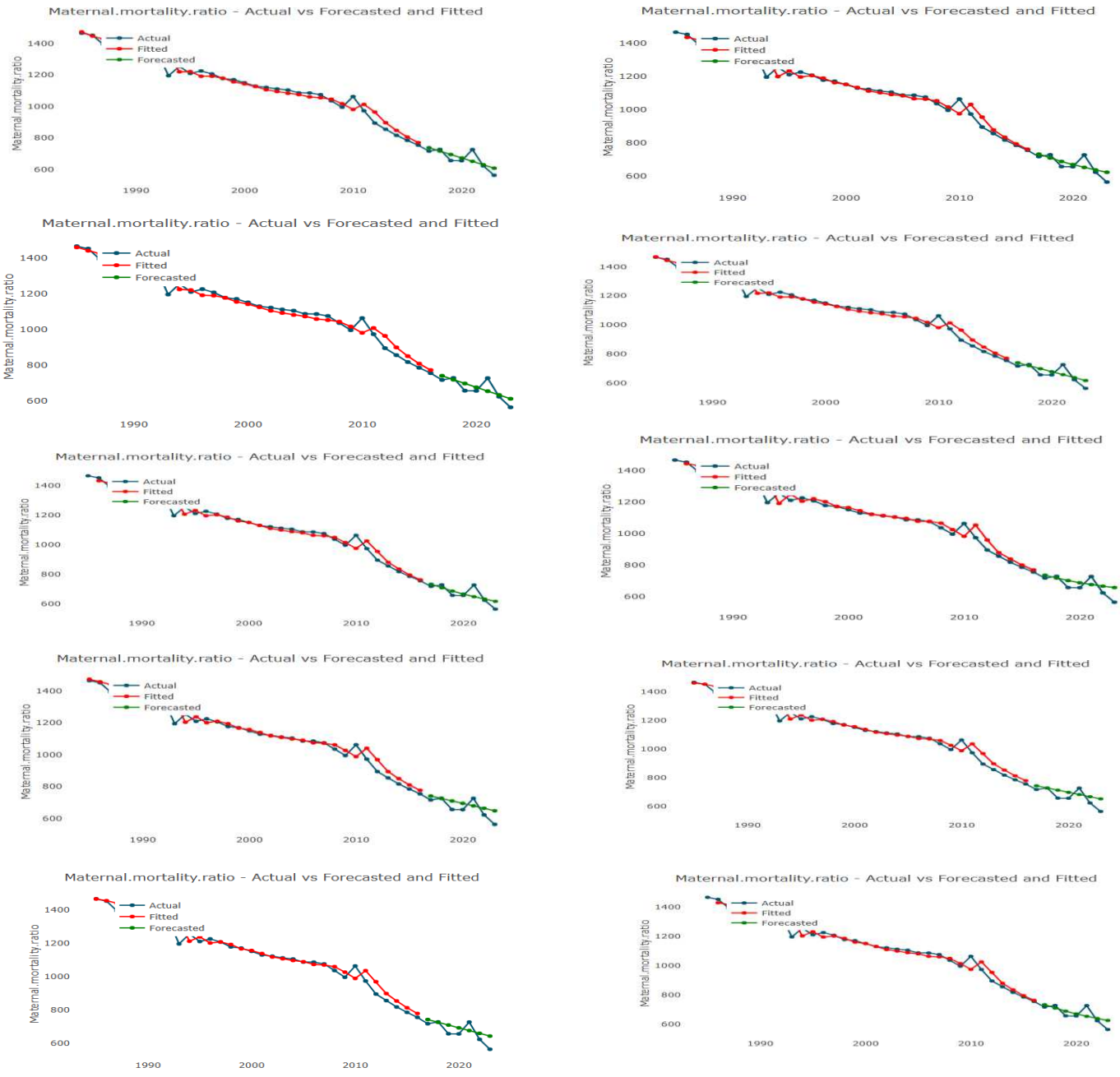


Fig. 4: Actual, fitted, and forecasted values obtained from ten hybrid time series models constructed from combinations of ARIMA, ETS, Theta, TBATS, and NNAR models, namely: ARIMA–ETS, ARIMA–Theta, ARIMA–TBATS, ARIMA–NNAR, ETS–Theta, ETS–NNAR, ETS–TBATS, Theta–NNAR, Theta–TBATS, and NNAR–TBATS.
The x-axis represents the year, while the y-axis represents the maternal mortality ratio (per 100,000 live births).
(Part 1 of 5).

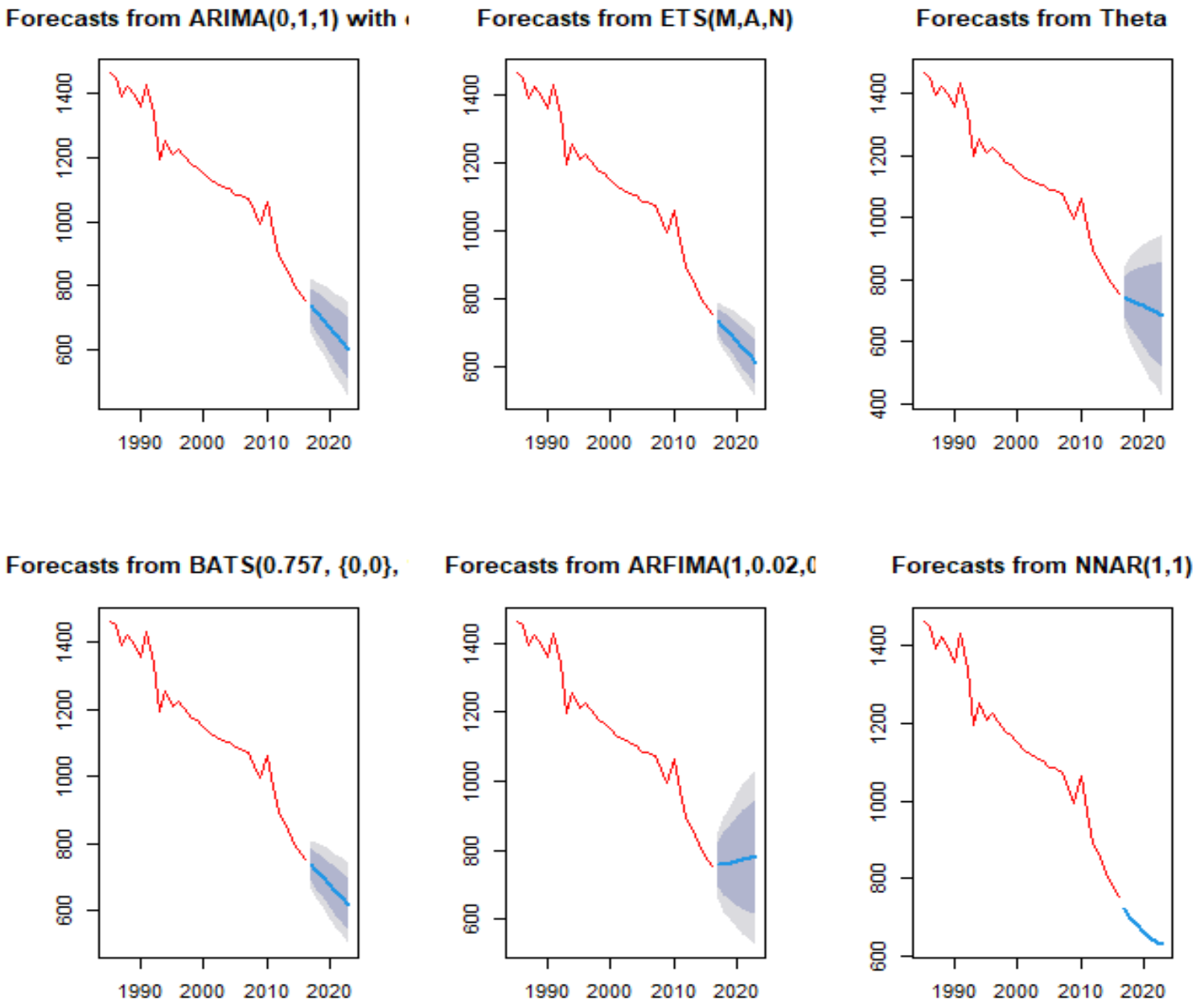


Fig. 5. Forecasts of the maternal mortality ratio (per 100,000 live births) *(blue line)* from the ARIMA, ETS, Theta, TBATS, ARFIMA, and NNAR models.

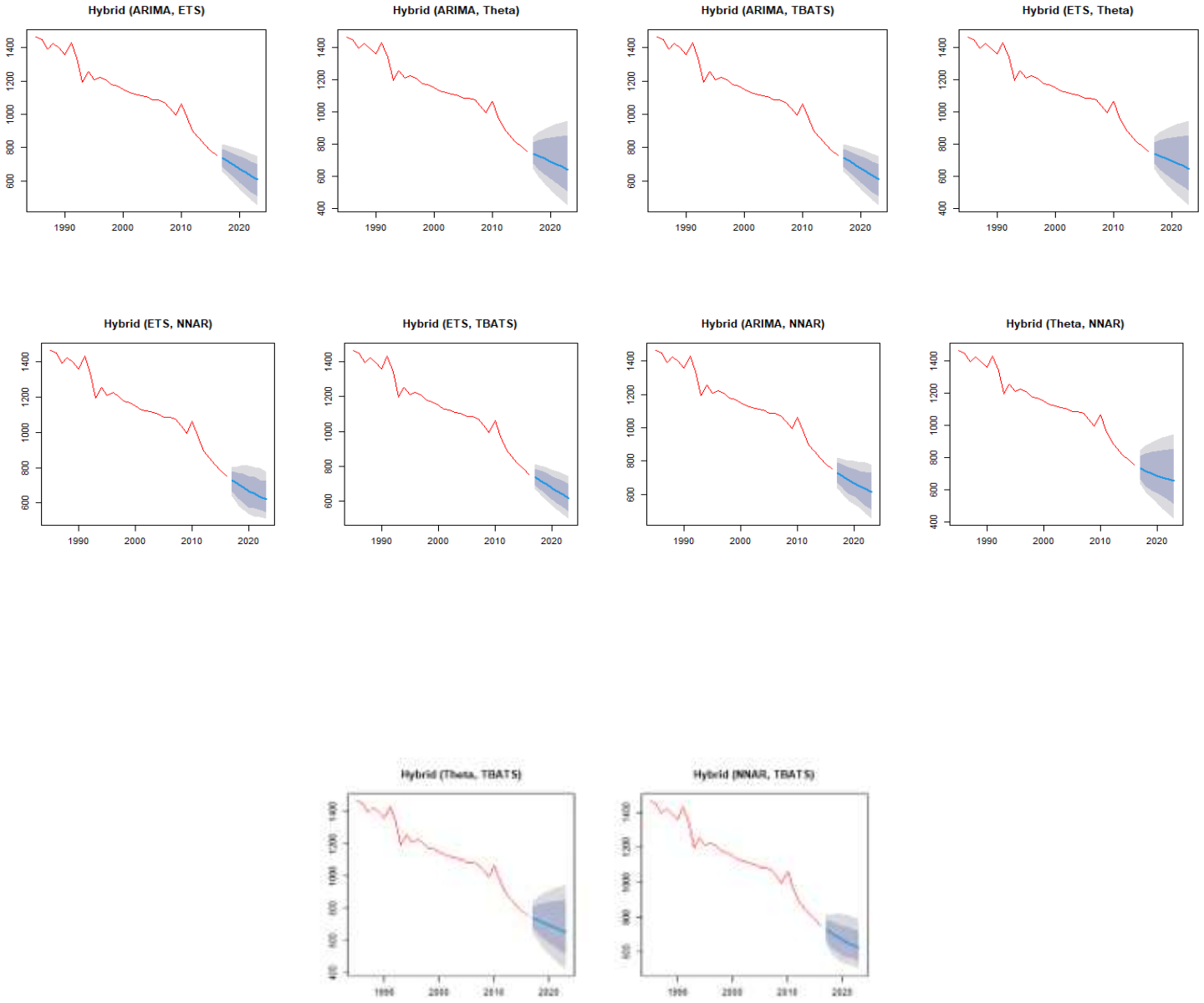


Fig. 6. Actual, fitted, and forecasted values of the maternal mortality ratio (per 100,000 live births) obtained from ten hybrid time-series models. The hybrid combinations include ARIMA–ETS, ARIMA–Theta, ARIMA–TBATS, ETS–Theta, ETS–NNAR, ETS–TBATS, ARIMA–NNAR, Theta–NNAR, Theta–TBATS, and NNAR–TBATS. In each panel, the red line represents the observed historical values, while the blue line indicates the forecasted values with corresponding prediction intervals. The x-axis represents the year, and the y-axis represents the maternal mortality ratio (per 100,000 live births).

Discussion

In this study, we explored advanced time series and hybrid modeling approaches to forecast maternal mortality trends in conflict-affected Somalia. A comprehensive set of single and hybrid time series models—including ARIMA, ETS, TBATS, Theta, ARFIMA, NNAR, and selected hybrid combinations—were systematically evaluated using out-of-sample validation. The analysis covered the period 1985–2023, with a training set (1985–2015) and a testing set (2016–2023). Forecasts were subsequently generated for the period 2024–2030, a critical horizon for monitoring progress toward Sustainable Development Goal (SDG) 3.1.

Stationarity testing using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and KPSS procedures confirmed the non-stationary nature of the maternal mortality ratio (MMR) series. First differencing successfully achieved stationarity, satisfying a key assumption for ARIMA-based modeling and ensuring reliable statistical inference. This preprocessing step was essential given Somalia's exposure to structural shocks and long-term volatility in maternal health indicators.

Among the single-model approaches, ARIMA demonstrated the strongest predictive performance across multiple accuracy measures, including MAPE, sMAPE, and Theil's U statistic. This finding suggests that linear dynamics remain dominant in the long-run evolution of maternal mortality in Somalia. In contrast, more complex seasonal structures such as TBATS exhibited comparatively higher forecast errors, indicating limited seasonal patterns in annual MMR data.

Hybrid models further enhanced predictive robustness by integrating complementary model strengths. In particular, combinations incorporating ARIMA and ETS structures demonstrated competitive accuracy, reinforcing the value of ensemble forecasting in volatile and data-constrained environments. By combining linear trend extraction with flexible error–trend modeling components, hybrid approaches improved stability while maintaining interpretability.

The generation of maternal mortality forecasts through 2030 provides actionable insights for health policymakers and development partners. Given Somalia's fragility, recurrent drought, displacement, and health system instability, forward-looking projections are essential for strategic planning and resource allocation. Forecasted trends can inform maternal health investments, emergency obstetric capacity expansion, and targeted interventions aimed at accelerating progress toward SDG 3.1.

Nevertheless, this study has important limitations. Forecasting inherently assumes continuity of historical patterns, yet Somalia remains vulnerable to environmental shocks, armed conflict, and humanitarian crises that may induce abrupt deviations from projected trajectories. Historical spikes in mortality during periods of severe instability illustrate the sensitivity of maternal health outcomes to exogenous shocks. Although point forecasts indicate gradual stabilization, confidence intervals remain wide due to structural volatility, reflecting inherent uncertainty.

Data quality also represents a significant constraint. The maternal mortality estimates used in this study are derived from internationally harmonized secondary sources that rely partly on statistical

modeling due to limited civil registration coverage. Periods of intense conflict and institutional collapse may have affected reporting accuracy, particularly in rural areas. Consequently, while the dataset provides the most consistent national series available, results should be interpreted with appropriate caution.

In conclusion, this study advances epidemiological forecasting in fragile contexts by systematically benchmarking single and hybrid time series models for maternal mortality in Somalia. The findings underscore the utility of structured out-of-sample validation and ensemble modeling for improving predictive reliability in unstable settings. The forecasts generated offer a quantitative foundation for evidence-based maternal health planning and progress monitoring toward SDG 3.1. Future research should incorporate multivariate frameworks that integrate socioeconomic, climatic, and health system indicators to enhance the responsiveness and precision of maternal mortality projections in Somalia.

Recommendations

Based on the findings of this study, it is recommended that policymakers prioritize sustained and evidence-based strategies to reduce maternal mortality in Somalia. Although the ARIMA model projections suggest a gradual decline in maternal mortality through 2030, the relatively wide prediction intervals indicate persistent uncertainty driven by structural fragility and exposure to recurrent shocks. Therefore, maternal health planning should incorporate both projected trends and uncertainty bounds rather than relying solely on point forecasts.

First, strengthening emergency obstetric and neonatal care (EmONC) capacity remains essential, particularly in rural and conflict-affected areas where delays in referral and service access continue to elevate maternal risk. Investment in skilled birth attendance, improved referral networks, and functional health facility infrastructure should be prioritized.

Second, resilience-based planning must be integrated into maternal health strategies. Given Somalia's vulnerability to drought, displacement, and political instability, maternal health systems should incorporate contingency mechanisms capable of responding to humanitarian crises. Early warning systems and coordinated humanitarian-health responses may help mitigate mortality spikes during periods of instability.

Third, targeted resource allocation should be guided by forecast-based planning frameworks. The projections generated in this study provide a quantitative foundation for medium-term budgeting, workforce planning, and supply chain management for maternal health services.

Fourth, investments in maternal education, reproductive health awareness, and access to antenatal care remain critical structural interventions that address both direct and indirect determinants of maternal mortality.

Finally, improving national civil registration and vital statistics systems is crucial for strengthening the reliability of future maternal mortality monitoring and forecasting efforts. Enhanced data systems will reduce uncertainty in long-term projections and improve policy responsiveness.

Future Directions

While this study provides a comprehensive univariate time series assessment of maternal mortality in Somalia, several avenues exist for further methodological advancement.

First, future research should incorporate multivariate time series models that integrate socioeconomic, climatic, and health system covariates—such as fertility rates, female education levels, conflict intensity indices, drought indicators, and health service coverage—to capture structural drivers of maternal mortality more explicitly.

Second, spatially disaggregated forecasting at regional or district levels would allow for more targeted intervention planning and improved identification of subnational disparities.

Third, ensemble forecasting frameworks that compare weighted and performance-based hybrid combinations could be explored to determine whether adaptive weighting schemes yield incremental improvements over equal-weight approaches.

Fourth, scenario-based forecasting models incorporating shock simulations (e.g., drought or conflict scenarios) could enhance preparedness planning in fragile settings.

Fifth, integrating machine learning techniques with traditional econometric models may further improve predictive performance, particularly if longer or higher-frequency datasets become available.

Overall, advancing forecasting methodologies while strengthening data systems will be essential for improving the precision, resilience, and policy relevance of maternal mortality projections in Somalia.

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