Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Forecasting Maternal Mortality in Sub-Saharan Africa to 2035: Evidence from the Global Burden of Disease 2023 Study

Abraham Keffale Mengistu

abreham_keffale@dmu.edu.et

Debre Markos University

Article

Keywords: maternal mortality, forecasting, machine learning, deep learning, Global Burden of Disease, Sub-Saharan Africa, time series

Posted Date: September 1st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10879103/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Forecasting Maternal Mortality in Sub-Saharan Africa to 2035: Evidence from the Global Burden of Disease 2023 Study

Abraham Keffale Mengistu[1*]

Author Affiliation

[1]Department of Health Informatics, College of Medicine and Health Sciences, Debre Markos University, Debre Markos, Ethiopia.

Corresponding author: Abraham Keffale Mengistu

Email: abreham_keffale@dmu.edu.et/keffaleabrahame2@gmail.com

Abstract

Maternal mortality continues to be an enduring measure of global health disparity, with Sub-Saharan Africa disproportionately contributing to the global burden of maternal mortality despite a reduction over the past three decades. Forecasts of future trends play a critical role in health policy decision-making. No prior study has used a unified statistical, machine learning, and deep learning comparative approach to model maternal mortality in Sub-Saharan Africa, based on the most recent Global Burden of Disease (GBD) estimates. In this study, GBD 2023 maternal mortality ratio (MMR) estimates for Sub-Saharan Africa (1980-2023, 44 yearly observations) were analyzed to compare eight models under three different methods: statistical methods (Holt damped-trend exponential smoothing, ARIMA, log-linear regression), machine learning (Random Forest, Gradient Boosting, XGBoost, Support Vector Regression), and deep learning (Long Short-Term Memory). Model selection was performed using a walk-forward, expanding-window out-of-sample validation for 10 years (2014-2023) based on RMSE, MAE, and MAPE criteria, and the best-selected model was re-estimated on the full series to forecast MMR through 2035. Between 1980 and 2023, MMR decreased from 674.5 to 396.2 deaths per 100,000 live births (EAPC 2013-2023: -2.17%/year). The lowest and nearly identical RMSEs and MAPEs were obtained for ARIMA and Holt's damped-trend exponential smoothing (RMSE = 2.74 and 2.75; MAPE = 0.55% and 0.52%), clearly outperforming all four ML models, especially LSTM (RMSE = 388.33, MAPE = 88.52%). The best-fitting ARIMA model predicts MMR to rise to 344.7 (95% confidence interval [CI]: 301.7 – 387.7) by 2030 and 313.0 (95% CI: 231.6 – 394.4) by 2035, or about five times higher than the SDG 3.1 target. The classical statistical approach was clearly better than the ML and DL approaches in the case of short annual time series, and Sub-Saharan Africa will miss the SDG 3.1 target by 2030 and beyond 2035.

Keywords: maternal mortality; forecasting; machine learning; deep learning; Global Burden of Disease; Sub-Saharan Africa; time series

Introduction

Maternal mortality continues to be among the most enduring indicators of the gap in global health [1-5]. While there has been steady decline during the past three decades, the latest Global Burden of Disease 2023 estimates indicate 240,000 maternal deaths globally in 2023, amounting to a global maternal mortality ratio of 190.5 per 100,000 livebirths, with countries with the greatest burden found in sub-Saharan Africa and South Asia, including the Democratic Republic of the Congo, Ethiopia, Nigeria, India, and Pakistan (GBD 2023 Maternal Mortality Collaborators, 2026) [6, 7]. The proportion of maternal deaths in the world from sub-Saharan Africa has been dominant over time, even though there have been considerable reductions in MMR since 1990 in the region [8-10]. Nevertheless, 104 out of 204 countries and territories in the world have yet to meet the SDG 3.1 target of below 70 maternal deaths per 100,000 livebirths (GBD 2023 Maternal Mortality Collaborators, 2026) [6].

In fact, there is a recent systematic analysis of the GBD 2023 data on maternal conditions in sub-Saharan Africa that showed significant subregional disparities in 2023, including high burden in Central Africa and rapid historical reduction in Eastern Africa, while there were disturbing increases in hypertension-related and HIV-related maternal mortality in Southern Africa from 1990 to 2023 (regional inequalities analysis, Archives of Public Health, 2026) [9]. These and similar studies utilizing the GBD data have made great advances in the understanding of the historical burden and the subregional variation of maternal mortality in the region; nevertheless, they are essentially descriptive and retrospective in nature and use GBD's CODEm modeling to estimate historical burden rather than make projections about the future [11, 12].

There is an additional and smaller set of literature that has used time series forecasting models to predict future trends in maternal mortality. In 2023, the joinpoint regression, ARIMA model, Holt method, and the machine learning-based Prophet prediction model were applied to the World Bank maternal mortality dataset for Africa from 1990 to 2015 to predict the MMR up to 2030 and conclude that none of the regions of Africa will be able to meet the SDG 3.1 target [13]. Although methodologically very important, this analysis has faced several limitations that are addressed in the current research paper. Firstly, the study used the World Bank estimates of MMR until 2015, which came before both the impact of the COVID-19 pandemic on the maternal healthcare system and the release of GBD 2023, which currently represents the most recent and complete source of maternal mortality estimates, including data up to 2023. Secondly, the comparison of machine learning methods was carried out only with the use of the Prophet algorithm, without comparison with other algorithms and neural networks commonly used in the field of health forecasting, such as Random Forest, Gradient Boosting, XGBoost, and LSTM networks.

This gap is particularly striking, considering how recent comparative forecasting models based on statistical machine learning deep learning techniques, when assessed using the same walk-forward validation technique, have been used effectively in forecasting other maternal and child health metrics in the region for instance, in forecasting neonatal mortality in Ethiopia, which shows that model performance rankings for this type of analysis cannot be assumed a priori but need to be empirically determined on a case-by-case basis [14-18]. To the best of our knowledge, there has been no study published that employs this kind of forecasting approach to sub-Saharan maternal mortality, in particular based on GBD 2023 data.

This paper fills the research gap. The GBD 2023 estimates of the maternal mortality ratio in sub-Saharan Africa for years from 1980 to 2023 were used to apply and thoroughly compare eight forecasting models belonging to three methodological groups: statistical (Holt damped-trend exponential smoothing, ARIMA, log-linear regression), machine learning (Random Forest, Gradient Boosting, XGBoost, Support Vector Regression), and deep learning (Long Short-Term Memory). By choosing the most effective model through walk-forward out-of-sample validation and forecasting maternal mortality in sub-Saharan Africa until 2035 based on the chosen model, this paper aims to (1) make the most recent projection of the sub-Saharan African maternal mortality based on the most recent GBD data, (2) determine, through thorough out-of-sample comparison, which forecasting method is the empirically best one for short annual regional health indicators time series, and (3) estimate the expected gap between the projected and the SDG 3.1 target in 2030.

Methodology

Study Design and Data Source

This research was based on the secondary time series analysis of MMR in sub-Saharan Africa, obtained from the Global Burden of Disease (GBD) 2023 Study that was undertaken by the Institute for Health Metrics and Evaluation (IHME) at the University of Washington. The GBD 2023 is the latest and most comprehensive systematic effort made to measure the impact of diseases, injuries, and risk factors on health in 204 countries and territories, which included the maternal mortality statistics obtained through vital registration, verbal autopsy, household surveys, censuses, surveillance systems, and maternal mortality audit data (GBD 2023 Maternal Mortality Collaborators, 2026).

Data were obtained from the GBD Results Tool (https://vizhub.healthdata.org/gbd-results/) using the following parameters: location: Sub-Saharan Africa (regional aggregate); cause: maternal disorders; measure: maternal mortality ratio; sex: female; age: all ages; metric: rate; years: 1980-2023. The result is 44 observations per year of age-standardized MMR (deaths per 100,000 live births) with GBD

Descriptive and Trend Analysis

Historical data from the MMR series were first analyzed descriptively through the computation of the percent change between 1980 and 2023, as well as the estimated annual percent change (EAPC) for the last decade (2013 to 2023) based on an ordinary least squares regression of the natural log of MMR against year.

Walk-Forward Out-of-Sample Validation Framework

In order to make sure that the comparison between the models would reflect actual forecasting performance instead of the model's ability to fit the in-sample data, an expanding-window walk-forward validation was performed for each of the models under consideration [19-24]. The last ten years of the dataset (2014 – 2023) were used as the testing period for the models; at each step, a certain model was trained on all data available up to that moment and made a forecast for one year ahead, after which the sample window was expanded by one year, and the procedure was repeated until the end of the dataset.

Candidate Forecasting Models

Eight forecasting models, spanning three methodological families, were evaluated:

Statistical models: First, Holt's exponential smoothing model using a damped trend, which is widely used when there is a trend present that could potentially dampen [25, 26]. Second, an

ARIMA (1,1,1) model, which is chosen because of its parsimony and relevance to a single annual nonseasonal series with one order of differencing [27]. Third, a log-linear regression using MMR with the calendar year as the predictor, similar to EAPC-based trend extrapolation on the log scale, which is well-supported by GBD literature [28].

Machine learning models: Because standard machine learning regressors are not designed to consider the time-series nature of the data, the time series was reformulated as a supervised learning task by employing a feature lag technique: for each model to be considered, the past three annual MMR values served as predictors for the next annual value [29-31]. In total, four machine learning regressors were considered: Random Forest, Gradient Boosting, Extreme Gradient Boosting (XGBoost), and Support Vector Regression with a radial basis function kernel. All continuous variables were scaled to have zero mean and unit variance before training the models; scaling parameters were recomputed in each growing training window to avoid lookahead bias.

Deep learning model: A Long Short-Term Memory (LSTM) Recurrent Neural Network was constructed with the use of the same three-lag input configuration with one LSTM layer, four units, L2 kernel regularization, dropout layer, and dense output layer, trained for 100 epochs per walk-forward iteration [32]. The model design and hyperparameters were purposefully kept simple and highly regularized in view of the relatively small sample size.

Model Evaluation and Selection

Performance of the models was evaluated using three error measures computed from ten out-of-sample forecasts: root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The model that scored the minimum RMSE in the out-of-sample data was selected as the forecasting model.

Final Forecast Generation

After the selection of the best model, it was then fitted using the entire historical dataset (1980–2023) and used to produce forecasts and 95% prediction intervals for the years 2024 to 2035. In cases where the model fitted was based on the likelihood function (like the ARIMA model), the prediction intervals were calculated analytically using the fitted model. For other models where prediction intervals cannot be calculated analytically, prediction intervals were estimated using the forecast horizon multiplied by the residual standard error.

Software

All computations were performed using Python, where pandas and NumPy were used for data handling, statsmodels for statistical time series analysis, scikit-learn for building machine learning models and preprocessing, XGBoost for gradient boosting, and TensorFlow/Keras for deep learning. A fixed random seed was utilized across all random procedures, namely model initialization and weight initialization.

Ethical Considerations

The present study utilized only publicly available, aggregated, anonymized estimates from the GBD 2023 Study; there was no utilization of individual or identifiable data, thus no ethical clearance was necessary for the secondary analysis of aggregate public health estimates.

Results

Historical Trend

This analytic time series included 44 annual values of maternal mortality ratio (MMR) in Sub-Saharan Africa, from 1980 through 2023, sourced from the GBD 2023 Study. The MMR value has fallen from 674.5 per 100,000 live births in 1980 to 396.2 in 2023, marking an overall decrease of 41.3% (Figure 1). It is not true that the reduction was stable throughout this period; rather, the MMR remained stable and varied within a narrow band of 670-680 until the mid-1990s, after which the MMR began to steadily decline. During the latest decade (2013-2023), the EAPC value was −2.17% per year, representing a continuing albeit moderate improvement. Even though progress had been made, the estimate for 2023 was more than five times the SDG 3.1 target of 70 per 100,000 livebirths (Figure 1).

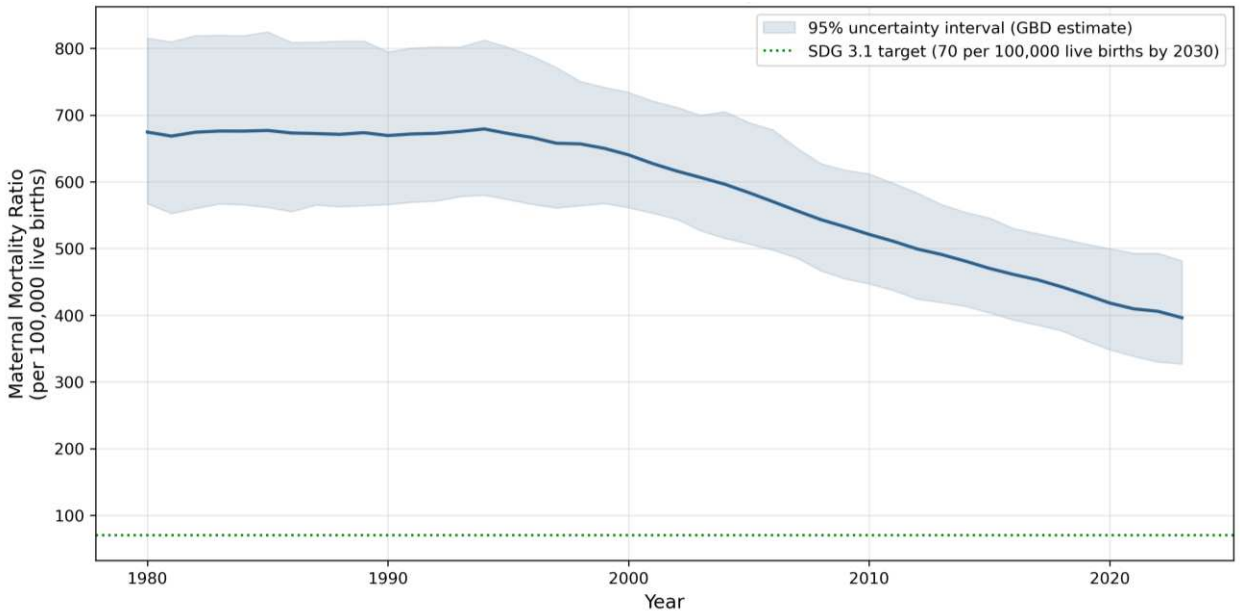


Figure 1:Sub-Saharan Africa Maternal Mortality Ratio, 1980–2023 (GBD 2023 Study). The shaded band represents the 95% uncertainty interval of the GBD estimate. The dotted line marks the SDG 3.1 target (70 per 100,000 livebirths).

Walk-Forward Model Comparison

A total of eight forecasting models, from the statistical, machine learning, and deep learning categories, were compared through the use of walk-forward validation in a ten-year out-of-sample period from 2014 to 2023, with each model being trained on an increasing amount of historical data and evaluated by one step forward out-of-sample forecast (Table 1). There was variation in performance by more than two orders of magnitude among the eight forecasting models. The two forecasting models that used time series structure formally, namely ARIMA (1,1,1) and Holt's damped trend exponential smoothing models, attained the minimum and virtually similar out-of-sample error (RMSE = 2.74 and 2.75, respectively; MAPE = 0.55% and 0.52%, respectively), with ARIMA being slightly better performing by RMSE and yet in practical terms, the two models performed equally well (Table 1, Figure 2). Four machine learning models generated moderately good errors, about an order of magnitude higher than the two better statistical models: Gradient Boosting (RMSE = 10.15), XGBoost (RMSE = 11.18), Random Forest (RMSE = 15.34), and Support Vector Regression (RMSE = 16.61). Though the log-linear regression was quite simple in terms of methodology, it proved to be much less effective compared to either the more advanced statistical models or the machine learning models (RMSE = 46.57, MAPE = 10.66%), due to its inability to account for the deceleration of the trend present in the historical data (Figure 1). The LSTM model developed through the use of deep learning algorithms showed by far the worst results among all the models considered (RMSE = 388.33, MAPE = 88.52%), an error similar to the value of the dependent variable itself, meaning that it was incapable of learning any meaningful pattern in the data (Table 1, Figure 2).

Table 1:Walk-forward out-of-sample performance of eight forecasting models, 2014–2023 test window.

Model	RMSE	MAE	MAPE (%)
ARIMA	2.74	2.31	0.55
Holt-Winters Damped Exp. Smoothing	2.75	2.21	0.52
Gradient Boosting	10.15	9.88	2.26
XGBoost	11.18	10.94	2.50
Random Forest	15.34	15.20	3.49
SVR	16.61	15.88	3.66
Log-Linear Regression	46.57	46.48	10.66
LSTM	388.33	387.09	88.52

Note. RMSE = root mean squared error; MAE = mean absolute error; MAPE = mean absolute percentage error. All values in deaths per 100,000 live births, except MAPE. Models are ordered by ascending RMSE (best to worst).

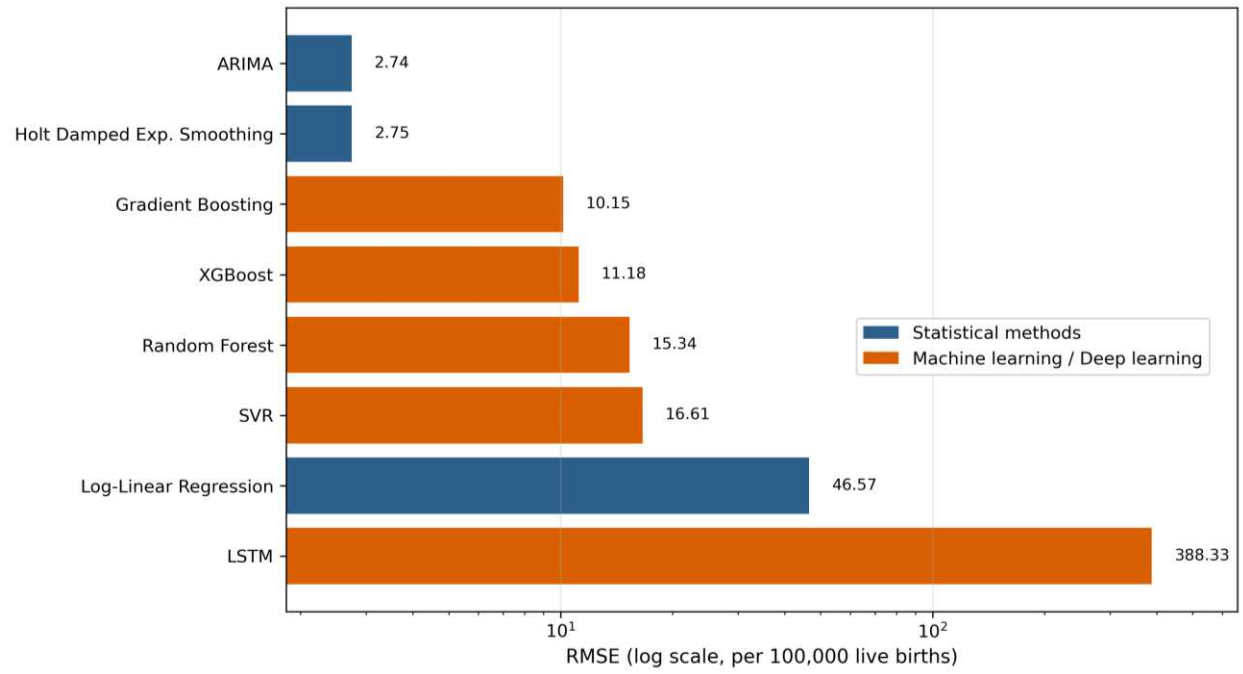


Figure 2:Out-of-sample forecast accuracy comparison (RMSE, log scale), walk-forward validation, 2014–2023 test window.

Graphical comparison of the walk forward one-step ahead forecast vis-à-vis actual data (Fig 3; LSTM omitted from the figure due to its distortion of the graphical scale) validates the ranking based on quantification presented in Table 1: both the ARIMA and Holt models follow the actual GBD curve very closely throughout the test period, even during the period of accelerated decline starting in 2018, while the machine learning models become increasingly inaccurate in their

prediction of the declining rate as the test period advances, and the log linear regression model deviates quite dramatically from the actual trend line at the end of the test period.

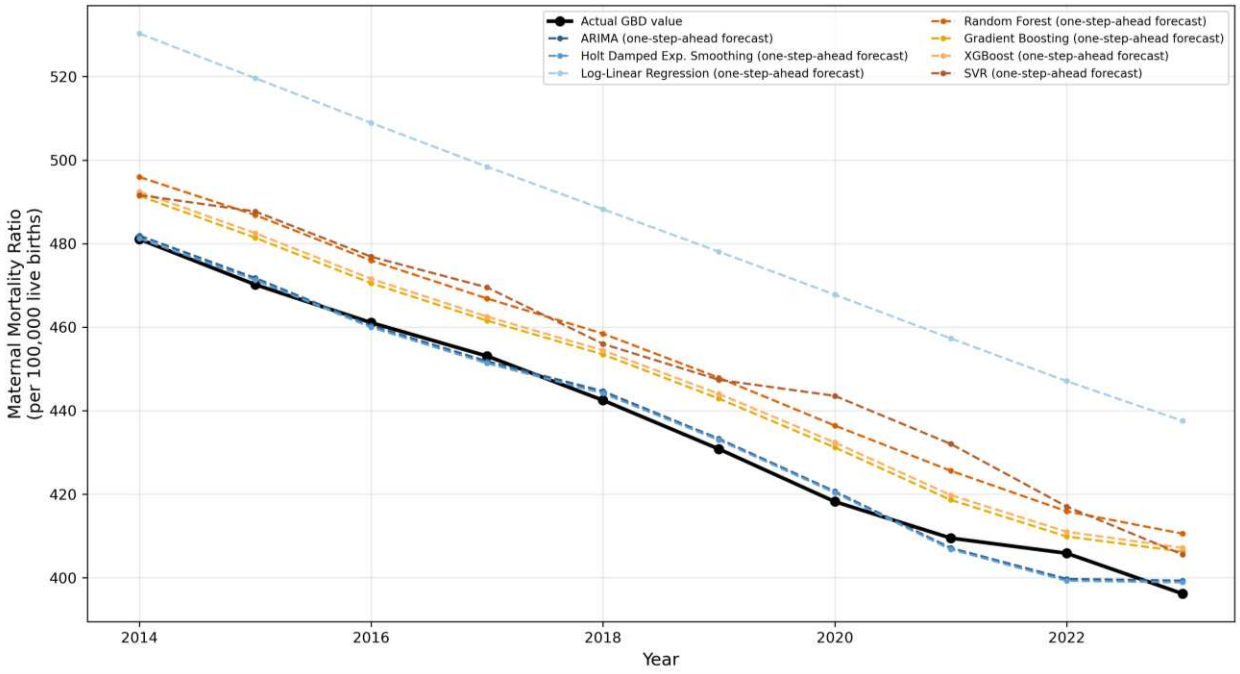


Figure 3:Walk-forward one-step-ahead forecasts versus actual values, all models except LSTM (excluded owing to scale; see Table 1 for its metrics).

Final Forecast, 2024–2035

After selecting the best model, the ARIMA (1,1,1) was re-estimated using the whole 1980-2023 data and applied for forecasting up to 2035 (see Table 2, Figure 4). MMR is predicted to decrease further to 344.7 (95% prediction interval: 301.7-387.7) by 2030 and 313.0 (95% prediction interval: 231.6-394.4) by 2035. By 2030, the projected Sub-Saharan African MMR level would still be about 4.9 times greater than the SDG 3.1 goal of 70 deaths per 100,000 live births, which means that continuation of the current trend is very unlikely to be consistent with meeting this goal (see Figure 4). As seen from Table 2 and Figure 4, the width of the prediction interval increases noticeably with the forecast horizon due to compounding uncertainties associated with projecting 44 yearly data up to 12 years ahead.

Table 2:Final ARIMA (1,1,1) forecast of Sub-Saharan African maternal mortality ratio, 2024–2035.

Year	Forecast MMR	95% CI Lower	95% CI Upper
2024	388.3	381.4	395.1
2025	380.6	368.6	392.5
2026	373.0	355.6	390.4
2027	365.7	342.5	388.9
2028	358.5	329.0	388.0
2029	351.5	315.5	387.6
2030	344.7	301.7	387.7
2031	338.1	287.9	388.3
2032	331.6	273.9	389.2
2033	325.2	259.9	390.6
2034	319.0	245.8	392.3
2035	313.0	231.6	394.4

Note. MMR = maternal mortality ratio, deaths per 100,000 live births. CI = confidence interval (95% prediction interval from the fitted ARIMA (1,1,1) model).

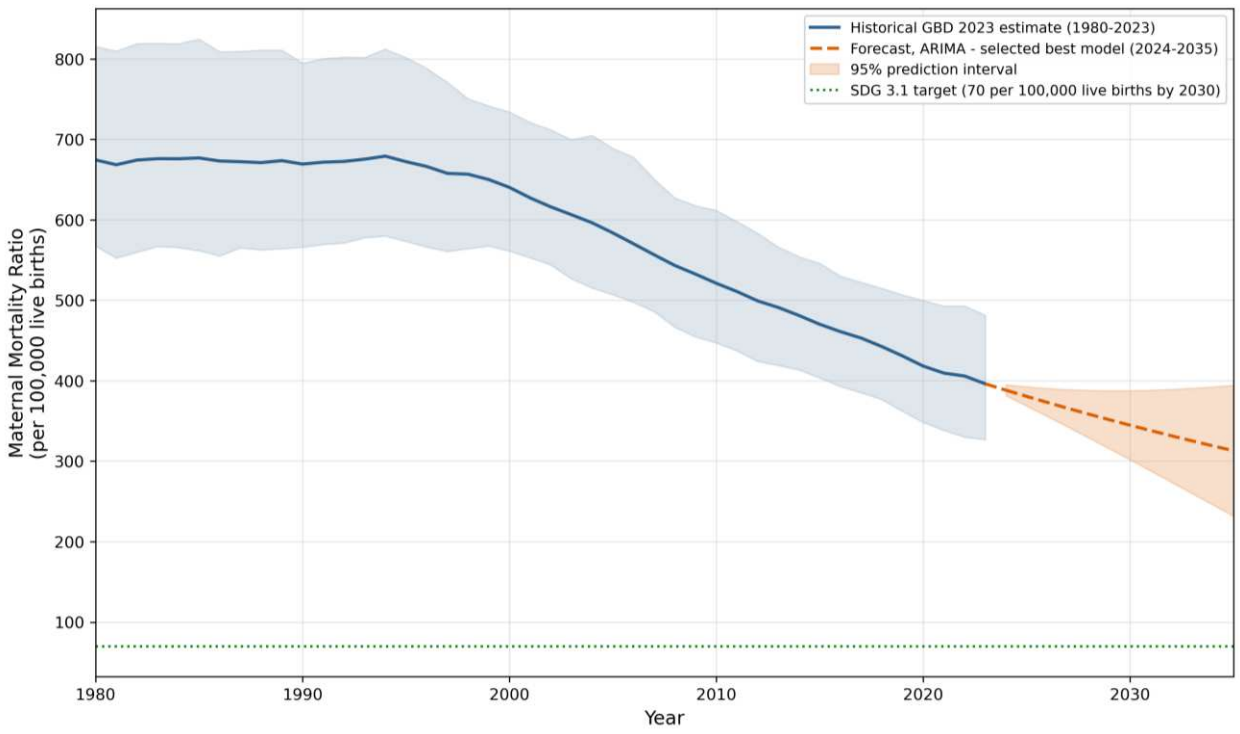


Figure 4:Sub-Saharan Africa maternal mortality ratio forecast to 2035, selected model: ARIMA (GBD 2023 data). The shaded band represents the 95% prediction interval; the dotted line marks the SDG 3.1 target (70 per 100,000 livebirths).

Discussion

This research employed and compared eight statistical, machine-learning, and deep learning methods to make predictions about maternal mortality in Sub-Saharan Africa based on the latest available estimates from Global Burden of Disease studies, choosing the best-performing approach via walk-forward out-of-sample validation instead of in-sample prediction. The following three observations can be made regarding this comparison: the degree of difference in the performance of statistical and machine-learning methods, the meaning of the prediction for the future development of the region according to SDG 3.1, and the lessons learned from it.

Statistical Dominance over Machine Learning and Deep Learning

That classical statistical approaches, ARIMA and Holt's damped-trend exponential smoothing, outperformed all machine learning and deep learning models tested (see Table 1, Figure 2) is one of the key findings of this study, and not just a secondary observation. The size of this difference, in the form of an order of magnitude improvement in RMSE achieved by the best statistical approaches relative to the best machine learning approach, and almost two orders of magnitude achieved by the former relative to the latter, is much greater than is usually assumed when applying machine learning/deep learning to health forecasting, where such approaches have become the default choice. Indeed, this finding is consistent with and provides region- and indicator-specific support for a general phenomenon observed in the forecasting literature [33] that for short, low-dimensional annual time series, classical statistical models which take account of trend and autocorrelation structure typically perform at least as well as more flexible data-hungry methods, the former of which have the unique ability of being able to learn complicated non-linear structures from data, but require more data to do so (Figure 4). Indeed, the catastrophic failure of the LSTM model in this case can be seen not as an indication that deep learning models are flawed per se, but rather as a direct empirical example of such a limitation, because the model was trained using no more than 34 to 43 observations, which constitutes only a small part of the amount of data usually thought to be sufficient for reliable generalization in an RNN structure [34].

Substantive Implications for the SDG 3.1 Trajectory

If this selected model's prediction (Table 2, Figure 3) is accurate and MMR reaches 344.7 for 2030 and 313.0 for 2035, then Sub-Saharan Africa will be left with about five times the SDG 3.1 target goal even five years past the 2030 deadline date. This outcome is congruent with the conclusions of previous forecasting research based on older data sets and comparator models, which concluded

that none of the African regions were on course to meet the SDG 3.1 target by 2030 [18]. This current research suggests that this remains the case even after considering the most up-to-date information and applying a far more robust process for model selection.

Methodological Implications

In addition to this forecast, there is a more general lesson about methodology related to the forecast of maternal and child health indicators that is provided by this study: the choice of the model family should be empirical, based on rigorous out-of-sample validation specific to the indicator in question rather than being derived from previous use of this type of modeling in other areas or just the reputation of the approach in general. It is important to note that walk-forward comparative methodology used in other regions to forecast other indicators of maternal and child health has identified different model families, with a deep learning model having the lowest error rate out of sample. Combined with the results of the present research, this shows that no model family can be assumed a priori superior in all situations in terms of health forecasts; the methodology is more important in this case.

Strengths and Limitations

However, this paper possesses some significant advantages. First, the paper offers, to our best knowledge, the first comparative forecasting study based on a unified framework that includes statistics, machine learning, and deep learning for maternal mortality in Sub-Saharan Africa using the latest (GBD 2023) data, compared to the former forecasts which relied only on older pre-pandemic World Bank-sourced data. Furthermore, the model selection process was carried out through strict walk-forward out-of-sample validation and not in-sample validation, which is much rarer than it should be in applied studies and, in this particular case, was absolutely crucial because

an in-sample comparison only would greatly underestimate the differences between the models (Table 1, Figure 4). The comparison was performed on eight different models, representing three different methodological groups, unlike previous regional forecast comparisons that included only one machine learning model, while the inferiority of the deep learning model was noted explicitly rather than concealed as in previous papers.

Some issues should also be noted. First and foremost, the dataset only consisted of 44 annual observations, which, although sufficient for classical statistical time series techniques, represents a crucial limitation of the performance of the deep learning algorithm and should reduce the degree of confidence in any health forecast using a similar number of annual observations generated by a deep learning algorithm elsewhere. Second, the study was conducted at the overall Sub-Saharan African region level and does not consider the considerable differences at the subregional level revealed in the recent GBD-based burden studies; the forecast made in this study should not be viewed as relevant to each country or subregion in Sub-Saharan Africa that is already on a different path. Third, the forecasting method used in this study extends the statistical pattern of the series into the future but does not imply any causal or intervention-related mechanisms; it is the statistical extension of the trend that has been observed before and not the simulation of the future impact of any particular interventions in the health systems. Fourth, the GBD estimates, even for the historical period, are themselves modeled outputs from the Cause of Death Ensemble model and thus have their own associated uncertainties and possible estimation errors; the prediction intervals we report (Tables 2 & 3, Figures 3 & 4) are uncertainty intervals from the forecasting model based on the given GBD estimates, and do not include the full uncertainty associated with the entire GBD estimation process. Lastly, the increased width of the prediction intervals for forecasted values further out into the future (Figures 3 & 4, Tables 2 & 3) suggests that the forecast for 2035, in

particular, has significant uncertainty and should be viewed as indicating the approximate order of magnitude and direction of the trend.

Conclusion

The results from this study show that when making predictions about maternal mortality in Sub-Saharan Africa based on GBD 2023 data, classical statistical time series models significantly outperform their machine learning and deep learning counterparts through walk-forward out-of-sample validation, with ARIMA and damped trend Holt's exponential smoothing giving almost identical and significantly better results compared to four machine learning models and one deep learning model (Table 1, Figure 2). The use of the chosen ARIMA model on the full 1980-2023 dataset suggests that maternal mortality in Sub-Saharan Africa will continue to fall and reach around 345 per 100,000 livebirths in 2030 and 313 in 2035 (Table 2, Figure 3), which is still about five times higher than the SDG 3.1 target even past the originally set year 2030 goal if trends persist. This highlights the fact that, apart from showing that the gap between the trajectory of the region's maternal mortality rates and its Sustainable Development Goal remains wide, these results reveal the more general methodology-related lesson regarding the empirical nature of forecasting model choice in the applied health literature.

Recommendations

From the above findings, the following suggestions have been made. First, in light of the size of the projected gap in relation to the SDG 3.1 target (Table 2, Figure 3), the Sub-Saharan African healthcare systems, together with their international partners, need to consider the course of maternal mortality in the region as being well off track and warranting urgent action, considering that the projected shortfall persists up until 2035 compared to the initial 2030 target year. Second,

given the supremacy of the classical statistical methods when it comes to forecasting maternal mortality (Table 1, Figure 2), any future efforts to project the same using the type of short-term annual time series used in this study should place emphasis on statistical time series methods and leave machine/deep learning approaches for situations where large training datasets are available. Thirdly, future research should apply this comparative framework to sub-regional and national levels within Sub-Saharan Africa, where past observations on differences in trends and burden composition have demonstrated that there is a possibility that the forecasts and even the model families which yield the most accurate predictions will be different from those seen at the overall regional level. Lastly, considering the different ranking of models across this study compared to maternal and child health forecasts in other Sub-Saharan countries, future forecasts should view model family choice as an empirical exercise that should be done based on the rigorous walk-forward validation framework adopted in this study.

Abbreviations and Acronyms

ARIMA: Autoregressive Integrated Moving Average

CI: Confidence Interval

EAPC: Estimated Annual Percentage Change

GBD: Global Burden of Disease

IHME: Institute for Health Metrics and Evaluation

LSTM: Long Short-Term Memory

MAE: Mean Absolute Error

MAPE: Mean Absolute Percentage Error

MMR: Maternal Mortality Ratio

RMSE: Root Mean Squared Error

SDG: Sustainable Development Goal

SVR: Support Vector Regression

XGBoost: Extreme Gradient Boosting

Declarations

Data Availability

The dataset analyzed in this study was extracted from the Global Burden of Disease (GBD) 2023 Study, publicly accessible through the GBD Results Tool (https://vizhub.healthdata.org/gbd-results/), maintained by the Institute for Health Metrics and Evaluation (IHME) at the University of Washington. Access requires free registration, and any researcher may retrieve the specific estimates used in this study by querying the tool for maternal mortality ratio, Sub-Saharan Africa, maternal disorders, female, all ages, rate, 1980–2023. The author did not receive any special or privileged access to this data. The extracted dataset and analysis code used to produce the results presented in this study are available from the corresponding author upon reasonable request.

Ethics Approval and Consent to Participate

This study involved secondary analysis of publicly available, aggregate, de-identified estimates from the GBD 2023 Study. No individual-level or identifiable data were used at any stage of this analysis, and no human participants were directly involved in this research. As such, this study did not require ethical approval or informed consent, consistent with the aggregate, non-identifiable nature of the GBD estimates used.

Competing Interests

The author declares no competing interests.

Clinical Trial Number

Not applicable.

Consent for Publication

Not applicable. No identifying details, images, or personal information of any individual are included in this manuscript, as this study relied exclusively on publicly available, aggregate population-level estimates.

Funding

No funding was received for this research.

Author Contributions Statement

A.K.M. solely conceptualized the study, designed the methodology, extracted and preprocessed the data, performed the analysis, interpreted the results, and drafted and approved the final version of the manuscript for submission.

Acknowledgments

The author would like to thank the Institute for Health Metrics and Evaluation (IHME) and the Global Burden of Disease Collaborative Network for producing and maintaining the GBD 2023 Study estimates used in this analysis. The views expressed in this paper are those of the author and do not necessarily reflect the views of IHME or the GBD Collaborative Network.

References

[1] "Trends in maternal mortality estimates 2000 to 2023."

[2] S. I. Anumudu, C. C. Uhegwu, and C. K. Anumudu, "A scoping review of maternal mortality, its health determinants, and factors that influence care utilization in women of

child-bearing years in Nigeria," *Global Health Journal*, vol. 9, no. 3, pp. 185–199, 2025, doi: https://doi.org/10.1016/j.glohj.2025.10.004.

[3] B. Sharma, R. Smith, and C. E Pennell, "Global Trends in Maternal Mortality and Efforts to Improve Maternal Outcomes Through Sociomedical Interventions," May 01, 2026, *Springer Nature*. doi: 10.1007/s43032-026-02086-8.

[4] M. S. Ekpenyong, "Breaking the silence: barriers to maternal healthcare utilisation among women in South-South Nigeria," *Front. Glob. Womens Health*, vol. 6, 2025, doi: 10.3389/fgwh.2025.1623067.

[5] M. L. Ajegbile, "Closing the gap in maternal health access and quality through targeted investments in low-resource settings," *J. Glob. Health Rep.*, vol. 7, 2023, doi: 10.29392/001c.88917.

[6] "Global, Regional, and National Levels and Trends in Maternal Mortality, Progress Towards the Sustainable Development Goals, and Mortality From COVID-19 Infection in Pregnant Women, 1990-2023: A Systematic Analysis for the Global Burden of Disease Study 2023." [Online]. Available: https://ssrn.com/abstract=6234879

[7] J. Yang, "Trends and inequities in the global burden of maternal mortality, 1990–2023: Findings from the global burden of disease study 2023," *International Journal of Gynecology & Obstetrics*, p. n/a-n/a, Jun. 2026, doi: 10.1002/ijgo.71143.

[8] L. Onambele *et al.*, *Trends, Projections, and Regional Disparities of Maternal Mortality in Africa (1990-2030): An ARIMA Forecasting Approach*. 2023. doi: 10.20944/preprints202306.2080.v1.

[9] Y. H. Abdi *et al.*, "Regional inequalities and temporal trends in maternal disorders across sub-Saharan Africa, 1990–2023: a systematic analysis of the global burden of disease 2023 data," *Archives of Public Health*, Jun. 2026, doi: 10.1186/s13690-026-01979-z.

[10] M. M. Fasina, G. P. Kovane, I. L. Elisha, and A. Phuti, "Fifty years of maternal mortality research in sub-Saharan Africa: a bibliometric analysis of trends, gaps, and opportunities for health equity," Jul. 08, 2026, *Frontiers Media SA*. doi: 10.3389/fgwh.2026.1717410.

[11] J. Wei, Y. Yi, X. Li, Y. Xu, L. S. Fan, and H. Huang, "Global, regional, and national burden of maternal hemorrhage: a systematic analysis from the global burden of disease 2021 and projections to 2030," *BMC Pregnancy Childbirth*, vol. 25, no. 1, Dec. 2025, doi: 10.1186/s12884-025-08353-x.

[12] J. Zhu *et al.*, "Global burden of maternal disorders, 1990–2021: insights from the Global Burden of Disease Study 2021 and challenges for achieving 2030 Sustainable Development Goals," *J. Glob. Health*, vol. 16, 2026, doi: 10.7189/jogh.16.04147.

[13] L. Onambele *et al.*, "Trends, Projections, and Regional Disparities of Maternal Mortality in Africa (1990–2030): An ARIMA Forecasting Approach," *Epidemiologia*, vol. 4, pp. 322–351, Aug. 2023, doi: 10.3390/epidemiologia4030032.

[14] L. Manai, W. Mchara, M. A. Khalfa, M. Raissi, and W. Dimassi, "WOA-FCM-CNN-WNN-informer: An advanced hybrid deep learning model for ultra-accurate PV power forecasting in electric mobility," *Intelligent Systems with Applications*, vol. 29, p. 200630, 2026, doi: https://doi.org/10.1016/j.iswa.2026.200630.

[15] S. Makridakis, E. Spiliotis, V. Assimakopoulos, A.-A. Semenoglou, G. Mulder, and K. Nikolopoulos, "Statistical, machine learning and deep learning forecasting methods: Comparisons and ways forward," *Journal of the Operational Research Society*, vol. 74, pp. 1–20, Sep. 2022, doi: 10.1080/01605682.2022.2118629.

[16] K. Al-Saeedi, D. Zhou, A. Fish, K. Tsakiri, and A. Marsellos, "A Methodological Comparison of Forecasting Models Using KZ Decomposition and Walk-Forward Validation," *Mathematics*, vol. 13, no. 21, Nov. 2025, doi: 10.3390/math13213410.

[17] T. Kubahoniyesu, I. Kayijuka, and F. Niragire, "Comparing the performance of statistical and machine learning survival models in predicting timing and determinants of postnatal care in Rwanda," *BMC Pregnancy Childbirth*, May 2026, doi: 10.1186/s12884-026-09313-9.

[18] L. Onambele *et al.*, "Trends, Projections, and Regional Disparities of Maternal Mortality in Africa (1990–2030): An ARIMA Forecasting Approach," *Epidemiologia*, vol. 4, pp. 322–351, Aug. 2023, doi: 10.3390/epidemiologia4030032.

[19] J. Kim, H. Kim, H. G. Kim, D. Lee, and S. Yoon, "A comprehensive survey of deep learning for time series forecasting: architectural diversity and open challenges," *Artif. Intell. Rev.*, vol. 58, no. 7, Jul. 2025, doi: 10.1007/s10462-025-11223-9.

[20] H. Hewamalage, K. Ackermann, and C. Bergmeir, "Forecast evaluation for data scientists: common pitfalls and best practices," *Data Min. Knowl. Discov.*, vol. 37, no. 2, pp. 788–832, Mar. 2023, doi: 10.1007/s10618-022-00894-5.

[21] A. Micallef, M. Apap, J. Licari, C. Spiteri Staines, and Z. Xiao, "A comparative framework for evaluating machine learning models in forecasting electricity demand for port microgrids," *Energy and AI*, vol. 20, p. 100494, 2025, doi: https://doi.org/10.1016/j.egyai.2025.100494.

[22] S. Karakulath, "Comparing Time Series Forecasting Models and Validation Methods for Non-Transparent Markets (Wood Waste)," 2024. doi: 10.13140/RG.2.2.20867.11047.

[23] V. Cerqueira, L. Torgo, and I. Mozetic, "Evaluating time series forecasting models: An empirical study on performance estimation methods," May 2019, doi: 10.1007/s10994-020-05910-7.

[24] P. Kumar, P. Priyanka, D. Jaya, U. Kala, and V. Dutt, "Analyzing the Performance of Univariate and Multivariate Machine Learning Models in Soil Movement Prediction: A Comparative Study," *IEEE Access*, vol. 11, pp. 62368–62381, Jun. 2023, doi: 10.1109/ACCESS.2023.3287851.

[25] G. Sbrana and A. Silvestrini, “Forecasting with the damped trend model using the structural approach,” *Int. J. Prod. Econ.*, vol. 226, p. 107654, 2020, doi: https://doi.org/10.1016/j.ijpe.2020.107654.

[26] E. McKenzie and E. Gardner, “Damped trend exponential smoothing: A modelling viewpoint,” *Int. J. Forecast.*, vol. 26, pp. 661–665, Oct. 2010, doi: 10.1016/j.ijforecast.2009.07.001.

[27] M. Melina *et al.*, “COMPARATIVE ANALYSIS OF TIME SERIES FORECASTING MODELS USING ARIMA AND NEURAL NETWORK AUTOREGRESSION METHODS,” *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, vol. 18, pp. 2563–2576, Oct. 2024, doi: 10.30598/barekengvol18iss4pp2563-2576.

[28] C. Kim, S.-H. Nam, and I. Joe, “A Log Regression Seasonality Based Approach for Time Series Decomposition Prediction in System Resources,” 2015, pp. 843–849. doi: 10.1007/978-981-10-0281-6_118.

[29] T. Hall and K. Rasheed, “A Survey of Machine Learning Methods for Time Series Prediction,” Jun. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/app15115957.

[30] A. Pagliaro and A. Anzalone, *Time Series Analysis in Machine Learning*. 2026. doi: 10.48550/arXiv.2606.11746.

[31] L. Aversano, M. Iammarino, A. Madau, and F. Pecorelli, “Time series forecasting for bug resolution using machine learning and deep learning models,” *Front. Big Data*, vol. 8, 2025, doi: 10.3389/fdata.2025.1745751.

[32] M. Krichen and A. Mihoub, “Long Short-Term Memory Networks: A Comprehensive Survey,” Sep. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/ai6090215.

[33] F. Dama and C. Sinoquet, *Analysis and modeling to forecast in time series: a systematic review*. 2021. doi: 10.48550/arXiv.2104.00164.

[34] I. D. Mienye, T. G. Swart, and G. Obaido, “Recurrent Neural Networks: A Comprehensive Review of Architectures, Variants, and Applications,” Sep. 01, 2024, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/info15090517.