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# Modelling and forecasting Masvingo Province maternal mortality using time series models

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**Abstract** In light of the Zimbabwean government's efforts, particularly through the Ministry of Health and Child Care (MoHCC), to reduce maternal mortality rates and achieve the aim of Sustainable Development Goal (SDG) number three, target one (SDG 3.1), which aims to reduce the global maternal mortality rate to fewer than 70 deaths per 100,000 live births, maternal mortality rates in Zimbabwe continue to rise. Time series techniques were used to model and predict quarterly maternal mortality statistics for Masvingo Province from January 2014 to December 2021. The time plot analysis revealed significant fluctuations in mortality, with the highest rates of maternal deaths recorded in 2018. The application of the Box-Jenkins methodology identified the ARIMA(2, 1, 1) model as the most suitable for modeling and forecasting quarterly maternal deaths among the fitted models. The suitability of the model was validated by the Akaike Information Criterion (AIC), and its forecast accuracy was confirmed by the Mean Absolute Error (MAE) and the root mean square error (RMSE). Consequently, it was used to project future maternal deaths. The projected values indicate a slight increase in quarterly mortality rates during the period, but there appears to be a relatively stable trend with moderate fluctuations, suggesting that Zimbabwe has not met the targets of SDG 3.1. These results underscore the need to re-assess current intervention programs aimed at reducing maternal mortality. The findings of the study could guide the refinement of existing strategies and the implementation of innovative solutions to urgently address unacceptably high mortality rates. Using statistical models such as the one used in this study, the Ministry of Health and Child Care (MoHCC) can make informed decisions in the health sector and implement effective interventions to combat maternal mortality.

**Keywords** Masvingo Province, Maternal mortality deaths, modelling, maternal mortality ratio, maternal mortality trends.

**AMS 2010 subject classifications** 62M10, 93A30

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## 1. Introduction

Maternal mortality, as defined by [1], encompasses fatalities affecting women during pregnancy or within 42 days of pregnancy termination. Despite global efforts, [2] reported a 38% reduction in the global maternal mortality ratio from 2000 to 2017, declining from 342 to 211 deaths per 100,000 live births, respectively. This translates to an average annual decline rate of 2.9%, falling short of the 6.4% required to meet the Sustainable Development Goal (SDG) 3.1 of 70 maternal deaths per 100,000 live births, as outlined by [3]. [4] deemed the 295,000 women who died globally during and after pregnancy in 2017 as unacceptably high, with the burden disproportionately higher in developing countries compared to developed ones.

The resurgence of maternal mortality rates in numerous countries, including Zimbabwe, has been largely overlooked by both medical and general media outlets, as noted by [5]. [6] findings reveal that preventable pregnancy-related causes claimed the life of one woman every two minutes in 2020, highlighting the urgent need for action. As [5] outlined, the global maternal mortality ratio (MMR) decreased by 34.8% between 2000 and 2020,

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dropping from 342 deaths per 100,000 live births to 223 deaths per 100,000 live births. This trend underscores significant progress in maternal healthcare over the past two decades but also highlights the ongoing need for continued efforts to reduce maternal mortality rates further worldwide.

In 2020, [6] noted that nearly 95% of maternal deaths occurred in low and lower-middle-income countries, many of which were preventable. Zimbabwe, identified as a low-income nation, falls within this category. Sub-Saharan Africa and Southern Asia collectively represented about 87% of global maternal deaths, with Sub-Saharan Africa contributing roughly 70% and Southern Asia about 16% in 2020. Despite the elevated maternal mortality ratio (MMR) observed in Sub-Saharan Africa in 2020, [6] reports a noteworthy 33% decline in MMR over the period spanning from 2000 to 2020. This achievement suggests that targeted interventions and investments in maternal healthcare infrastructure and services have the potential to yield substantial reductions in maternal mortality rates over time, even in regions facing significant challenges.

Sub-Saharan Africa encountered a substantial challenge of HIV/AIDS-related maternal mortality, accounting for 9% of all maternal fatalities. [7] additionally highlighted the high prevalence of Tuberculosis and HIV among pregnant women in this region. Addressing the intersecting issues of HIV/AIDS, Tuberculosis, and maternal mortality in Sub-Saharan Africa requires comprehensive strategies that integrate maternal healthcare with effective prevention, testing, and treatment programs for HIV/AIDS and Tuberculosis among pregnant women. This underscores the importance of targeted interventions and improved healthcare infrastructure to mitigate the impact of these diseases on maternal health outcomes in the region.

[8] emphasised that nearly all maternal deaths (99%) occur in the developing world, with more than half in Sub-Saharan Africa. Developing countries experience a stark contrast in maternal mortality ratios, with one in every 180 pregnant women facing the risk of death during childbirth, compared to one in every 4,900 in developed countries ([9]). Zimbabwe is not exempt from this crisis, facing challenges like obstructed labor, maternal hemorrhage, postpartum sepsis, eclampsia, unsafe abortion, and anemia as leading causes of maternal death.

Despite notable health achievements in Zimbabwe, highlighted by [10], maternal mortality remains unacceptably high. While progress has been made in various health indicators, addressing maternal mortality requires timely and qualified healthcare interventions in supportive settings.

According to [11], maternal mortality serves as a critical indicator, alongside infant mortality and life expectancy, reflecting the overall health of a nation and providing a key measure for assessing both human rights and public health. A low maternal mortality rate is indicative of a healthy nation. In Zimbabwe, various interventions have been implemented to address pregnancy-related and maternal deaths, as highlighted by [12]. Notable initiatives include the rollout of Antiretroviral therapy (ART) in 2004, resulting in 50% of HIV-positive mothers being on ART and receiving antenatal care (ANC) by 2017, as reported by [13].

To enhance data collection and response to maternal and perinatal deaths, the MoHCC developed guidelines for a Maternal and Perinatal Death Surveillance and Response (MPDSR) system. This system involved auditing maternal and perinatal deaths across all medical facilities, with standardised forms submitted to the MoHCC. A national database was established to compile information on reported deaths.

Government efforts to reduce maternal mortality further included eliminating user fees for maternity care in government-funded medical facilities. This initiative, supported by the Health Transition Fund (HTF) from 2012 to 2015 and the Health Development Fund (HDF) from 2016 to 2022, aimed to make maternity care more accessible. Despite these significant efforts, the burden of maternal mortality in Zimbabwe remains high, highlighting the complexity and persistent challenges in addressing this critical public health issue.

The Zimbabwe Multiple Indicator Cluster Survey of 2019 reported a maternal mortality ratio of 462 deaths per 100,000 live births in 2019, improving from the 614 deaths per 100,000 live births recorded in 2014. However, the slow rate of improvement suggests that Zimbabwe might need help to meet the SDG target for reducing maternal mortality. Notably, the majority of maternal deaths occur in rural areas compared to urban areas.

Approximately 3,000 women lose their lives annually during childbirth in Zimbabwe, resulting in a substantial economic impact, with at least 1.23% of the Gross Domestic Product (GDP) lost each year due to maternal complications ([14]). According to [15], Zimbabwe ranks among the countries with high maternal mortality and pregnancy-related complications, reporting rates of 790 deaths per 100,000, 570 deaths per 100,000, and 443 deaths per 100,000 in 2008, 2010, and 2015, respectively.

Preventable maternal mortality not only constitutes a violation of a mother's right to life and quality health care but also acts as a catalyst for various vulnerabilities affecting orphaned children. These vulnerabilities encompass health, early marriages, nutrition, employment, education, pregnancy, household responsibilities, and caretaking duties ([16]), negatively impacting future generations. Research by [17] establishes a correlation between maternal death and child and infant mortality, especially in the first year of life. This underscores the importance of establishing trends, modelling, and projecting maternal mortality in Masvingo Province to assess the feasibility of achieving SDG 3.1.

Despite considerable interventions and collaborative efforts by governments and development partners to attain the objectives outlined in Millennium Development Goals (MDGs) 5, the Maternal Mortality Ratio (MMR) in developing countries remains persistently high, as highlighted by the UNDP (2010). Notably, Masvingo, a predominantly rural province in Zimbabwe with a 90% rural population, faces an elevated risk of maternal mortality. According to the 2022 census results, Masvingo has a total population of 1,638,539, comprising 10.8% of Zimbabwe's total population, ranking as the sixth-largest province ([18]) with 763,537 males and 875,002 females.

The importance of robust statistical models to precisely measure and predict maternal mortality in healthcare, especially in developing nations like Zimbabwe, cannot be overstated. Such models are essential for effective planning and for achieving the targets outlined in SDG 3.1. [12] highlighted the importance of consistently analysing maternal mortality trends, patterns, and causes. This analytical approach is crucial for achieving the target outlined in SDG 3.1. Consequently, it becomes imperative to employ statistical methods to model and project maternal mortality, enabling informed, data-driven decisions within the health sector. These models will support the government, policymakers, and stakeholders in implementing policy measures to reduce maternal mortality drastically.

## 2. Literature review

Numerous studies have employed the Box Jenkins methodology to examine maternal mortality trends, as evidenced by [19], [20], and [21]. In Ghana, [22]used the Box-Jenkins (1970) methodology, fitting an Autoregressive Moving Average (ARIMA) model to forecast maternal mortality. The ARIMA (1, 0, 2) model demonstrated a good fit with quarterly maternal mortality ratios data from Ghana's Okomfo Anokye Teaching Hospital, producing sensible forecasts.

Similarly, [23] applied the Box-Jenkins technique to predict maternal mortality ratios at Juba Teaching Hospital in South Sudan. Using time series data from January 2008 to December 2014, an ARIMA (3, 0, 1) model proved suitable for maternal mortality ratio data. The model was employed to forecast the monthly MMR for the subsequent six months, revealing a positive trend of gradual decline in the maternal mortality ratio, which was deemed encouraging.

[24] studied maternal mortality at the Korle-bu Teaching Hospital in Ghana from 2001 to 2013, fitting ARMA models. The MMR data exhibited a platykurtic distribution, leading to the application of an ARIMA model for further analysis. [25] used an ARIMA (1, 1, 1) model to predict maternal mortality records from a public health facility in Ghana, drawing on time series data from January 2000 to December 2013. The forecasts from this model indicated a decline in monthly maternal cases.

In Zimbabwe, [14] employed the Box-Jenkins approach to predict maternal fatalities and MMR using annual time series data from 1990 to 2015. Diagnostic testing revealed that both maternal deaths and MMR were I (2) variables. The ARIMA (0, 2, 2) and ARIMA (2, 2, 0) models were identified as parsimonious models for projecting maternal fatalities and MMR based on minimal AIC statistics. These models demonstrated stability through diagnostic tests and strongly suggested an increase in maternal fatalities and MMR in Zimbabwe from 2016 to 2025, serving as a crucial warning about the urgency of addressing maternal health.

[26] estimated maternal mortality levels and trends for 183 countries in 2016, evaluating the success of the MDGs using a Bayesian model. Based on MMR 2015 estimates, their forecasts were instrumental in assessing the need for SDG 3.1, which aims for a global maternal mortality ratio of less than 70 per 100,000 live births. This

study significantly contributed to the UN Maternal Mortality Estimation Inter-Agency Group (MMEIG) database by adding almost 200 entries from vital statistics, civil registration systems, surveys, studies, or reports.

[27] used the daily count of COVID-19 deaths to forecast COVID-19-related mortality, employing a Markov switching (MS)-generalized autoregressive conditional heteroscedasticity (GARCH)-type model. Their findings identified the MS(3)-GARCH(1,1) model paired with Pearson's type IV distribution (PIVD) as the optimal approach. The chosen approach plays a critical role in mortality modelling. However, the study did not incorporate maternal mortality, given that pregnant women were generally not exposed to COVID-19 vaccinations in many, if not all, regions of the country. [28] applied ARIMA, SARIMA, and Exponential Smoothing methods to analyse recurring patterns, seasonality, and long-term trends in MMR using data from 181 countries from 1990 to 2015 sourced from Kaggle. Their findings indicated that SARIMA demonstrated superior performance to ARIMA and exponential smoothing, offering the most accurate and insightful results.

[29] examined the influence of the COVID-19 pandemic on the Brazilian Maternal Mortality Ratio (BMMR) from 1996 to 2021, employing the Holt-Winters, Neural Networks Autoregression (NNA) and ARIMA techniques. Their findings indicate that while the NNA model better fits past data, the Holt-Winters and ARIMA models exhibited superior predictive performance beyond the sample data. Moreover, the study suggests that using the Holt-Winters and ARIMA models for BMMR forecasting may result in lower errors.

[30] investigated the impact of the SARS-CoV-2 pandemic on maternal mortality causes in Chile during the outbreak's peak from 2020 to 2021. They used segmented regression to analyse trend changes in the MMR. They employed interrupted time series (ITS) and an ARIMA model to assess the effects of the SARS-CoV-2 outbreak and forecast expected MMR rates. Their findings from ITS analysis indicate that the SARS-CoV-2 outbreak notably affected MMR due to indirect causes, particularly non-respiratory ones. Furthermore, the ARIMA forecast aligned with ITS, revealing that the anticipated MMR for indirect causes was significantly lower than the observed rates.

## 3. Methods

Adopting a time series model, specifically ARIMA, is justified based on its demonstrated ability to generate precise forecasts, as highlighted by [31] and [32]. This approach has proven effective in previous studies conducted in Ghana by [22], [24] and [25]. Furthermore, it was successfully applied in South Sudan by [23] when modelling maternal mortality at various hospitals, producing sensible and reliable forecasts.

### 3.1. *Time series plot*

The use of a time series plot in this analysis serves to scrutinise the trends in provincial quarterly maternal deaths over time. This approach facilitates a clear visualisation of the patterns and enables a straightforward interpretation of the trajectory of maternal mortality in Masvingo Province.

### 3.2. *Box-Jenkins approach*

The [33] approach fits the ideal ARIMA model. An ARIMA model can be written as ARIMA(p,d,q) where p, d, and q represent the number of non-seasonal autoregressive terms, non-seasonal difference, and non-seasonal moving-average terms.

### 3.3. *ARIMA (p,d,q) model*

An ARIMA (p,d,q) model can be stated as follows:

$$\Phi(B)\nabla^d Y_t = \Theta(B)\varepsilon_t, \tag{1}$$

where $Y_t$ is the maternal mortality series being modelled, $\nabla^d = (1-B)^d$, $\varepsilon_t$ is a white noise process, $\Phi's$ and $\Theta's$ are unknown AR and MA model coefficients to be estimated using the maximum likelihood estimation (MLE) method, and B is a backward difference operator with $B^k Y_t = Y_{t-k}$. The Argumented Dicky-Fuller (ADF) test checks the presence of unit roots on the quarterly mortality series before fitting an ARIMA model. The ADF test is conducted under the null hypothesis of quarterly Masvingo Province Maternal Mortality Statistics $Y_t$, which has a unit root. The autocorrelation function (ACF), partial correlation function (PACF), and extended autocorrelation function (EACF) are used to identify the order of the proposed ARIMA model. The Akaike Information Criterion (AIC) is used in model selection. A better model is seen by having the smallest AIC and BIC values.

### *3.4. Model diagnostics*

The Box-Ljung test is used for the autocorrelation of model residuals under the null hypothesis of model residuals being correlated. The Jarque Bera test and the Q-Q plot are used to test for normality of the model residuals under the null hypothesis, which states that the model residuals are normally distributed. Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) are used to assess the estimated models' forecasting accuracy. The RMSE and MAE are given by:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2} \quad \text{and} \quad \text{MAE} = \left(\frac{1}{n}\sum_{t=1}^{n}|Y_t - F_t|\right). \tag{2}$$

$Y_t$ is the original maternal death, $F_t$ is the corresponding predicted maternal deaths, and n is the total number of predicted maternal deaths.

## 4. Results and discussion of results

Quarterly Masvingo Province maternal mortality statistics ($Y_t$) from January 2014 to December 2021 obtained from the Zimbabwe MoHCC Demographic Health Information Software (DHIS2) database are used. The descriptive statistics are presented in Table 1. Table 1 results show that the total quarterly maternal statistics range from 3 to

Table 1. Descriptive statistics

| Minimum | Maximum | Mean | Std.Dev | Skewness | Kurtosis |
|---|---|---|---|---|---|
| 3 | 18 | 8.34 | 3.29 | 0.88 | 0.59 |

18 cases, with an average of 8.34 cases per quarter and a standard deviation of 3.29. The data shows slight positive skewness (0.88) and light-tailedness (kurtosis of 0.59).

### *4.1. Trend analysis*

A time series plot, presented in Figure 1, is constructed to show the significant maternal mortality data patterns.

Figure 1 illustrates a noticeable secular variation in the trend, marked by a sudden spike in 2018. [34] attribute this spike to higher reported abortion-related deaths in Zimbabwe during that year. Identifying such deaths posed challenges due to restrictive legislation and religious objections.

### *4.2. Stationarity test and model identification*

An ADF test is conducted to test the stationarity of the quarterly maternal mortality data ($Y_t$). Table 2 presents the ADF test results.

Table 2. ADF test results of $(Y_t)$

| Dickey-Fuller | Lag order | p-value |
|---|---|---|
| -1.7976 | 3 | 0.6509 |

The results of Table 2 confirmed the original series' non-stationarity, as suggested by the p-value of 0.4053; thus, we failed to reject the null hypothesis. An ordinary first difference is applied to $(Y_t)$ to get $(Z_t)$, and the ADF test is employed on $Z_t$ to check the presence of the unit root. Table 3 summarises the results.

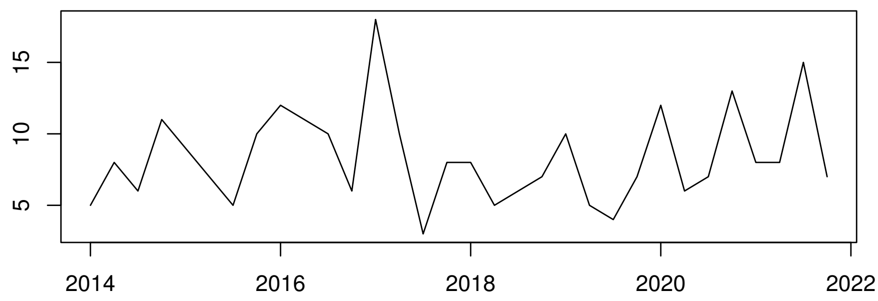


Figure 1. Masvingo Province's quarterly maternal mortality statistics.

Table 3. ADF Test of $(Z_t)$

| Dickey-Fuller | Lag order | p-value |
|---|---|---|
| -4.2646 | 3 | 0.0125 |

According to the presented results, at a 5% significant level, $Z_t$ is stationary, as evidenced by the p-value of 0.0125. The ACF and PACF of $Z_t$ are done to envision the suitable $p$, $d$, and $q$ for the tentative model. Figure 2 presents the ACF and PACF results.

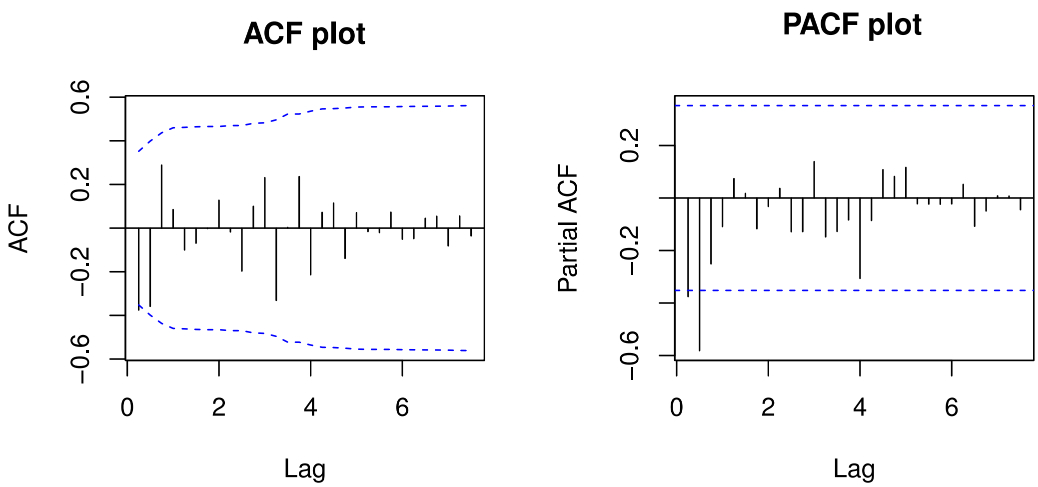


Figure 2. ACF and PACF of $Z_t$.

Figure 2 shows that the ACF plot cut-off at lag one and the PACF legs cut-off at lag 2, suggesting either the ARIMA (2,1,1) model or the ARIMA (2,1,0) model. The EACF is used to verify the model, as shown in Table 4.

Table 4. The EACF of $Z_t$ series

| AR/MA | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | x | o | o | o | x | x | o | x | o | o | x | x | x | o |
| 1 | x | x | x | o | x | o | o | x | o | o | o | x | x | x |
| 2 | x | o | o | o | o | o | o | x | o | o | o | x | x | x |
| 3 | x | o | o | o | o | o | o | o | o | o | o | x | x | o |
| 4 | x | x | o | o | x | o | o | o | o | o | o | x | o | x |
| 5 | x | x | o | o | x | o | o | o | o | o | o | x | o | o |
| 6 | o | x | o | x | o | x | o | o | o | x | o | x | o | o |
| 7 | x | x | x | x | o | o | o | x | o | o | o | x | o | x |

The EACF outcomes indicate the suitability of an ARIMA (2,1,1) model as the ACF and PACF recommended. These suggested models are fitted alongside other proposed models, and the AIC and BIC are employed to identify the most fitting model. Table 5 presents the AIC, BIC, RMSE, and MAPE results.

Table 5. Fitted models' AIC values

| Model | AIC | RMSE | MAE |
|---|---|---|---|
| ARIMA (2,1,1) without drift | 169.86 | 3.17 | 2.57 |
| ARIMA (2,1,1) with drift | 171.57 | 3.15 | 2.59 |
| ARIMA (2,1,0) without drift | 170.63 | 3.33 | 2.53 |
| ARIMA (2,1,0) with drift | 172.46 | 3.32 | 2.58 |
| ARIMA (2,2,0) without drift | 188.36 | 4.77 | 3.71 |
| ARIMA (1,1,0) without drift | 182.12 | 4.20 | 3.37 |
| ARIMA (1,1,0) with drift | 184.08 | 4.20 | 3.39 |

Based on the findings in Table 5, the ARIMA (2,1,1) model exhibits the lowest AIC, surpassing the other competing models. However, the forecasting accuracy of the ARIMA (2,1,1) model is comparatively lower, as indicated by the RMSE and MAE values, compared to other fitted models. Further scrutiny is given to the significance of parameters in the ARIMA (2,1,1) model, and the specific parameter values can be found in Table 6.

Table 6. ARIMA (2,1,1) model parameters

| Parameter | Coefficient | Standard Error | T-statistic | P-value |
|---|---|---|---|---|
| $\hat{\phi}_1$ | -0.3552 | 0.2109 | -1.6844 | 0.0921 |
| $\hat{\phi}_2$ | -0.5089 | 0.1821 | -2.7944 | 0.0052 |
| $\hat{\theta}_1$ | -0.4654 | 0.2279 | -2.0422 | 0.0411 |

The results in Table 6 indicate that all ARIMA (2,1,1) model parameters are statistically significant, as supported by the $t$-statistic and $p$-values. Consequently, it is deemed the most suitable model for the given data.

### *4.3. Model diagnostic tests*

The Box-Ljung test results suggest that the residuals are uncorrelated ($\chi^2 = 0.0385, \text{df} = 1, \text{p-value} = 0.8445$). According to the Shapiro-Wilk normality test ($\chi^2 = 0.9617, \text{p-value} = 0.3055$), the model residuals are normally distributed. The ARIMA (2,1,1) model is being confirmed to be the model that fits well with Masvingo Province's quarterly maternal mortality statistics and, hence, can be used for forecasting purposes. The model can be expressed as:

$$Z_t = 0.6448Z_{t-1} - 0.1537Z_{t-2} + 0.5089Z_{t-3} + 0.4654\varepsilon_{t-1} + \varepsilon_t \tag{3}$$

### 4.4. *Maternal mortality forecasting*

Accurate predictions of future maternal mortality statistics in Masvingo Province are crucial for government planning and health sector policy decisions. The ARIMA (2,1,1) model generates out-of-sample forecasts for 16 quarters (4 years) from 2022 to 2025. Figure 3 presents the forecasts, including a 95% confidence interval (CI).

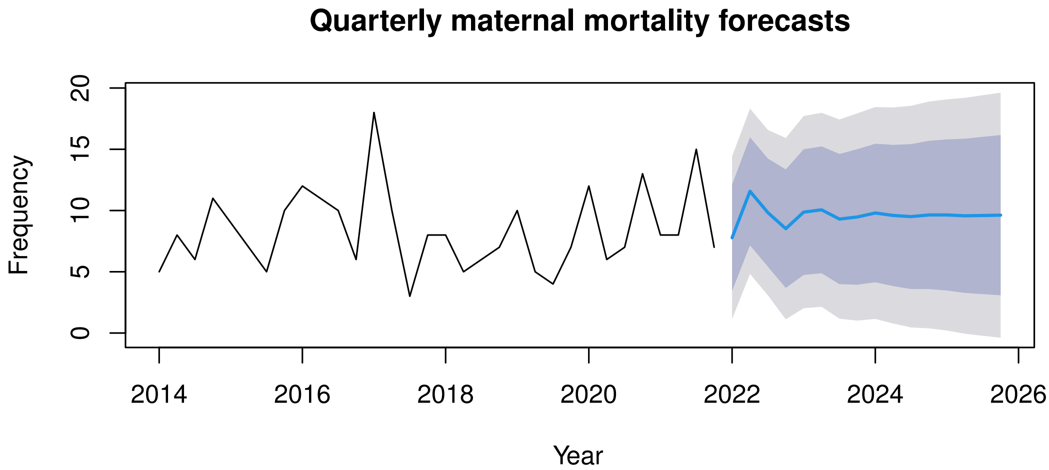


Figure 3. Masvingo Province quarterly maternal mortality forecasts.

The forecasted maternal mortality rates for Masvingo Province from 2022 to 2025, as depicted in Figure 3, reveal a projected slight increase in quarterly mortality rates over the period. While this increase may appear moderate, it signals a potential upward trend in mortality, underscoring the urgency for enhanced healthcare resources and interventions to address the rising rates. Furthermore, closely scrutinising factors contributing to mortality and implementing targeted strategies are warranted to mitigate its impact effectively.

This trend contrasts with findings from [12], which underscored Zimbabwe's successful reduction in pregnancy-related deaths through targeted interventions. The observed relatively stable trend or decrease in maternal deaths over the period can be attributed to efforts to address direct causes, such as pregnancy-related infections, obstetric hemorrhage, and hypertensive diseases during pregnancy. However, despite this progress, achieving SDG 3.1 remains challenging, necessitating more comprehensive strategies and innovative approaches to meet the target effectively.

The observed maternal mortality rates ranging from 7 to 11 cases per quarter per 100,000 live births, as per the [35], are considered relatively high and conflict with SDG 3.1's objective of achieving a global maternal mortality ratio of less than 70 per 100,000 live births. As Zimbabwe continues to work towards this international goal, sustained progress in maternal healthcare requires ongoing efforts and innovative measures to address the persisting challenges.

## 5. Conclusions and Recommendations

The Box-Jenkins approach was employed to model and forecast maternal death cases in Masvingo Province. The time plot revealed fluctuations in mortality rates, with 2018 registering the highest maternal death rates. Initially non-stationary, as indicated by the time series plot and confirmed by the ADF test, the data became stationary after an initial adjustment. Subsequent analysis, guided by ACF and PACF plots, identified an ARIMA (2,1,1) model, which successfully passed all diagnostic tests. This ARIMA model predicted maternal mortality cases in Masvingo Province for the next three years. The forecasted values fell within the 95% confidence interval, affirming the adequacy of the fitted model. The forecast suggests a gradual decline in maternal mortality rates, particularly in 2024, with an average of 7 to 11 cases quarterly per 100,000 live births. However, these quarterly rates appear higher than desired, conflicting with the goal of SDG 3.1. The findings prompt a reevaluation of existing intervention programs to reduce maternal mortality. The projections also hold practical utility for planning, resource mobilisation, and allocation in addressing maternal health challenges.

### *5.1. Limitations*

The precision and reliability of the projected maternal mortality rates depend on the quality and completeness of the data. Errors or gaps in the data can introduce bias, affecting the validity of the predictions. This study did not account for all external factors influencing maternal mortality, which could limit the comprehensiveness and accuracy of the model. Furthermore, the results might be specific to certain provinces and not widely applicable due to regional differences in healthcare systems, demographics, and socio-economic conditions.

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