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Temporal Dynamics and Predictive Modelling of Tuberculosis Mortality Trends: A Comparative Analysis of Ghana, Nigeria and Côte d'Ivoire

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Abstract

Tuberculosis (TB) remains a major global health challenge, particularly in sub-Saharan Africa, where the burden of disease is disproportionately high. This study investigates the temporal dynamics and predictive modeling of TB mortality in Ghana, Nigeria, and Côte d'Ivoire using data obtained from the World Bank's open data portal. Autoregressive Integrated Moving Average (ARIMA) models were employed to analyze past trends and forecasts were done in country-specific contexts. The results revealed divergent patterns: Ghana's TB mortality showed relative stability with ARIMA(1,2,3) model, Nigeria exhibited heightened variability with ARIMA(2,2,3), while Côte d'Ivoire indicated a steady decline in mortality under ARIMA(4,1,1). These findings demonstrate the usefulness of ARIMA models in capturing mortality dynamics, identifying high-risk periods, and guiding timely allocation of resources. The study concludes that predictive modelling offers a valuable tool for supporting evidence-based TB interventions, aligning with WHO's End TB Strategy by 2035.

Keywords

Tuberculosis; ARIMA models; Temporal dynamics; Forecasting

1. Introduction

Tuberculosis (TB) continues to be one of the leading infectious disease killers worldwide (World Health Organization, 2022), despite advances in diagnostics, treatment, and prevention strategies. According to (World Health Organization, 2022) nearly 10 million people develop TB annually, with Africa accounting for a significant portion of cases and deaths. Ghana, Nigeria, and Côte d'Ivoire represent three West African nations with distinct TB epidemiological profiles, making them ideal for comparative analysis. TB dynamics in these countries are shaped by socioeconomic disparities, healthcare infrastructure, HIV co-infection and political instability.

Nigeria bears one of the heaviest global burdens of TB (Ogbo, et al., 2018), Côte d'Ivoire's epidemic is strongly linked with HIV prevalence and past healthcare disruptions, while Ghana has made moderate progress through improved diagnostic tools but still faces underreporting challenges (Iddrisu, Amikiya, & Bukari, 2024). According to (World Health Organization, 2022), TB is the second deadliest communicable disease globally, surpassed only by COVID-19 during the peak of the pandemic (Falzon, Zignol, Bastard, Floyd, & Kasaeva, 2023).
(Barter, Agboola, Murray, & Bärnighausen, 2012), where weak health systems, high HIV co-infection rates, and socioeconomic vulnerabilities continue to drive transmission. Although global incidence has declined slightly since 2000, the rate of decline remains insufficient to meet the milestones set by the WHO's End TB Strategy. This strategy seeks to eliminate TB as a public health threat by 2035.

This difficulty is seen in West Africa. Together, Ghana, Nigeria, and Côte d'Ivoire show the range of TB prevalence in the Sub-Saharan area. Ghana, a country with a moderate TB burden, has benefited from improved diagnostics and a comparatively stable health infrastructure, but it still faces treatment gaps and underdiagnosis, particularly in rural areas (Adu, Spiegel, & Yassi, 2021). With its big population and intricate healthcare system, Nigeria is one of the nations with the highest rates of tuberculosis worldwide, with over 450,000 new cases reported each year (Ogunniyi, Abdulganiyu, Issa, Abdulhameed, & Batisani, 2024). This situation is made worse by HIV/TB co-infection, delayed diagnosis, and restricted access to treatment.
Côte d'Ivoire on the other hand shows the consequences of fragile health systems and political instability as TB incidence remains high, with 25–30% of patients co-infected with HIV (N'Guessan, et al., 2018). Together, these countries capture the heterogeneity of TB dynamics.

Desai et al. (2019) revealed that despite the availability of epidemiological data, one of the ongoing challenges to TB control is the difficulty to precisely forecast temporal trends and anticipate high-risk periods. Also, it must be noted that according to Busari & Bolanle (2025) most predictive models rely heavily on historical case data while neglecting wider contextual determinants such as healthcare infrastructure, urbanization, poverty, and conflict. This limited scope diminishes the precision and relevance of forecasts, frequently leading to "one-size-fits-all" policy recommendations that do not reflect country-specific realities. For decision-makers, the lack of integrated and context-specific modelling approaches hinders the capacity to allocate resources efficiently, craft targeted interventions, and gauge progress toward global TB reduction targets (World Health Organization, 2022) and (Menzies, McQuaid, Gomez Guillen, & Houben, 2018) concurs.

Time series modelling offers a powerful framework to address these gaps. It picks up on the fluctuations in disease incidence and mortality patterns over time. Time series allows for forecasting that is not only statistically robust but also adaptable to low-resource settings where data quality may be limited (Imai, Armstrong, Chalabi, Mangtani, & Hashizume, 2015). Realistically, comparative time series modelling across countries with diverse epidemiological and healthcare profiles can yield deeper insights into both shared and unique drivers of TB burden. It helps to give evidence-based decision-making, guiding timely interventions, and shapes control plans that fit each region's setup.

Time-series methods such as the Autoregressive Integrated Moving Average (ARIMA) models are particularly useful in capturing temporal trends, even with noisy or incomplete datasets (Hssayeni & Ghoraani, 2024) and this was confirmed by (Lipton, Kale, & Wetzel, 2016). This study applies ARIMA modelling by comparing mortality trends across these countries.

It aims to identify context-specific drivers of TB burden, assess the performance of predictive models, and highlight opportunities for improving disease surveillance and control. The findings contribute not only to the scientific understanding of TB epidemiology in West Africa but also to the refinement of predictive approaches that can better inform health policies and facilitate speed toward the WHO End TB targets. The subsequent sections will take into consideration the methods and the analysis and results.

2. Materials and Methods

This study used secondary data from World Bank’s open data to analyze tuberculosis (TB) mortality trends and develop predictive models. The study involved identifying patient mortalities arriving from TB cases monthly in these countries over a defined time period (2020-2022). The retrospective design enabled analysis of existing data to evaluate trends. Furthermore, the retrospective study design was used because of the availability of high quality historical data from World Bank which was cost effective and very practical and it aligns with the objectives of the study which has it that, an analysis of long-term trends and predictive models are forecasted.

2.1. ARIMA Modelling

The data was then modelled using Autoregressive Integrated Moving Average (ARIMA), a stochastic model popularised by (Box & Jenkins, 1970). This is the structured method of building and analysing the Autoregressive Integrated Moving Average for temporal-historical data. Some of the key applications of ARMA models in statistics are modelling and forecasting stationary and series. This ARIMA model predicts future values for a single variable based on its historical values (Allard, 1998). (Naylor, Seaks, & Wichern, 1972). This is made possible by considering a discrete time series of observations spaced equally in time.

The ARIMA (p, d, q) model is a combination of Autoregressive (AR) model and the Integrated Moving Average which shows that, the present value has something to do with the past residuals. The ARIMA process can be defined as:

$$\phi(\boldsymbol{B})\Delta^{\boldsymbol{d}}\boldsymbol{Y_t} = \Theta(\boldsymbol{B})\boldsymbol{e_t} \tag{1}$$

where: $Y_t =$ the number of TB cases recorded at time

Δ^d = is the order of differencing

Using the backshift notation, the Autoregressive (AR) operator is given as;

$$\phi(\boldsymbol{B}) = (\boldsymbol{1} - \phi_1\boldsymbol{B} - \phi_2\boldsymbol{B^2} \ldots \phi_p\boldsymbol{B^p}) \tag{2}$$

The Moving Average (MA) is given as:

$$\Theta(\boldsymbol{B}) = (\boldsymbol{1} - \Theta_1\boldsymbol{B} - \Theta_2\boldsymbol{B^2} \ldots \Theta_q\boldsymbol{B^q}) \tag{3}$$

To estimate the model, three steps are required in country-specific situations; model identification and diagnostic checking.

2.2. Trend Analysis on TB Mortality cases

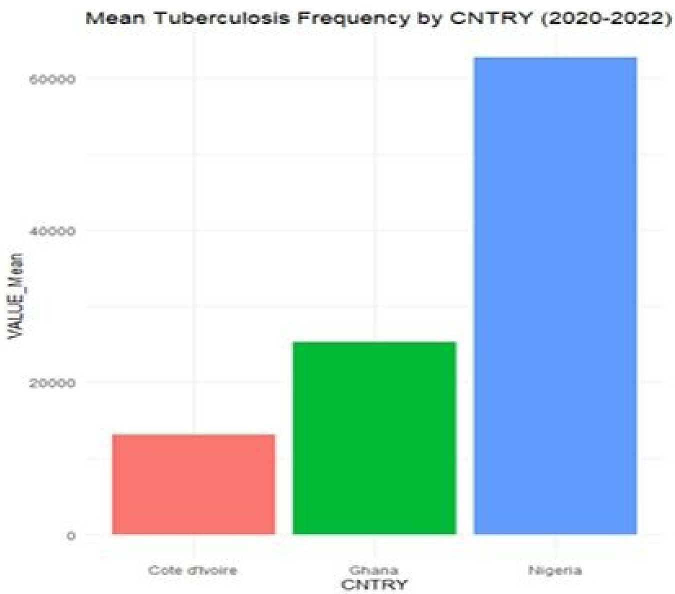


Figure 1 - Average tuberculosis case count by country

The figure above demonstrates the average number of TB cases amongst the three countries. It can obviously be seen that of the three countries, Nigeria visibly has the largest average followed by Ghana and then Cote d'Ivoire respectively.

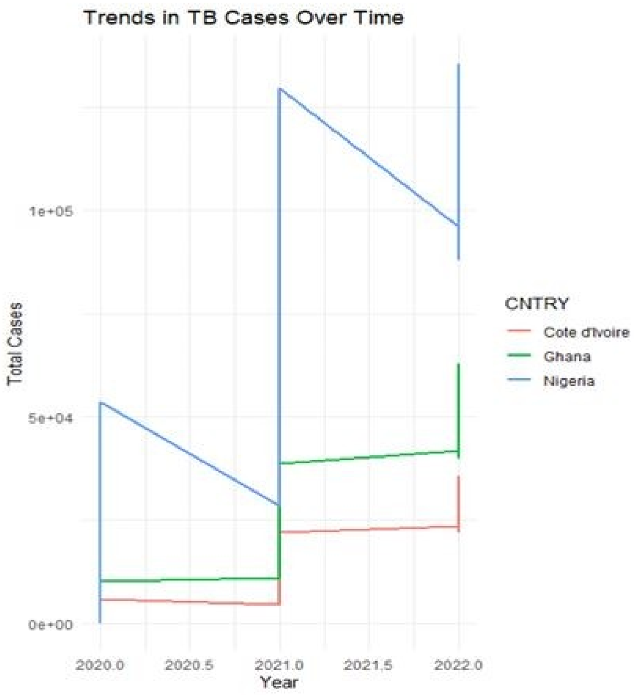


Figure 2 - Trend plots for all three countries

The figure above backs up the TB case number trends over time in Cote d'Ivoire, Ghana, and Nigeria. Nigeria's TB cases shoot up around 2020 hitting the highest count among the three countries. But right after that peak, the cases drop off fast. This might point to an epidemic-like event followed by a strong public health push or more people becoming aware.

Ghana's trend stays steady with a small slow rise in TB cases over the shown time. The case count stays always lower than Nigeria's peak but higher than Cote d'Ivoire's. Cote d'Ivoire has the lowest TB case count of the three countries. A small uptick is observed at first then a flat period, and another slight increase as we reach the end of the timeline.

3. Stationarity and Differencing

For the ARIMA (p, d, q) process, identifying the model(s) involves determining the values of p, d and q. The values are found using Autocorrelation function (ACF) and Partial Autocorrelation function (PACF). In this study, several tentative models were fitted. The (auto.arima) function was used and the best model was selected based on their information criteria. Since the data was non-stationary, it has to be differenced in order to achieve stationarity and the number of times it is differenced is denoted by d. The output below reveals that the series for all of the three countries are non-stationary and would need differencing. This is because the ADF tests have p-values of (0.4011, 0.4082 and 0.3082) for Ghana, Nigeria and

Cote d'Ivoire respectively. This indicates a value > 0.05. Hence We fail to reject the null and then conclude that the series is non-stationary.

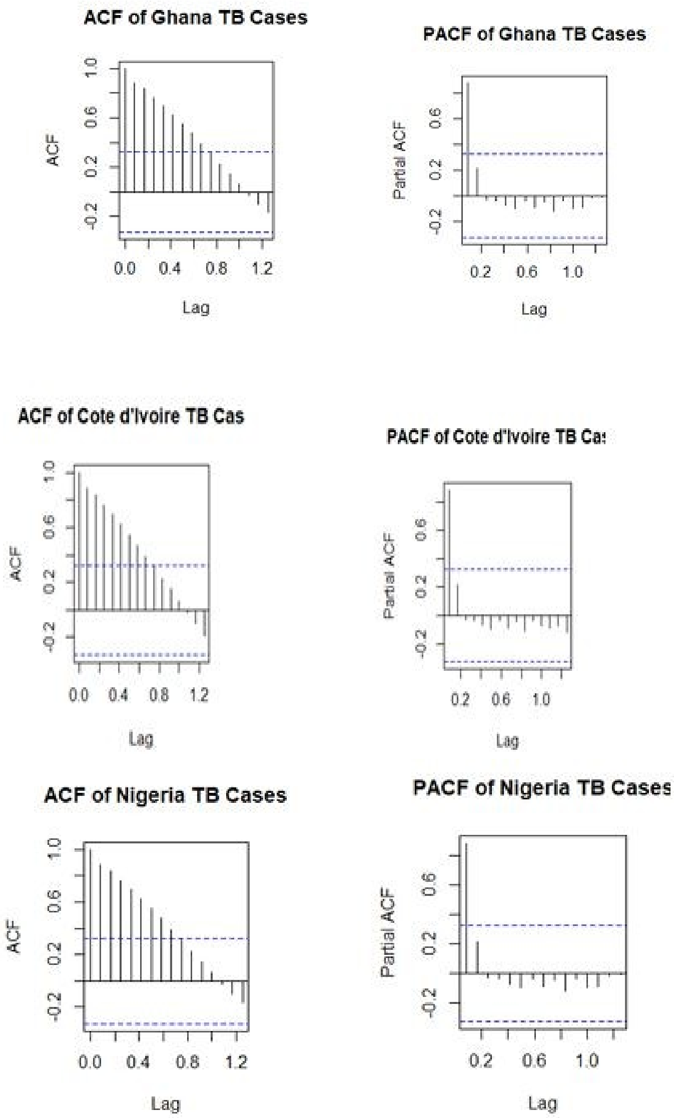


Figure 3 - ACF and PACF plots for non-stationary series for the three countries

After differencing, the p-value for the series for all the countries are displayed and the stationarity test for the series using the ADF test are done below;

Table 1 - Stationary time series after differencing for all three countries and the order of differencing

Country	Differencing order (p_value)	Hypothesis
Ghana	2 (0.02621)	H_0 : *Series is not stationary*
Nigeria	2 (0.01621)	H_1 : *Series is stationary*
Cote d'Ivoire	1 (0.01)	

4. Data Analysis and Results

For the sake of time constraint and the purpose of efficiency, the (auto.arima) which automatically fits the best model for each series will be used in order to come out with the best of several competing models for the country-specific series.

4.1. Model selection

Table 2 - Selected models for each country

Country	Selected Model (p,d,q)	AIC
Ghana	(1,2,3)	663.65
Nigeria	(2,2,3)	664.54
Cote d'Ivoire	(4,1,1)	649.84

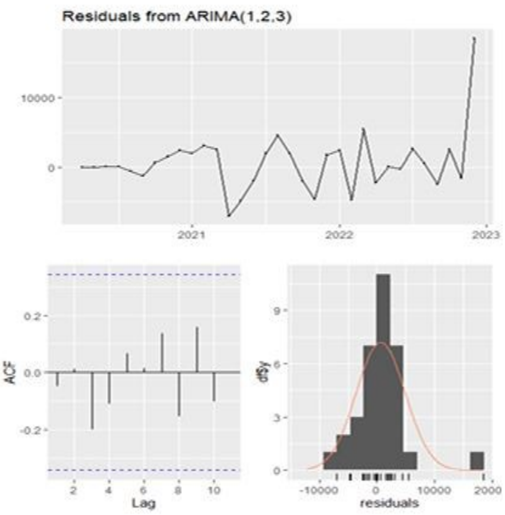
The ARIMA models estimated were given in the above Table 2. Considering the models were in different contexts, and fitted with the auto.arima function , the information criteria values cannot be directly compared. Information criteria are relative measures of model fit for a given dataset and not absolute indicators across datasets. The information criteria (AIC/BIC) used by this study were used as the basis for selecting the optimal model for each country setting. Take note that the absolute values of AIC or BIC are not directly comparable across countries because they are being computed on different datasets with varying sample sizes and likelihood functions. Nigeria's most parsimonious model was ARIMA (2,2,3) while for Ghana, ARIMA (1,2,3) was the best.

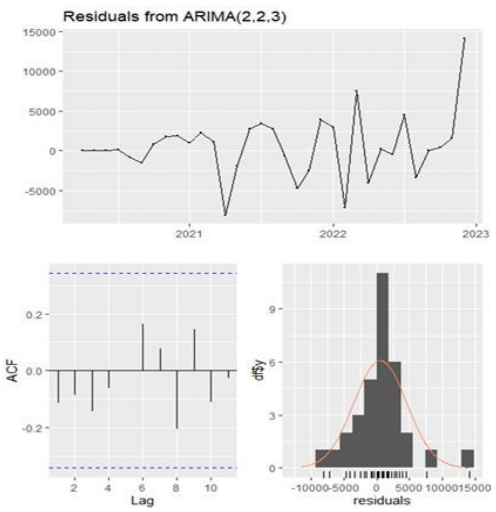
For Côte d'Ivoire, however, the series was best described by ARIMA (4,1,1). Rather than comparing the numerical values of the criteria by country, a sensible comparison follows from comparing the orders of the models. Both Nigeria and Ghana, for instance, required second-order differencing (d=2), which suggests greater non-stationarity than that of Côte d'Ivoire (d=1). Similarly, the higher autoregressive order in the Côte d'Ivoire model (p=4) implies higher persistence and memory in the series relative to the Nigerian and Ghanaian examples. The comparative understanding is thus elicited not from the AIC values themselves, but from the structural dynamics behind the selected models.

As observed in Figure 4, the residual plots for the selected model for Ghana shows that the residuals are largely centred around zero and display no strong autocorrelation. This means that the main dynamics of the series were adequately captured. However, there is a noticeable spike in residuals gearing towards the end of the period and a slight skewness in the histogram means there were some extreme values that the model did not fully account for. While the overall model is good, these results suggest that forecast performance should be interpreted with caution, particularly around periods of structural change.

For Nigeria, the residuals of the ARIMA (2,2,3) model are generally centred around zero and no sign of autocorrelation is shown. Again, no strong patterns are left and the variance is fairly stable through most of the period. However, the normal distribution shows fat tails which means the extreme values were not handled well by the model. This means that while the model is good enough, it may underperform during periods of heightened volatility. For Cote d'Ivoire, the ARIMA (4,1,1) had similar traits as residuals were also centered near zero and showed no major autocorrelation, residuals were heavy-tailed and a sharp spike toward the end of the period suggested unmodeled volatility.

For the three countries, diagnostics indicated that the selected ARIMA models had picked up the overall shapes of the data but with certain limitations. For Ghana ARIMA (1,2,3), the residuals were largely concentrated around zero but for a major spike towards the end of the series and minor skewness, which was a reflection of outliers. Nigeria's ARIMA (2,2,3) residuals had relatively constant variance and minimal autocorrelation but were fat-tailed and occasionally experienced large swings in the histogram, indicating the effects of structural shocks. In Côte d'Ivoire, the ARIMA (4,1,1) residuals also grouped around zero and were without high levels of autocorrelation but were heavy-tailed. Overall, while the selected models in each environment are adequate and parsimonious, the residual structures reveal that forecast accuracy can suffer with shocks or breakdown in structure in the event of surprises, particularly at the later segments of the series.





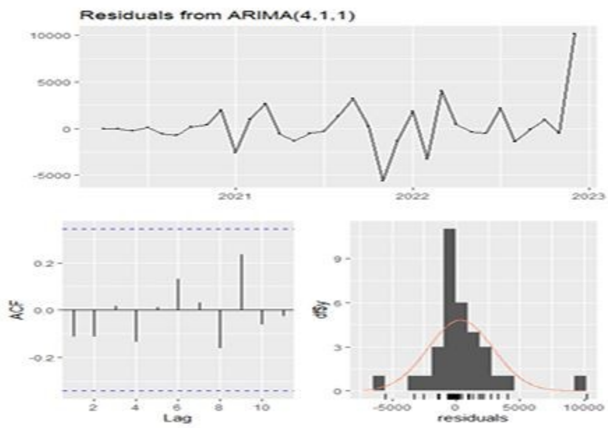


Figure 3 - Residual Plots for chosen models for each country

Table 3 - Residual diagnostics and stability conditions of selected ARIMA models

Country	Ljung–Box Test (p-value)	Invertibility (MA roots < 1?)	Stationarity (AR roots < 1?)	σ² (Residual Variance)
Ghana	0.9563 (no autocorr)	(0.70, 0.87 < 1)	(0.6264 < 1)	11,684,614
Nigeria	0.9755 (no autocorr)	(0.70, 0.87 < 1)	(0.8058,0.81<1)	10,436,603
Cote d'Ivoire	0.6747 (no autocorr)	(0.70, 0.87 < 1)	(0.9974, 0.7156, 0.5111, 0.5111<1)	4,607,320

The Ljung–Box tests for all three models yielded high p-values (> 0.05) and this indicates that no significant autocorrelation remained in the residuals and that the models adequately captured the time series dynamics. The MA roots for each country satisfied the invertibility condition and this confirmed that the moving average structures are stable and the models are uniquely identifiable. Similarly, all AR roots were below unity showing that the autoregressive parts are stationary. However, Côte d'Ivoire's largest AR root (0.9974) lies very close to the unit circle, suggesting near non-stationary behavior and long-lasting persistence of shocks compared to Ghana and Nigeria. Finally, the residual variance was lowest for Côte d'Ivoire ($\sigma^2 \approx 4.6$ million), implying a relatively better fit compared to Ghana and Nigeria.

4.2. Interpretation of ARIMA Parameters

Beyond model adequacy, the differences in ARIMA specifications across countries also give useful insights. Both Ghana and Nigeria required second-order differencing. This means their data showed stronger non-stationarity and more structural changes over time compared to Côte d'Ivoire, which only required first-order differencing. In simple terms, Ghana and Nigeria's series were less stable and needed more adjustments to become stationary, which may reflect greater exposure to repeated shocks or policy changes. On the other hand, Côte d'Ivoire's model required a higher autoregressive order, meaning that past values have a stronger and longer-lasting influence on the present. This suggests that shocks in Côte d'Ivoire tend to persist for a longer time, even if the overall series is relatively more stable.

From a policy perspective, this implies that Ghana and Nigeria may need measures aimed at reducing frequent fluctuations, while Côte d'Ivoire may require strategies that focus on managing the long-lasting effects of shocks once they occur. The table 3 below, presents estimated parameters of the selected ARIMA models and table 4, a summary of diagnostic tests. Expressing the models in backshift notation shows the AR and MA structures and that allows for direct comparison of their behaviours across the three settings.

Table 4 - Parameter Estimates for selected models

Country	**Parameter estimates**
Ghana	AR(1) = -0.6264 MA(1) = -0.4529 MA(2) = -0.1234 MA(3) = -0.4237
Nigeria	AR(1) = -0.6392 AR(2) = -0.6494 MA(1) = -0.3557 MA(2) = 0.3557 MA(3) = -0.9999
Cote d'Ivoire	AR(1) = 0.9281, AR(2) = 0.2704 AR(3) = -0.3877, AR(4) = 0.1865, MA(1) = -0.9654

Using the estimates above, we have the following equations for each country:

Ghana – ARIMA (1,2,3)

$$(\mathbf{1}+\mathbf{0.6264}\boldsymbol{B})(\mathbf{1}-\boldsymbol{B})^{\mathbf{2}}\boldsymbol{Y}_{\boldsymbol{t}}=(\mathbf{1}-\mathbf{0.4529}\boldsymbol{B}-\mathbf{0.1234}\boldsymbol{B}^{\mathbf{2}}-\mathbf{0.4237}\boldsymbol{B}^{\mathbf{3}})\boldsymbol{e}_{\boldsymbol{t}} \qquad \mathbf{(4)}$$

Nigeria – ARIMA (2,2,3)

$$(\mathbf{1}+\mathbf{0.6392}\boldsymbol{B}+\mathbf{0.6494}\boldsymbol{B}^{\mathbf{2}})(\mathbf{1}-\boldsymbol{B})^{\mathbf{2}}\boldsymbol{Y}_{\boldsymbol{t}}=(\mathbf{1}-\mathbf{0.3557}\boldsymbol{B}+\mathbf{0.3557}\boldsymbol{B}^{\mathbf{2}}-\mathbf{0.9999}\boldsymbol{B}^{\mathbf{3}})\boldsymbol{e}_{\boldsymbol{t}} \qquad \mathbf{(5)}$$

Cote d'Ivoire – ARIMA (4,1,1)

$$(\mathbf{1}-\mathbf{0.9281}\boldsymbol{B}+\mathbf{0.2704}\boldsymbol{B}^{\mathbf{2}}+\mathbf{0.3877}\boldsymbol{B}^{\mathbf{3}}-\mathbf{0.1865}\boldsymbol{B}^{\mathbf{4}})(\mathbf{1}-\boldsymbol{B})\boldsymbol{Y}_{\boldsymbol{t}}=(\mathbf{1}-\mathbf{0.9654})\boldsymbol{e}_{\boldsymbol{t}} \qquad \mathbf{(6)}$$

The above equations reveal that while Ghana and Nigeria's series required more differencing, Côte d'Ivoire's dynamics are explained more by past values. Nigeria shows the strongest echo of past shocks (high MA influence) whereas Côte d'Ivoire reflects persistence through long AR lags.

4.3. Forecasting

The following plot in Figure 4 indicates that the TB mortality cases will stabilize around the average level of the historical data. This is shown by the flat trajectory of the line. In the future, the ARIMA (1,2,3) model expects that there will be little to no growth and possibly decline in the number of TB mortalities. However, the confidence boundaries spread overtime and could be an indication of uncertainty as time goes on.

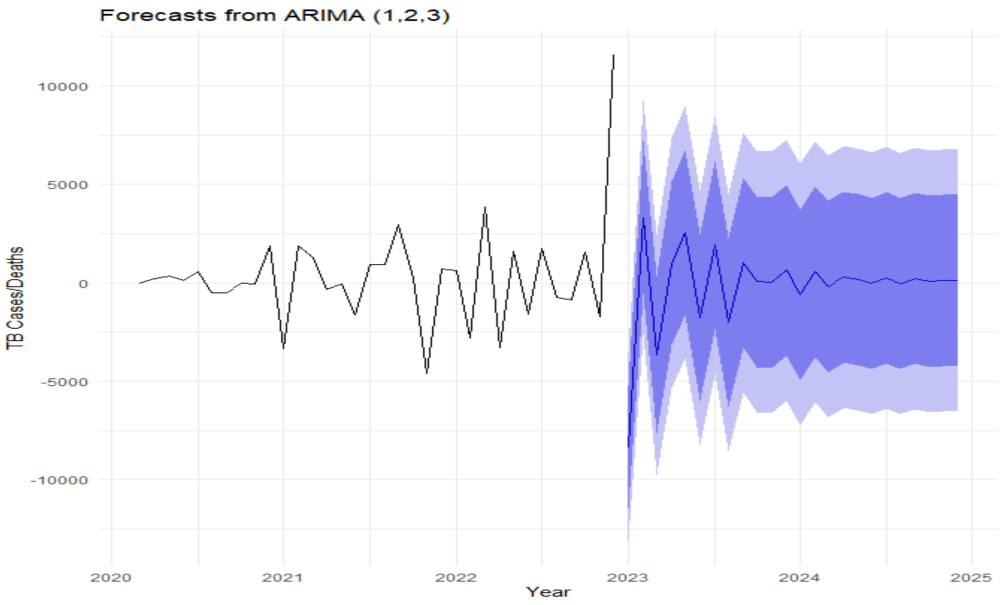


Figure 4 - Forecast plot for Ghana

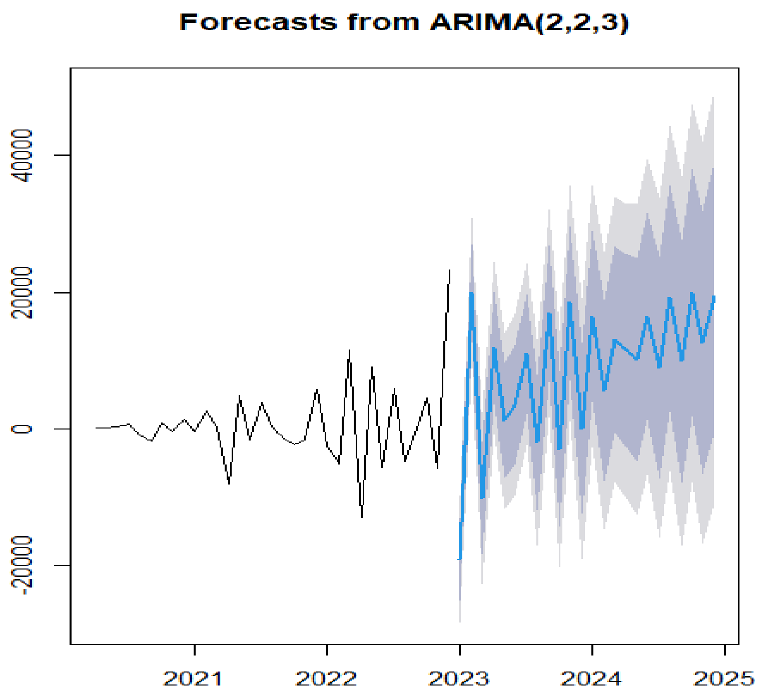


Figure 5 - Forecast plot for Nigeria

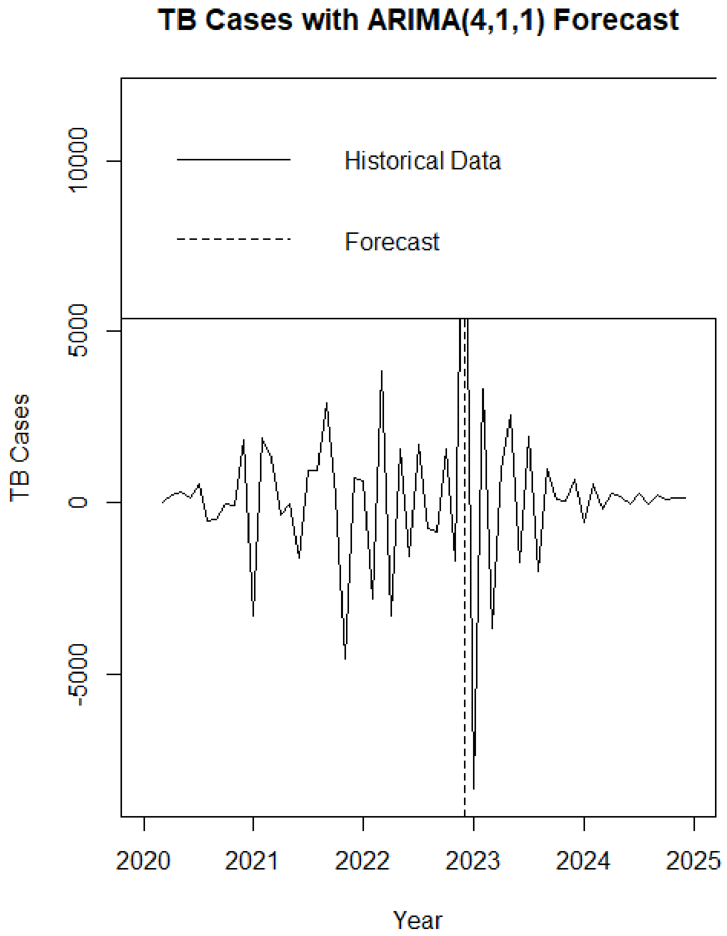


Figure 6 - Forecast plot for Cote d'Ivoire

From the above forecast plots in figure 5 & 6, it can be seen that the ARIMA (4,1,1) model predicts a much more stable number but a gradual decrease as time goes on over the next two years. The model might possibly be capturing underlying factors possibly due to the high HIV/AIDs incidence in the country and changes in population dynamics and so on. Nigeria's ARIMA (2,2,3) model suggests fluctuating periods of TB mortality cases in Nigeria. However, there is some degree of uncertainty to the forecast as shown in the forecast plot with the high fluctuations in the forecast and that could reflect the dynamics of TB transmission and control in Nigeria.

5. Conclusions

The study showed that for Cote d'Ivoire, the ARIMA (4,1,1) was the best predictive model. The model projects a gradual downward trend in cases through 2025. This could mean that the current Tuberculosis control in the country is good enough and can even be better in order to avoid complacency. This should be done to mitigate the possible rise in disease and mortality burdens emanating from Tuberculosis. Since the forecast provides a valuable projection, the time frame within which the data was accessed was deemed to be short hence the absence of strong historical trends and the inherent limitations of the forecasting.

This stresses on the need to consider adaptive measures. Ghana's ARIMA (1,2,3) model predicts a very stable trend but with a slightly upward trajectory. Compared to the other countries, Ghana's model exhibited less dynamism in its forecast. This could possibly mean that the Transmission of TB in Ghana could be influenced by more predictable factors or the current control efforts being put in place controls the epidemic much better. This again suggests, that Ghana has a relatively robust health management system and that the data reporting in Ghana is also better relative to these countries. Ghana's ARIMA (1,2,3) seems to be more reliable and complete. Lastly, the ARIMA (2,2,3) model applied to Nigeria's TB case data informs a fluctuating trend where there could be increases or decreases in the TB mortality cases. This could mean that there is a complex relationship and interplay of factors and may be more challenging to predict. The wide prediction gap in the forecast underscores the big uncertainty related to the forecast. Nigeria's model informs us that there is a dynamic nature which points the need for adaptive and better public health interventions.

Considering the short scope of the study, it would be better to extend the analysis to cover a longer period of time in order to capture more robust long-term trends, fish out cyclical and seasonal patterns which would improve the model accuracy. Furthermore, when data is available, including socio-economic and health system indicators which could be covariates into predictive models like the ARIMAX or GARCH models will help assess the influence of these variables on TB mortality trends. Future work could again investigate potential links between Tuberculosis trends and seasonal or climatic factors.

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Conflict of Interest Declaration

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report.

References

1. Adu, P. A., Spiegel, J. M., & Yassi, A. (2021). Towards TB elimination: how are macro-level factors perceived and addressed in policy initiatives in a high burden country?. *Globalization and Health*, 11.
2. Allard, R. (1998). Use of time-series analysis in infectious disease surveillance. *Bulletin of the World Health Organization*, 327.

3. Barter, D. M., Agboola, S. O., Murray, M. B., & Bärnighausen, T. (2012). Tuberculosis and poverty: the contribution of patient costs in sub-Saharan Africa–a systematic review. *BMC public health*, 980.
4. Box, G. E., & Jenkins, G. M. (1970). Time series analysis: forecasting and control.
5. Busari, M., & Bolanle. (2025). Integrating social determinants into predictive models for us public health forecasting.
6. Corbett, E. L., Marston, B., Churchyard, G. J., & De Cock, K. M. (2006). Tuberculosis in sub-Saharan Africa: opportunities, challenges, and change in the era of antiretroviral treatment. *The Lancet*, 926–937.
7. Desai, A. N., Kraemer, M. U., Bhatia, S., Cori, A., Nouvellet, P., Herringer, M., ... & Lassmann, B. (2019). Real-time epidemic forecasting: challenges and opportunities. *Health security*, *17*(4), 268-275.
8. Falzon, D., Zignol, M., Bastard, M., Floyd, K., & Kasaeva, T. (2023). he impact of the COVID-19 pandemic on the global tuberculosis epidemic. *Frontiers in Immunology*, 14.
9. Hssayeni, M. D., & Ghoraani, B. (2024). Deep Regression Modeling for Imbalanced and Incomplete Time-Series Data. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 3767-3778.
10. Iddrisu, A. K., Amikiya, E. A., & Bukari, F. K. (2024). Spatio-temporal characteristics of Tuberculosis in Ghana. *F1000Research*, 11, 200.
11. Imai, C., Armstrong, B., Chalabi, Z., Mangtani, P., & Hashizume, M. (2015). Time series regression model for infectious disease and weather. *Environmental research*, 319-327.
12. Lipton, Z. C., Kale, D. C., & Wetzel, R. (2016). Modeling missing data in clinical time series with rnns. *Machine Learning for Healthcare*, 253-270.
13. Menzies, N. A., McQuaid, C. F., Gomez Guillen, G., & Houben, R. M. (2018). Guidance for country-level TB modelling. *World Health Organization, & Analysis Consortium.*
14. N'Guessan, K., Ouassa, T., Dean, A. S., Alagna, R., Adagra, G. D., Ibode, V., & ... & Kouakou, J. (2018). Multidrug-Resistant tuberculosis in Côte d'Ivoire from 1995 to 2016: results of national surveys. *European Journal of Microbiology and Immunology*, 91-94.
15. Naylor, T. H., Seaks, T. G., & Wichern, D. W. (1972). Box-Jenkins methods: An alternative to econometric models. *International Statistical Review/Revue Internationale de Statistique*, 123-137.
16. Ogbo, F. A., Ogeleka, P., Okoro, A., Olusanya, B. O., Olusanya, J., Ifegwu, I. K., ... & Page, A. (2018). Tuberculosis disease burden and attributable risk factors in Nigeria, 1990–2016. *Tropical medicine and health*, *46*(1), 34.
17. Ogunniyi, T. J., Abdulganiyu, M. O., Issa, J. B., Abdulhameed, I., & Batisani, K. (2024). Ending tuberculosis in Nigeria: a priority by 2030. *BMJ Global Health*, 9(12).
18. World Health Organization. (2022). *Global tuberculosis report 2021: supplementary material.*
19. World Health Organization. (2022). Guidance for national strategic planning for tuberculosis. *World Health Organization.*