Infection and Drug Resistance

ORIGINAL RESEARCH

Predicting Tuberculosis Incidence and Its Trend in Tigray, Ethiopia: A Reality-Counterfactual Modeling Approach

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Background: The Tigray region of Ethiopia, which has been affected by civil war from 2020 to 2022, is facing an increase in tuberculosis in the damaged health system. Our study employed mathematical modeling to predict the incidence of tuberculosis and its trends during the war and in the post-conflict setting of Tigray, Northern Ethiopia.

Methods: We predicted the incidence of tuberculosis from 2020 to 2025 in Tigray using the SEIRD model in the context of the recent war and compared it with its counterfactual trend in the absence of war. The counterfactual trend was forecasted using an autoregressive integrated moving average (ARIMA) model for stationary time-series data. We performed rolling origin cross-validation for ARIMA and sensitivity analysis for the SEIRD model. The initial tuberculosis data and model parameters were obtained from the Institute for Health Metrics and Evaluation and the literature, respectively.

Results: Between 2000 and 2017, the incidence of tuberculosis in Tigray decreased at an annual rate of 3.0%. Shortly before the war, the incidence of tuberculosis in the region was 178 per 100,000 people. In a counterfactual scenario where there was no war, the incidence was projected to decrease to 144.3 in 2022 and 126.3 in 2025. However, owing to the war and siege, the SEIRD-projected incidence of tuberculosis would have increased to 965.5 (95% CI: 958.5–972.7) in 2022 and 372.4 (95% CI: 367.7–376.6) in 2025. Over 800 cases of tuberculosis per 100,000 people were attributed to the war in 2022. In the postwar period, the incidence is projected to decrease by 30% by 2023.

Conclusion: The Tigray War reversed a two-decade decline in tuberculosis cases, causing a five-fold increase compared to the no-war scenario. Urgent interventions are needed to support tuberculosis prevention, testing, and treatment, particularly in key and vulnerable populations.

Keywords: war, tuberculosis, incidence, mathematical model, Ethiopia

Introduction

Tuberculosis (TB) is a significant global health concern and is ranked as the second most lethal infectious disease.[1] In previous years, the global burden of TB has been decreasing; however, since 2020, the figure has increased by 3.9% in 2022, with 10.6 million people falling ill.[1] In 2021, Ethiopia ranked fifteenth among the high-burden TB countries.[2] Between 2010 and 2020, the country saw an average annual drop of 5% in TB incidence.[3]

Despite Ethiopia's progress in reducing the incidence of TB at the national level, the war in the Tigray region has resulted in a data blackout, making it difficult to accurately determine the burden of the disease in the region. The Tigray War caused partial or complete destruction of health facilities, disruptions in supply chains, and limited access to essential diagnostic and treatment services.[4–6] During the war, only 21% of patients with chronic diseases were able to access healthcare services in the region.[7] For two years, surveillance data were not collected in the region, including information on TB. The absence of data made it difficult to determine how widespread TB was in Tigray, leaving

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a significant gap in Ethiopia's overall understanding of its burden. Evidence shows that the Tigray War worsened existing TB challenges in the region, potentially leading to an increase in both incidence and death.[8]

In TB high-burden settings, such as Ethiopia, where national disease notification and vital registration systems lack quality, the World Health Organization recommends a prevalence survey as the most reliable way to determine TB burden.[9] However, securing financial support for TB research in the post-conflict period often becomes challenging due to limited resources, with priority given to rebuilding and revitalizing healthcare programs. Despite funding constraints, studying the impact of armed conflict in post-conflict settings can yield crucial evidence for designing data-driven solutions to community health problems, ultimately improving health-care outcomes.[10] In other settings, analysis of health data has led to the development of effective interventions or control strategies for TB.[11]

Predicting the course of TB and developing effective control strategies are critical global health challenges. Mathematical models have been developed as important tools to solve these complex dynamics.[12] ReVelle introduced a probabilistic method to calculate the infection rate, a concept that underpins most current TB epidemic models and provides a deeper understanding of the transmission dynamics.[13] A SEIR-type model, which considers susceptible, exposed, infected, and recovered populations, was presented by Castillo-Chavez to investigate the transmission of TB.[14] This model is relevant to proactive disease prevention and control. To date, there have been no robust predictions for TB incidence and trends in conflict-affected regions, such as Tigray, Ethiopia. Hence, this study could be relevant in Tigray's context, in which the conflict itself raises concerns about future increases in the TB burden. Therefore, we used mathematical modeling to predict the incidence and patterns of TB in Tigray, Northern Ethiopia.

Methods

Study Setting

Tigray is Ethiopia's northernmost region; Eritrea borders it to the north, Amhara to the south, Afar to the east, and Sudan to the west. The region is home to over six million people.[15] Before the start of the war, Tigray had 741 health posts, 224 health centers, 24 primary hospitals, 14 general hospitals, and two referral hospitals.[16] In addition, there were 750 private health facilities, including clinics, hospitals, and pharmacies.[16] All public health facilities provide free testing and treatment for TB, whereas private medical facilities only provide diagnostic services. Since the start of the war in November 2020, over 80% of health facilities have been damaged, and only 3.6% of the remaining healthcare facilities function at full capacity.[7,17]

Data Sources

Annual incidence data of TB from 2000 to 2019 were collected from the Institute for Health Metrics and Evaluation (https://vizhub.healthdata.org/gbd-results/).[18] The institute collects health data from hospitals, governments, surveys, and databases around the world. It provides researchers and policymakers with access to the most recent Global Burden of Disease input sources and results. It also creates opportunities for discussing population health based on the best available data and acknowledging the contributions of data owners.

Empirical Analysis

Three scenarios were considered to estimate the incidence of TB in the Tigray region of Ethiopia from 2020 to 2025. Had there been no war in Tigray (the counterfactual), the presence of war and post-war settings (realistic approach) were assumed to forecast the incidence of the disease. The purpose of this counterfactual method is to establish historical control data with its hypothetical trajectory.

The Counterfactual Approach

An autoregressive integrated moving average (ARIMA) model was employed to forecast the incidence of TB in the region from 2020 to 2025. This was done to generate control data by analyzing historical trends in the study setting in the absence of war. The ARIMA model is an integral component of time-series analysis that analyzes data from previous periods to estimate forthcoming values and facilitate future decision-making.[19] ARIMA is a commonly used model when dealing with nonstationary time series in health data.[20] When discussing a non-seasonal ARIMA model, the fundamental notation is (p, d, q), where p, d, and q are positive integers.

– p = Order of the AR part of the model
– d = Degree of non-seasonal differencing; and
– q = Order of the MA part of model.[21]

The Time-Series Stationarity

The time-series stationarity of the reported TB data was examined using the Augmented Dickey-Fuller (ADF) test at a p-value of 0.05. First, we check the stationarity of the sample data. Next, we smoothed the vector using first- and second-order regular differences to make it stationary.

Selecting an Appropriate Model Order

The autocorrelation coefficient (ACF) and partial autocorrelation coefficient (PACF) of the stationary data sequence were plotted to identify optional model parameters (p, d, q) and to identify one or more alternative models.

Residual Diagnostics

We checked whether the autocorrelations of the residuals were significantly different from what would be expected from a white noise process using the Ljung-Box test. A model passes the Ljung–Box test if the p-value is greater than 0.05.

Model Suitability/Selection

We evaluated the forecast accuracy using a time-series cross-validation procedure. Owing to our short time-series data, we did not split it into training and test sets. Instead, we used a rolling origin technique, in which the forecasting origin was updated successively, and the forecasts were produced from each origin. We began with 14 observations in the training dataset (data from January 2000 to December 2013) and finished with 17 data points (Supplementary R scripts). This technique allows for obtaining several forecast errors for time series, which provides a better understanding of how the models perform.[22] We utilized accuracy measures, such as the mean absolute error (MAE) and root mean squared error (RMSE), to determine the best forecasting model. The model with the lowest RMSE value that passed the Ljung-Box test (p-value < 0.05) using all available data was chosen for prediction.

The ARIMA model was developed using the "tseries" and the "forecast" packages in the R software.

The Realistic Approach

To illustrate the transmission of the disease and forecast its progression during and after the war, we used a SEIRD epidemic model with demographics including birth and death rates. The siege and containment implemented by the federal government in the study area has created a closed population. This model comprises five compartments: susceptible (S(t)), exposed (E(t)), infected (I(t)), recovered (R(t)), and dead (M(t)) compartments.

Infection with Mycobacterium TB complex (MTB) is the first step in the development of TB in susceptible individuals. The illness may remain dormant or develop into an active TB. Although most individuals experience active TB years after infection, the risk of contracting the disease is highest in the first year following the infection.[23] The infection rate denoted by βSI (using the mass action law) was divided into two categories. A portion of pβSI results in immediate active cases (fast progression), while the rest (1-p) βSI leads to latent TB cases with a low risk of progressing to active TB (slow progression).[14] At any time, individuals who recovered from TB are susceptible to the disease. The disease transmission and population dynamics is illustrated in diagram (Figure 1).

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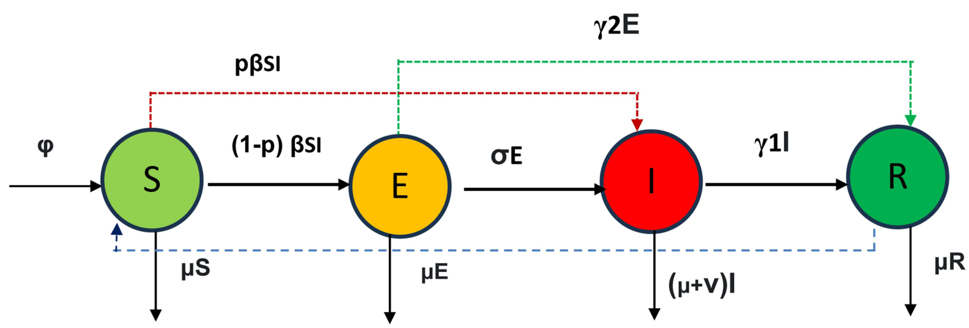

Figure 1 Flow diagram for the SEIRD model.
Abbreviations: P, proportion; φ, phi; μ, mu, β=beta; σ, sigma; γ, gamma; v, nu; S, susceptible; E, exposed; I, infected; R, recovered.

The total population is denoted by

$$N = \mathrm{S(t) + E(t) + I(t) + R(t) + M(t)}$$

for all t. The following equations were used to compute the number of individuals in each compartment at time (t):

$$\frac{\mathrm{dS(t)}}{dt} = (\varphi - \mu\,\mathrm{S}) - \frac{\beta\,\mathrm{S(t)*I(t)}}{\mathrm{N}} + (\gamma_2\mathrm{I(t)} + \gamma_1\mathrm{E(t)})$$

$$\frac{dE(t)}{dt} = (1 - \mathrm{P}) * \frac{\beta\,\mathrm{S(t)*I(t)}}{\mathrm{N}} - \sigma\,\mathrm{E(t)} - \gamma_1\mathrm{E(t)} - \mu\,\mathrm{E}$$

$$\frac{\mathrm{dI(t)}}{dt} = p * \frac{\beta\,\mathrm{S(t)*I(t)}}{\mathrm{N}} + \sigma\,\mathrm{E(t)} - \gamma_2\mathrm{I(t)} - \nu\,\mathrm{I(t)} - \mu\,\mathrm{I}$$

$$\frac{\mathrm{dR(t)}}{dt} = \gamma_2\mathrm{I(t)} + \gamma_1\mathrm{E(t)} - \mu\,\mathrm{R}$$

$$\frac{\mathrm{dM(t)}}{dt} = \mu\,\mathrm{S} + \mu\,\mathrm{E} + \mu\,\mathrm{I} + \nu\,\mathrm{I} + \mu\,\mathrm{R}$$

$$\mathrm{S(0)} \geq 0, \mathrm{E(0)} \geq 0, \mathrm{I(0)} \geq 0, \mathrm{R(0)} \geq 0, \mathrm{M(0)} \geq 0$$

The symbols and definitions of these parameters are listed in Table 1.

Estimation of Model Parameters

Models were solved numerically using R 4.2. This was done using the "deSolve" command, which is specifically designed for solving ordinary differential equations (ODEs) that result from partial differential equations. These equations were converted to "ODEs" by numerical differencing.

The model parameters were adjusted based on TB incidence data obtained from GBD.[18] Approximately 5% of immunocompetent individuals develop active TB within two years of MTB infection.[24] These individuals are referred to as fast progressors. The crude birth rate (Φ) in Ethiopia was 0.03 in 2020;[25] we used this figure for the region. During the war, the natural death rate in Tigray (μ) was estimated at approximately 0.032.[26] The model parameters are listed in Table 1. Finally, incidence was calculated by dividing the number of TB-infected people by the total population at risk.

Based on historical data and projections for service availability, we assumed an infection rate (to active TB) of 3%, recovery rate of 70% and a TB-related death rate of 15% in the postwar period, reflecting anticipated changes in access to diagnotic and treatment services.

Table 1 SEIRD Model Parameters and Initial Data During the War

Parameter	Description	Initial Data	Source
P	Proportion of fast progressors	0.05	CDC 2014[24]
φ	Birth rate	0.03	Macrotrend 2023[25]
μ	Natural death rate	0.032	Magana Tony 2021[26]
β	Rate of progression to latent TB	0.3	GBD 2019[18]
σ	Rate of progression to active TB	0.05	CDC 2014[24]
γ_1	The recovery rate from latent TB	0.19	Richards AS et al, 2021[27]
γ_2	The recovery rate from active TB	0.5	Ahmed T et al, 2020[28]
ν	TB-induced death rate	0.389	Richards AS et al, 2021[27]
S (0)	The initial number of susceptible	4252965	Calculated
E (0)	The initial number of exposed	1949713	GBD 2019[18]
I (0)	The initial number of infected	11076	GBD 2019[18]
R (0)	The initial number of recovered	7088	Calculated
M (0)	The initial number of dead	1721	GBD 2019[18]
N	Total population	6,222,472	GBD 2019[19]

Abbreviations: P, proportion; φ, phi; μ, mu, β=beta; σ, sigma; γ, gamma; ν, nu; S, susceptible; E, exposed; I, infected; R, recovered; M, dead; N, total population.

Sensitivity Analysis

Sensitivity analysis measures the extent to which changes in the input values of a variable affect the output of the mathematical model.[29] Therefore, we estimated the number of incident TB cases for various values of the infection to active TB rate (σ) and the recovery from TB rate (γ) in the SEIRD model. We varied the TB infection rate from 0.03 to 0.07 and the recovery rate from 0.4 to 0.6 taking the ill impact of the war in healthcare and similar evidence from other war-affected settings. These parameters had the greatest influence on the behavior of the model. We used the median rates for prediction.

Results

Prewar TB Incidence Status

Between 2000 and 2017, the average annual incidence of TB in Tigray was 229.3 per 100,000 people. This figure shows a declining trend, dropping from 294.5 per 100,000 (95% CI: 255.1–336.8) in 2000 to 176 per 100,000 (95% CI: 152.0–202.8) in 2017. During this period, the annual rate of decrease was 3.0%. However, this decreasing trend was interrupted in 2018 and 2019 (Figure 2). The absolute number of TB cases in Tigray increased 6.2% between 2015 and 2019. Source: GBD 2019 study.

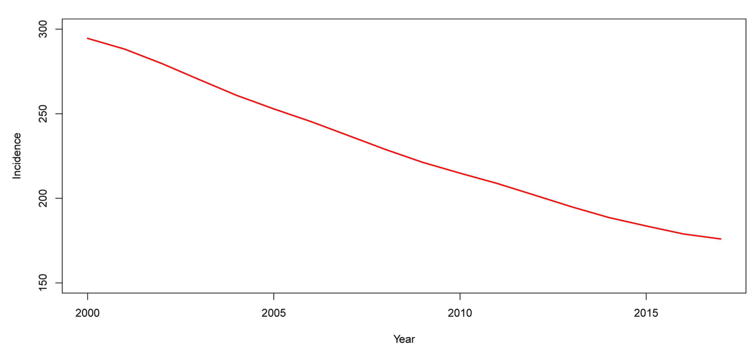

Figure 2 Graph of reported TB incidence in Tigray from 2000 to 2019.

ARIMA Model/Counterfactual Findings

Our ARIMA forecast was based on reported TB incidence from 2000 to 2017. The time series for the reported TB cases became stationary (ADF test: t = −5.96, P-value < 0.01) after the second-order regular difference. In this study, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the stationary (differenced) series did not help to identify the p and q parameters (Fig S1). Therefore, we used an automated algorithm, specifically auto. arima () in the forecast package for R, to identify the ARIMA model terms.

Based on our data, the optimal ARIMA model was ARIMA (2,2,0). The residual plots depicted the distribution of the differences between the predicted and actual values (Figure 3). To ensure the suitability of the model for predicting future TB cases, we conducted a Box-Ljung test using white noise. This test assesses whether the residuals exhibit significant patterns, indicating a lack of randomness. The resulting p-value of 0.8668 confirmed that the reported TB cases exhibited no significant lagged autocorrelations, thereby demonstrating the effectiveness of the model for future TB prediction.

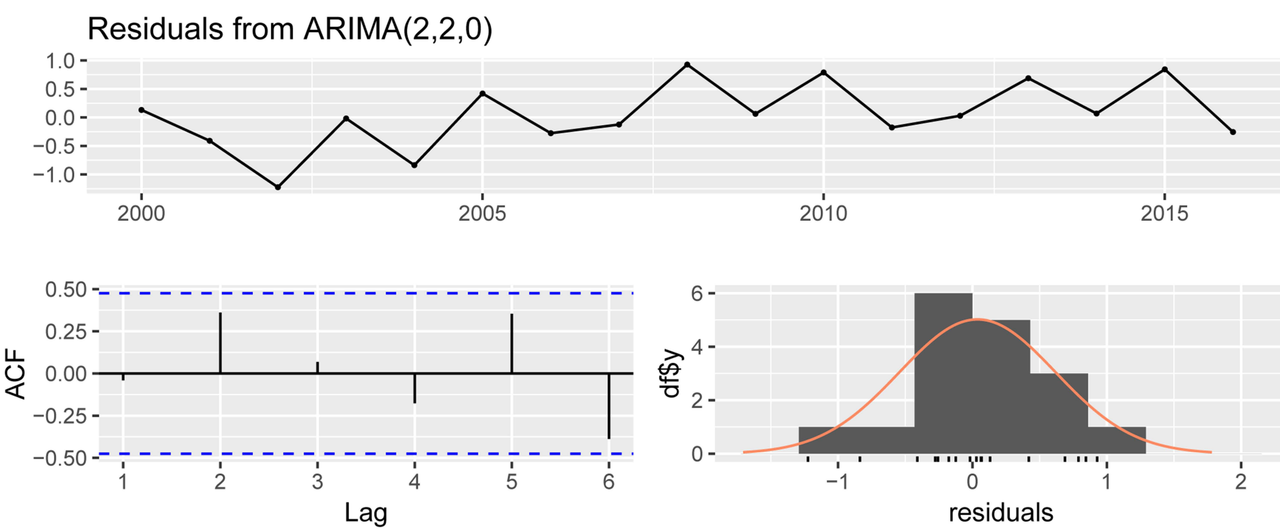

Figure 3 Residual check for the final model.
Abbreviations: ARIMA, autoregressive integrated moving average; ACF, autocorrelation function.

Evaluation of Forecast Accuracy

We used a rolling origin cross-validation to assess the performance of the ARIMA model. We began with 14 observations in the training dataset (data from January 2000 to December 2013) and ended with 17 datasets. The RMSE is smaller (0.08) for origin three, with 54% out-of-sample model accuracy. Hence these observations were used to forecast the future time horizon (Table 2).

Table 2 Forecast Accuracy Measures Computed Using Rolling Origin Cross-Validation

	Origin 1 (2014)	Origin 2 (2015)	Origin 3 (2016)
ME	1.86	0.93	−0.08
RMSE	1.86	0.93	0.08
MAE	1.86	0.93	0.08
MAPE	0.46	0.46	0.46

Abbreviations: MAE, mean absolute error; MAPE, mean absolute percentage error; ME, mean error; RMSE, root mean squared error.

According to the ARIMA forecast (Fig S2), in the absence of the war, starting from 178.2 per 100,000 people (95% CI: 153.3–207.9) in 2019, the incidence of TB would have decreased to 144.3 per 100,000 (95% CI: 130.6–157.9) in 2022 and further down to 126.3 per 100,000 (95% CI: 103.1–149.6) in 2025. This is equivalent to a 19% and 29% decrease in incidence by 2022 and 2025, respectively, compared with the 2019 level.

SEIRD Model Findings

We employed the SEIRD model to predict TB incidence during the war (2020–2022) and the postwar period (2023–2025). We did not anticipate a significant shift in the TB incidence rate for 2020 over 2019 because the war started at the end of 2020. Perhaps the two months of war in 2020 offset any reduction that was made in the first ten months of the year.

The table below shows that the projected TB incidence was high in 2022 (966 cases per 100,000 people). At the same time, the number of TB cases attributable to war and blockades was over 800 per 100,000 people in the general population. Despite the peace agreement of November 2022, the war's shadow persisted for several years (Table 3). By 2025, the incidence of TB is projected to be 372.4 per 100,000 individuals.

Our sensitivity analysis for the SEIR model showed that with a constant recovery rate (γ=0.5), increasing infection rates led to a consistent increase in projected TB cases across all periods. The year 2022 had the highest projections, ranging from 41,244 cases at a low transmission rate (σ=0.03) to 89,948 cases at a high rate (σ=0.07). In contrast, when the infection rate remained constant (σ=0.05), increasing recovery rates resulted in a decline in projected TB cases for all periods. Again, the year 2022 showed the highest figure, with 71,951 cases at a lower recovery rate (γ=0.4) and 60,992 TB cases at a higher recovery rate (γ=0.6).

Trend of TB Incidence

From 2000 to 2017, TB incidence steadily declined by an average of 3% annually. However, there is a steep rise from 178.0 per 100,000 people in 2019 to a peak in 2022, with an incidence of 966 cases (95% CI: 958.5–972.7). This change is equivalent to a 442% increase compared to the prewar level. However, in the postwar period, there was a 29.5% decline by 2023. Furthermore, the model projects a subsequent decline in incidence, dropping steadily to 372.4 (95% CI:367.7–376.6) by 2025 (Figure 4).

Table 3 Comparison of TB Incidence Predictions by Real and Counterfactual Models (2021–2025) per 100,000 People

Year	ARIMA Model (Counterfactual)			SEIRD Model (Real Prediction)			Excess TB Cases
	Point TB Incidence	Lower 95% CI	Higher 95% CI	Point TB Incidence	Lower 95% CI	Higher 95% CI	
2020	154.9	145.8	163.9	178.0	174.9	181.4	23.1
2021	149.7	138.4	161.0	905.3	897.8	912.4	755.6
2022	144.3	130.6	157.9	965.5	958.5	972.7	821.2
2023	138.4	121.9	154.8	681.0	674.7	687.5	542.6
2024	132.2	112.5	152.0	498.3	492.9	503.2	366.1
2025	126.3	103.1	149.6	372.4	367.7	376.6	246.1

Abbreviations: ARIMA, autoregressive integrated moving average; CI, confidence interval; SEIRD, susceptible, exposed, infected, recovered and dead; TB, tuberculosis.

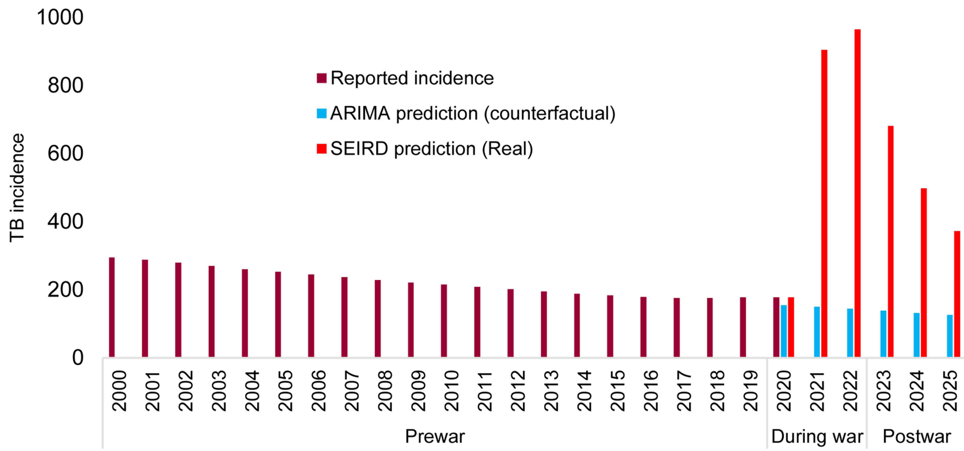

Figure 4 Trends in TB incidence in real and counterfactual scenarios in Tigray, Ethiopia.
Abbreviations: ARIMA, autoregressive integrated moving average; SEIRD, susceptible, exposed, infected, recovered, and dead; TB, tuberculosis.

Discussion

Addressing TB challenges and shifting from control to elimination requires intensified research and tailored solutions that are specific to each country's epidemic.[30,31] In this study, we predicted TB incidence and its trend in Tigray, Northern Ethiopia, using ARIMA and SEIRD models to quantify the potential impact of war and siege on the TB burden in the region.

From 2000 to 2017, Tigray reported an average annual decline of 3% in incidence of TB. During the same period, Ethiopia achieved a 5% annual drop in TB incidence. However, Tigray and the nation fell short of the 15% annual rate of reduction required to eliminate TB by 2035.[3] The reason may be multifactorial; however, poverty is the main risk factor for TB in the study setting. In 2015–2016, the Tigray, Benishangul Gumuz, and Amhara regions had the highest poverty rates in Ethiopia (27%, 26.5%, and 26.1%, respectively).[32] This suggests the need for poverty reduction initiatives to effectively combat TB and expedite its elimination, not only in Tigray, but across Ethiopia.

Shortly before the war, Tigray had a TB incidence of 178 cases Per 100,000 people.[18] Our projection indicates that without conflict, this figure would have declined by 19.0% and 29.1% by 2022 and 2025, respectively. However, due to war and blockade, the predicted TB incidence rose steeply by 442% in 2022 and 109% in 2025 compared to pre-war levels. This alarming increase indicates an opposite trend compared to the global plan for a 50% reduction in TB incidence by 2025.[30] In the postwar period, the SEIRD forecast showed a more significant decreasing trend in TB incidence than the ARIMA forecast. This finding suggests both the resumption of TB care services and the presence of potentially unreported TB deaths caused by the lasting impact of the war and the ongoing famine in the region. According to evidence from verbal autopsies, TB and HIV are the main causes of adult mortality in Ethiopia.[33]

"War is the enemy of health"[34] and the Tigray war is a testimony to this truth. War diverts essential and often limited resources away from those who depend on them for survival and toward its efforts.[35] Previous studies on armed conflict have shown an increase in TB incidence and mortality.[36,37] This has resulted from an increased risk of transmission, reactivation of latent TB infection, or exacerbation of active disease as a result of starvation, overcrowding, disruption of healthcare services, or discontinuation of ongoing therapy for HIV co-infection.[38,39]

Ethiopia is in a protracted civil war, from the two-year bloody war in Tigray to the ongoing instability in Amhara and Oromia.[40] This instability, together with rampant famine affecting an estimated 15.4 million people in 2023, presents a dire situation for future TB control in the country.[41] The Tigray region, which is particularly affected by the severity and duration of conflicts and droughts, faces an even greater challenge. Undernutrition is a major risk factor for TB, with a population attributable fraction of 15% compared to 7.6% for HIV; it weakens the immune system and increases vulnerability to TB infection.[42]

Studies have shown that migration from high-TB-burdened countries can significantly impact the spread of the disease in low- and medium-income countries.[43] This raises concerns for the world because the majority of Ethiopian migrants who travel over the Eastern migration route are from the three rural regions of Tigray, Oromia, and Amhara.[44] Supporting this concern, the recent war in Ukraine caused an increase in TB incidence in Germany, which is one of the destinations for Ukrainian migrants.[45] This shows that migration patterns in Tigray may have an impact on the dynamics of tuberculosis worldwide. A disease does not have borders and can reach anywhere in the world within 36 hours.[46,47] Thus, concerted international efforts are needed to prevent the spread of TB, especially in epidemic-affected areas. The International Health Regulation (2005) has established a framework of standards and responsibilities for nations to collaborate and ensure collective health security.[48] However, it has been criticized for prioritizing reactive measures over preventive measures for infectious diseases.[46] This reactive approach risks prolonged unnecessary suffering from TB. Considering the ambitious End TB goals of a 90% decrease in TB incidence and a 95% reduction in mortality by 2035 compared to 2015,[30] a proactive shift is crucial. This necessitates multi-sectoral action to address the social and economic origins and consequences of TB in addition to the provision of TB care services.

This study has some limitations. First, the ARIMA model assumes that data are normally distributed. To meet this assumption, we excluded outlier TB data from 2018 and 2019, potentially masking the complex dynamics. Second, using literature-based estimates for some initial SEIRD model parameters may have influenced prediction accuracy. We were unable to calibrate the SEIRD model parameters because of data blackout in the study setting. We mitigated this by using a sensitivity analysis to assess the prediction error. Finally, the integration of the models might have its limitations because ARIMA does not inherently capture disease spread mechanisms, and the SEIRD model might not perfectly reflect real-world complexities.

In conclusion, the recent armed conflict in Tigray has increased the TB incidence, with a peak in 2022. Both the counterfactual and reality projections indicate that the region will not achieve the target set for reducing TB incidence by 2025 and 2030. Therefore, immediate action is crucial. Strengthening community healthcare, ensuring TB resources, and supporting key and vulnerable populations are critical for combating this growing threat and protecting public health. To accurately assess the true extent of TB in a region, we strongly recommend conducting prevalence surveys.

Data Sharing Statement

All the data used to generate the results and conclusions were included in this study.

Ethical Approval and Informed Consent

This study was approved by the Institutional Review Board of the College of Health Sciences at Mekelle University (MU-IRB2171/2024). Informed consent was not obtained for this study because we did not collect personal data directly from individuals. We analyzed the aggregate data to maintain anonymity. We have acknowledged the source of the data and their collection methods as we used the existing data. The findings of this study will help in designing effective TB prevention and control strategies for conflict-affected areas.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis, and interpretation, or in all these areas; took part in drafting, revising, or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Disclosure

The authors declare that they have no conflicts of interest in this work.

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