ORIGINAL RESEARCH ARTICLE

Long-Term Trend Analysis of Tuberculosis Cases in The Philippines from 2016 To 2023

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ABSTRACT

Background: Tuberculosis (TB) remains a critical public health issue in the Philippines, a high-burden country. Understanding long-term trends is essential for evaluating the effectiveness of public health interventions. This study aims to analyse long-term trends and seasonal patterns of tuberculosis cases in the Philippines from 2016 to 2023. Using time series methods, it seeks to uncover significant trends, identify critical periods for intervention, generate short-term forecasts, and provide insights to inform and enhance public health strategies.

Methodology: This retrospective time series analysis used monthly TB notification data obtained from the Department of Health's eFOI (electronic Freedom of Information) portal from 2016 to 2023. We used the STL (Seasonal and Trend decomposition using Loess) technique to isolate the long-term and seasonal patterns in TB notifications. Trend assessment was performed with the Mann-Kendall test. We also fitted a seasonal ARIMA(0,1,2)(0,1,1) model to the Box-Cox-transformed series for forecasting.

Results: The analysis revealed a significant upward trend in total TB cases, with a mean monthly increase of 0.80%. Seasonal peaks occurred in March, and troughs in December. The Mann-Kendall test confirmed the statistical significance of these trends (p <0.0001). New and relapse TB cases exhibited consistent increases, while retreatment cases showed a slight decline. The seasonal ARIMA forecasts project peaks of approximately 55,213 cases in March 2024 and 58,964 cases in March 2025, followed by mid-year plateaus and December troughs.

Conclusions: The study identified a persistent increase in TB cases, emphasizing the need for continued and enhanced public health efforts. Forecasted surges in March 2024 and March 2025 highlight the need to intensify active case finding in January-March and to allocate resources adaptively for 2024-2025. Seasonal patterns highlight critical periods for intervention, particularly in the first quarter of the year. These findings can guide more timely resource allocation and targeted TB control measures at both national and local levels.

Keywords: Tuberculosis, Trend analysis, Seasonal decomposition, Philippines, Public health surveillance

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Introduction

Tuberculosis (TB) remains a major public health problem worldwide, and the Philippines continues to be listed among the high-burden countries.[1] Despite ongoing control efforts under the End TB framework[2], TB remains a major cause of illness and death. Understanding long-term trends in national TB notifications is important for evaluating program performance and planning future interventions.

TB burden is shaped by social determinants[3,4] and multimorbidity, including HIV and other coexisting conditions[5-8]. Treatment strategies continue to evolve[9,10], but evaluation of population-level progress still depends on robust surveillance analysis. Studies from other settings have used time-series methods to characterize secular trend and spatial-seasonal patterns in TB notifications[11,12], as well as short-term forecasts and seasonal variation[13,14]. In the Philippines, published work has largely been local or subnational, such as a time-series analysis from Pasig City.[15] To our knowledge, no published study has examined nationwide monthly Philippine TB notifications from 2016 to 2023 using STL decomposition and the Mann-Kendall test. We therefore analysed national monthly TB notifications to characterize long-term trend, seasonality, and short-term forecast patterns that may support program timing and resource allocation.

Methodology

Data Description: The dataset used in this study comprises monthly TB notification data for different registration groups from January 2016 to December 2023, provided by the Epidemiology Bureau of the DOH via the electronic Freedom of Information (eFOI) platform. It includes case counts for New, Relapse, and Other Retreatments categories. "New" cases refer to individuals diagnosed with TB who have never received treatment or who have undergone anti-TB treatment for under one month. "Relapse" cases refer to individuals who completed prior treatment and were deemed cured yet have reacquired active TB. "Other Retreatments" include cases requiring treatment after previous treatment failure, loss to follow-up, or unknown treatment history. The data is based on the location of the screening facility where each case was diagnosed, providing a nationwide perspective on TB trends. Since the dataset is secondary and aggregate, with no personal identifiers, ethical approval was not required. No missing or anomalous values were detected in the dataset, so no imputation or correction was necessary. Because these are passive notifications, the data may underrepresent true TB incidence due to reporting delays or underdiagnosis. Other potential limitations include classification errors between “new” and “relapse” cases, or delays in data entry. This may introduce misclassification or temporal lags, respectively, and should be kept in mind while interpretation.

Software and Packages: All analyses were conducted in R (version 4.2.3) using the packages *readxl* (for data import), *forecast* (for Box-Cox transformation and Seasonal ARIMA), *stats* (for time series objects), *trend* (for the Mann-Kendall test), and *xts* (for time-series handling).

Seasonal and Trend Decomposition using Loess (STL): Seasonal and Trend decomposition using Loess (STL) decomposes a time series into trend, seasonal, and remainder components using locally weighted regression (LOESS).[16] We used STL to separate long-term movement from recurring within-year variation and irregular noise. In R, we specified *s.window = "periodic"* to represent a 12-month seasonal cycle. Seasonal peak and trough months were then identified from the estimated seasonal component using *which.max()* and *which.min()*.

Mann-Kendall Test for Trend Significance: The Mann-Kendall test is a non-parametric procedure for detecting monotonic trend in ordered data.[17,18] We applied *mk.test()* to each STL-derived trend component and interpreted $p < 0.05$ as evidence of a statistically significant monotonic trend.

Seasonal ARIMA: To generate short-term projections, we fitted a seasonal ARIMA model to the Box-Cox-transformed total-case series following standard forecasting procedures.[19] We used *auto.arima()* in R to select the (p,d,q)(P,D,Q) specification by minimizing the Akaike Information Criterion (AIC) with seasonal period set to 12 months. Model adequacy was checked through residual diagnostics, including the Ljung-Box test, and forecasts were back-transformed to the original scale for reporting.

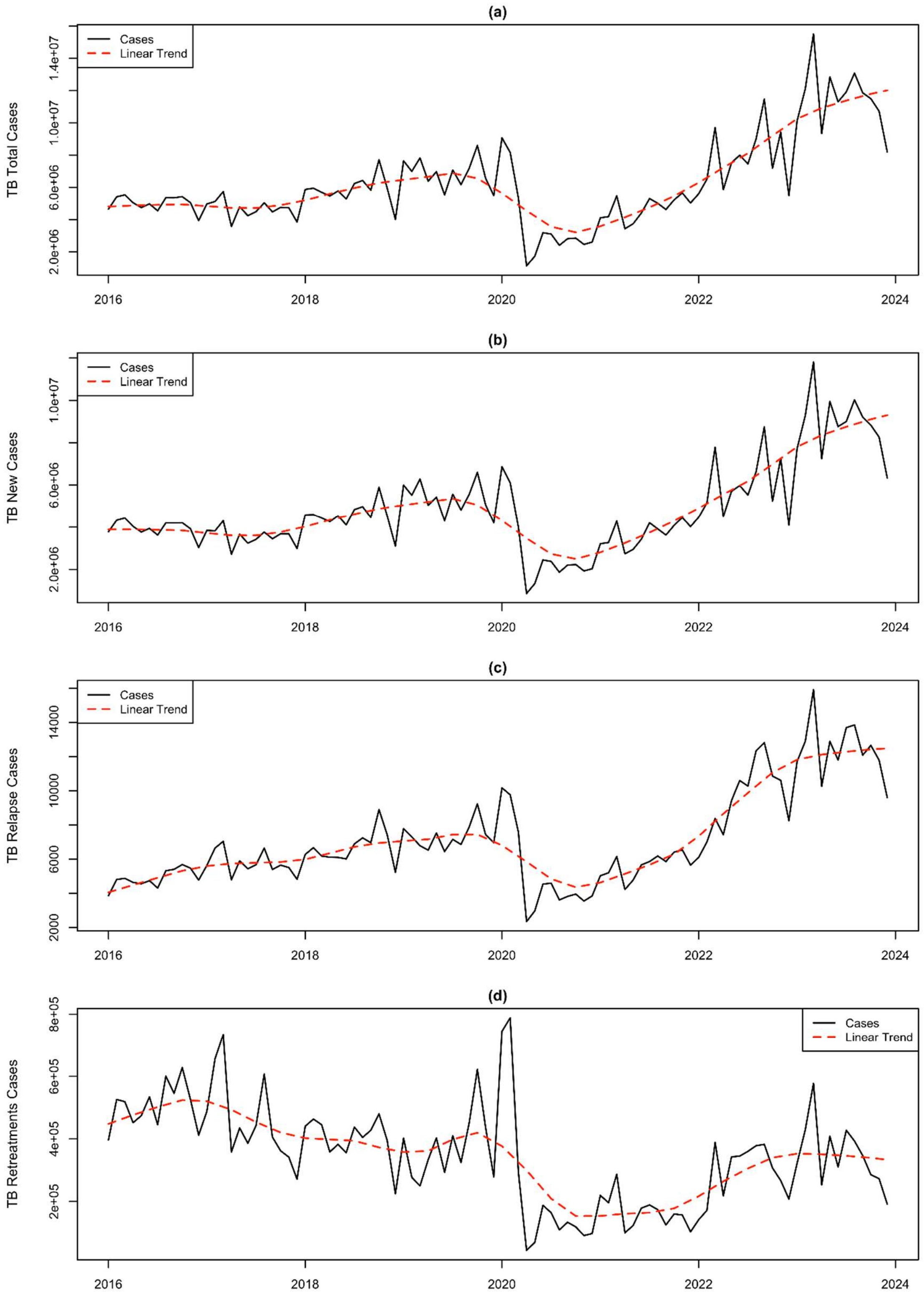
Results

This analysis examined long-term trends and seasonal fluctuations in TB notifications across the Philippines from January 2016 to December 2023, with a total of 3,100,935 TB cases reported during this period. The analysis revealed a steady increase in monthly notified TB cases, rising from 27,182 cases in January 2016 to 39,216 cases in December 2023. The STL method uncovered a significant upward trend in total TB cases, with a mean monthly increase of approximately 0.80% (SD 3.36; 95% CI: 0.11 - 1.49) (Table 1). This trend was statistically significant, as confirmed by the Mann-Kendall test (p <0.001), indicating a persistent rise in TB cases over the study period.

In addition to the overall trend, the analysis highlighted distinct seasonal patterns in TB notifications. The highest peaks in total TB cases occurred in March, with the lowest points in December (Figure 2a). This seasonality was observed across different registration groups, including new cases, relapses, and retreatments, though the specific timing of peaks and troughs varied slightly. For new TB cases, which comprised the majority of the reported cases, the

Table 1: Monthly TB case counts and monthly percent change in the trend for the Philippines

Registration Group	Mean monthly cases	Mean monthly % change in the trend component (SD; 95% CI)	Trend *p*-value (MK)	Seasonal peak/ trough month
Total	32301.41	0.80 (3.36; [0.11, 1.49])	<0.001	March/December
New	27896.09	0.75 (3.36; [0.06, 1.44])	<0.001	March/December
Relapse	3593.24	1.07 (2.68; [0.52, 1.62])	<0.001	March/December
Retreatments	809.9896	-0.54 (4.35; [-1.43, 0.35])	<0.001	February/December



TB = Tuberculosis; STL = Seasonal and Trend decomposition procedure based on LOESS

Figure 1: Monthly TB case notifications in the Philippines (solid line) and the STL-derived trend (dashed line), 2016-2023: a) Total; b) New; c) Relapse; d) Retreatments

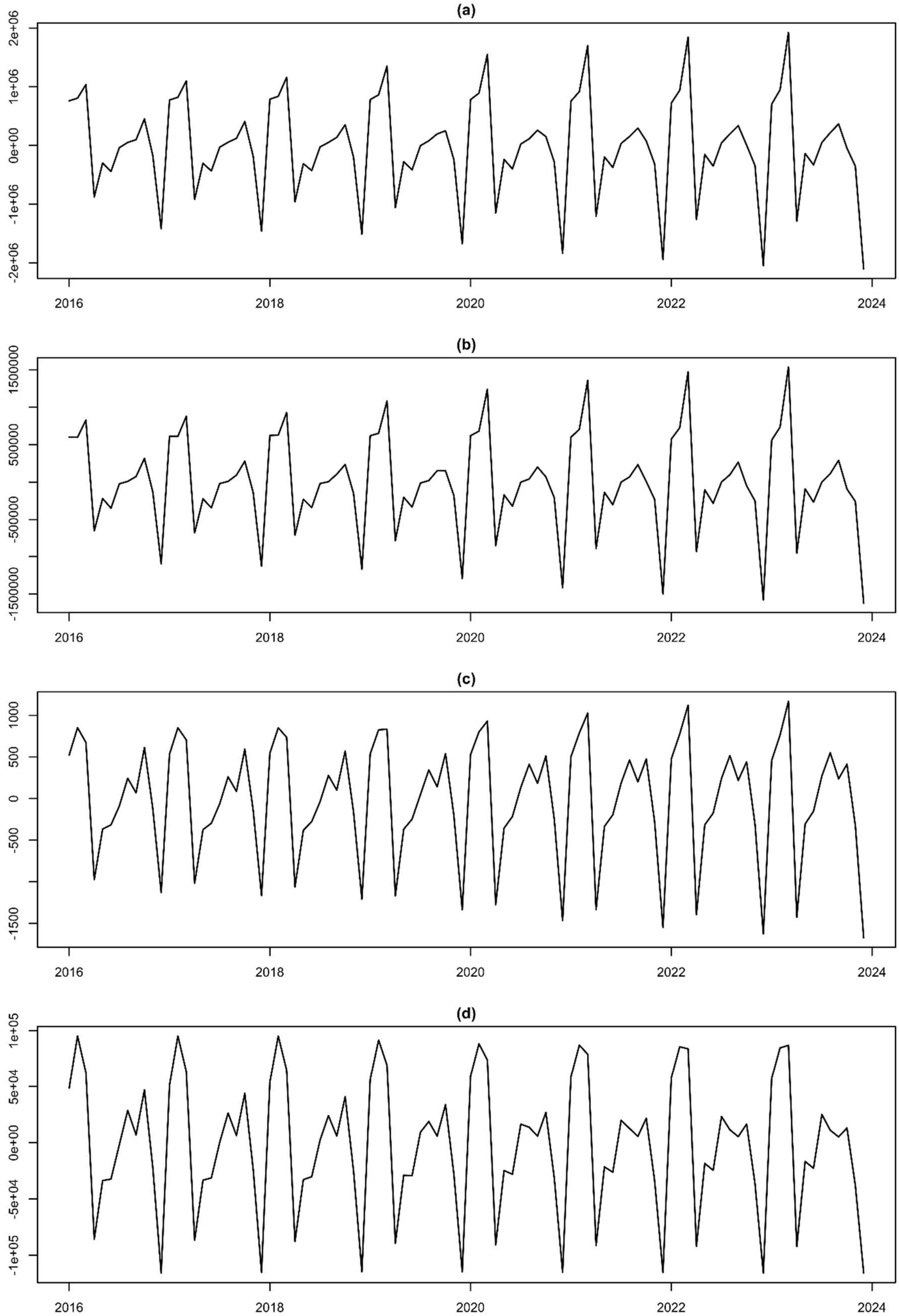


Figure 2: Seasonal components estimated from STL decomposition: a) Total; b) New; c) Relapse; d) Re-treatments

trend showed a consistent mean monthly increase of 0.75% (SD 3.36; 95% CI: 0.06 - 1.44), with the Mann-Kendall test yielding *p* <0.001. The seasonal component for new cases peaked in March, with a trough in December (Figure 2b). Relapse cases demonstrated the highest mean monthly increase at 1.07% (SD

2.68; 95% CI: 0.52 - 1.62), with a seasonal peak in March and a trough in December (Figure 2c). Interestingly, retreatment cases differed from the other groups, showing a mean monthly decline of approximately -0.54% (SD 4.35; 95% CI: -1.43 - 0.35; p <0.001, with peaks in February and troughs in December (Figure 2d).

The remainder component, which accounts for noise and unexplained variations after trend and seasonality adjustments, showed no significant trend across any registration group, as confirmed by the Mann-Kendall test (all p-values >0.05). This suggests that the observed trends and seasonal patterns effectively captured the inherent dynamics of TB notifications in the Philippines.

Table 1 summarizes these findings, providing a complete overview of the long-term trends and seasonal characteristics for each registration group. Figures 1 and 2 visually represent these trends and seasonal components. Figure 1 shows the monthly TB case notifications in the Philippines. The consistent upward trend, particularly for new and relapse cases, is clearly illustrated. Figure 2 displays the seasonal components for each registration group, highlighting the distinct patterns of seasonality, with peaks and troughs occurring at different times of the year across the groups.

Forecasting TB Notifications for 2024-2025

We fitted a seasonal ARIMA(0,1,2)(0,1,1) model (AIC = 567.2) to the Box-Cox-transformed series, applying one non-seasonal and one seasonal difference to ensure stationarity. The two non-seasonal MA terms (q = 2) capture short-term shocks, while the single seasonal MA term (Q = 1) smooths the annual cycle. Residual diagnostics (Ljung-Box p > 0.1) confirmed no remaining autocorrelation, indicating an adequate fit. The resulting 24-month forecasts (Table 2) project pronounced peaks in March of each year, approximately 55,213 cases in March 2024 and 58,964 cases in March 2025, followed by mid-year plateaus and troughs in December (Figure 3). These patterns highlight the importance of intensifying screening and diagnostic capacity in January-March, and of conducting end-of-year program reviews during lower incidence periods. Regular model updates as new data become available will further refine these projections and support adaptive resource planning.

Table 2: 24-Month Forecasted Total TB Case Notifications in the Philippines (Jan 2024-Dec 2025)

Month	Forecast	Month	Forecast
January 2024	50,518	January 2025	54,496
February 2024	51,877	February 2025	55,501
March 2024	55,213	March 2025	58,964
April 2024	42,909	April 2025	46,172
May 2024	47,435	May 2025	50,884
June 2024	47,910	June 2025	51,378
July 2024	49,581	July 2025	53,116
August 2024	50,400	August 2025	53,967
September 2024	50,984	September 2025	54,574
October 2024	50,894	October 2025	54,480
November 2024	49,680	November 2025	53,218
December 2024	43,387	December 2025	46,670

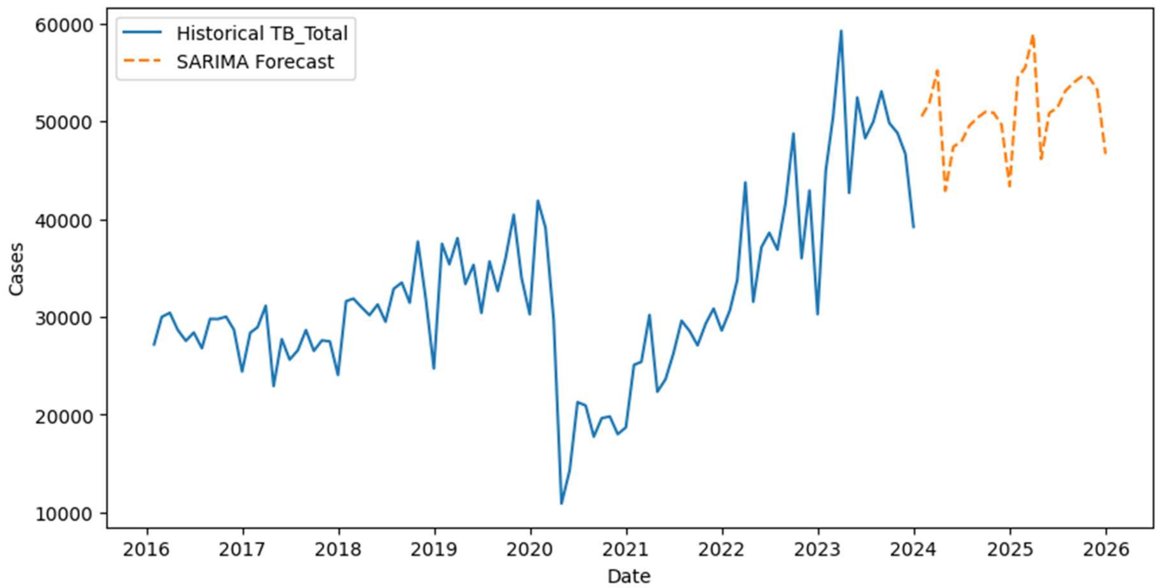


Figure 3: 24-Month Forecast of Total TB Case Notifications in the Philippines (Jan 2024-Dec 2025) Using a Seasonal ARIMA(0,1,2)(0,1,1) Model

Discussion

This study examined long-term trends and seasonal fluctuations in tuberculosis notifications across the Philippines from 2016 to 2023. The analysis revealed a consistent upward trend in TB notifications, with a significant increase in the number of reported cases over the study period. STL decomposition highlighted distinct seasonal variations, with peaks in March (and in February for retreatment cases) and troughs in December. The study also found that while new and relapse cases continued to rise, retreatment cases showed a slight decline.

The observed seasonality and upward trend should be interpreted cautiously. These patterns may reflect a combination of ongoing transmission, health-service access, case-detection intensity, and reporting dynamics rather than a single causal mechanism. More broadly, TB burden is shaped by social determinants and multimorbidity.[3-8] In addition, service disruptions during the COVID-19 period may have affected notification patterns and delayed diagnosis.[20]

Based on the observed March peaks, we recommend that national TB programs implement targeted screening campaigns in January and February, using mobile clinics and community outreach to identify cases before the seasonal surge.

This study adds to the literature by providing a nationwide description of long-term trend and seasonality in Philippine TB notifications. The present results extend prior local Philippine time-series work[15] by showing that similar seasonal structure is detectable at the national level. The slight decline in retreatment notifications is encouraging, but the available aggregate dataset does not permit direct inference about adherence, cure, or relapse mechanisms.

Our findings are also consistent with reports from other settings showing that TB notifications can exhibit measurable seasonal structure.[11-14] Together, these results support the value of routine time-series monitoring for national TB surveillance and program planning.

Limitations

There are several limitations to this study that should be acknowledged. First, the study relies on aggregate data provided by the Department of Health, which may not capture all nuances, such as regional disparities or specific population groups at higher risk. In particular, urban and rural differences may bias notification-based estimates, as access to diagnostic services and reporting completeness vary between settings. Additionally, the study's focus on reported cases means that undiagnosed or unreported cases of TB are not accounted for, which could result in an underestimation of the true burden of the disease. Passive notification systems are subject to data quality issues (such as reporting delays, incomplete records, and overall underreporting), especially during periods of health system strain, such as the COVID-19 pandemic. Furthermore, while the STL method is robust in detecting trends and seasonality, it may not fully account for external factors such as changes in public health policy, economic conditions, or the impact of other diseases, including COVID-19, which have likely influenced TB notification patterns during the study period. Finally, the absence of sociodemographic stratifiers (for example, age, gender, or socioeconomic status) prevents analysis of whether these key subgroups experienced different trends.

Conclusion

Our analysis revealed a mean monthly increase of 0.80% (95% CI: 0.11 - 1.49) in total notified TB cases across the Philippines between January 2016 and December 2023, with seasonal peaks in March for total, new, and relapse cases (and in February for retreatment cases) and troughs in December. These findings demonstrate that the first quarter of each year carries the highest TB burden. To act on this pattern, we recommend intensifying active case finding and screening efforts in January and February, including deploying mobile clinics and community outreach, to identify cases before the annual surge. Allocating additional diagnostic resources and staffing during Q1 will help address rising notifications, while enhanced surveillance and support in December can address underreporting and maintain continuity of care during the low-notification period. Strengthening these seasonally targeted interventions will be critical for accelerating progress toward national and global TB control goals.

Public health implications

Policymakers and TB program managers should be aware that intensifying active case finding through mobile units and community screening during the first quarter is essential to intercept the anticipated surge in March. By reallocating staff and diagnostic reagents ahead of Q1, diagnostic delays can be minimized and case detection accelerated. Equally important is maintaining robust surveillance and program support in December to prevent reporting drop-offs during the seasonal trough. Finally, leveraging these short-term forecasts for 2024-2025 will inform more accurate budgeting and help avert stock-outs of critical supplies.

Individual Authors' Contributions: **SJEP** conceptualized and formulated the design, conducted data analysis, carried out computational tasks, generated graphical representations, contributed to drafting and reviewing the manuscript, and granted approval for the final draft.

Availability of Data: The data supporting the find-

ings of this study are available from the corresponding author upon reasonable request.

Declaration of Non-use of Generative AI Tools: This article was prepared without the use of generative AI tools for content creation, analysis, or data generation. All findings and interpretations are based solely on the authors' independent work and expertise.

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