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A Cluster-Based Predictive Model of Tuberculosis Spatial Distribution as a Basis for Evaluating Community-Based Case Finding Program Management

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Abstract: *Tuberculosis (TB) remains a major public health challenge, particularly in urban and community settings where transmission risk varies spatially across regions. Conventional TB control programs often rely on aggregate indicators, which may obscure localized risk patterns and limit the effectiveness of community-based case finding interventions. This study aims to develop a cluster-based predictive model of TB spatial distribution and to utilize the model as a basis for evaluating the management of the Community-Based TB Case Finding Program. This study employed a quantitative observational design with a spatial–predictive approach. Secondary data on notified TB cases and program performance indicators were collected from primary health centers and local health offices. Spatial cluster analysis was conducted to identify TB hotspot and coldspot areas, followed by predictive modeling to classify regions into high-, medium-, and low-risk categories. The clustering results were then integrated with program indicators to evaluate planning, implementation, and resource allocation across regions. The results demonstrate that TB distribution forms significant spatial clusters, indicating non-random patterns of risk across subdistricts. The predictive model effectively classified regional TB risk and revealed mismatches between high-risk areas and program intervention intensity. Furthermore, substantial variations in screening coverage, community health worker activities, and referral processes were identified across risk clusters. In conclusion, the cluster-based predictive model proved effective as a tool for evaluating and strengthening the management of community-based TB case finding programs. This approach supports more targeted, risk-based interventions and enhances evidence-based decision-making in TB control.*

1. Introduction

The Tuberculosis (TB) Spatial Clustering Prediction Model is an analytical approach that integrates spatial analysis and predictive modeling to identify geographic clustering patterns of TB cases. This model is designed to detect areas with high case concentrations (hotspots) and low-risk areas (coldspots) based on case distribution, population characteristics, environmental factors, and access to health services. Through a clustering approach, TB distribution is no longer understood merely as an individual phenomenon, but rather as a spatial pattern reflecting complex interactions among social determinants, environmental conditions, and the performance of community-level health service systems. Similar approaches have been highlighted by Zhou et al. (2024), who demonstrated that integrating spatial analysis with risk prediction improves the accuracy of identifying priority areas for TB control, as well as by Kumar and Singh (2024), who emphasized that clustering models based on contextual area-level data are effective in capturing TB risk heterogeneity and supporting more targeted intervention planning.

The development of a spatial clustering–based tuberculosis (TB) prediction model plays a strategic role in strengthening planning and decision-making processes within TB control programs, particularly those relying on community-based case-finding approaches. By identifying spatial patterns, priority zones, and gradients of TB risk, the model enables health managers to move beyond uniform intervention strategies toward more targeted and resource-efficient actions. Risk-based spatial mapping supports the prioritization of high-burden areas for intensified screening, outreach, and community engagement, which is especially critical in settings with limited resources. As a result, program interventions become more evidence-driven, geographically responsive, and aligned with the underlying epidemiological dynamics of TB transmission. Beyond its predictive capacity, the spatial clustering model also functions as a robust framework for evaluating program performance and management effectiveness. By linking spatial risk clusters with indicators such as case-finding coverage, community participation, and screening outcomes, the model allows for a comparative assessment of program achievements between high- and low-risk areas. This spatially informed evaluation helps uncover implementation gaps that may be obscured in aggregate analyses, such as underperformance in high-risk zones or inefficient resource deployment in low-risk areas. Consequently, the model provides context-sensitive insights that support adaptive management, continuous program improvement, and the formulation of sustainable recommendations to enhance the overall impact of community-based TB case-finding initiatives.

Several previous studies have demonstrated that spatial clustering approaches and predictive modeling are effective in identifying the geographic distribution patterns of tuberculosis (TB) and in determining high-risk areas. Spatial analysis–based studies reveal that TB cases tend to form clusters associated with population density, housing conditions, poverty, and limited access to health services (Lönnroth et al., 2010; Tadesse et al., 2018). Other studies emphasize that cluster-based predictive models improve the accuracy of TB hotspot mapping compared to conventional descriptive analyses, thereby providing a more precise risk profile for public health intervention planning (Zhang et al., 2019; Adegboye et al., 2021). However, most of these studies primarily focus on epidemiological aspects and risk mapping, without explicitly linking clustering results to systematic evaluations of TB control program performance and management.

Research on Community-Based TB Case Finding Programs highlights the critical role of health cadres, community participation, and effective program management in improving case detection coverage and outcomes (Datiko & Lindtjørn, 2009; Storla et al., 2008). Several evaluative studies indicate that variations in program performance across regions are often influenced by managerial factors, such as outreach planning, resource allocation, and risk communication strategies (Ayles et al., 2013; MacPherson et al., 2014). Nevertheless, studies that integrate TB spatial clustering prediction models as a basis for evaluating community-based program management remain very limited. This gap underscores the need for a comprehensive approach that not only maps TB risk spatially but also utilizes predictive results to assess the alignment, effectiveness, and efficiency of TB case-finding program management at the community level (Kasaie et al., 2017; Houben & Dodd, 2016).

The mismatch between the spatial distribution of tuberculosis (TB) risk and the implementation of Community-Based TB Case Finding Programs indicates that current programmatic approaches remain largely generic and insufficiently responsive to local contexts. Several studies have emphasized that community-based TB case-finding strategies are often implemented uniformly, without differentiation based on local vulnerability levels and disease burden, thereby limiting their effectiveness. In fact, TB epidemiological characteristics are strongly influenced by spatial factors such as population density, socioeconomic conditions, and access to health services. When these factors are not incorporated into program planning, high-risk areas are more likely to experience delayed case detection and sustained transmission within communities (Horton et al., 2022; Rao et al., 2022). The weak integration of spatial data and risk analysis into program management suggests that TB case-finding evaluation and planning continue to focus primarily on quantitative outputs—such as the number of screenings conducted or cases detected—without adequately considering whether interventions align with disease distribution patterns. Recent studies demonstrate that the use of TB risk maps and clustering analysis can support program managers in prioritizing areas, optimizing resource allocation, and adjusting intervention intensity according to local needs. Without such an approach, programs risk becoming inefficient and insufficiently adaptive to the heterogeneous dynamics of TB epidemiology across regions. Therefore, strengthening the management of Community-Based TB Case Finding Programs through spatial risk–based approaches represents a strategic step toward achieving sustainable improvements in TB control outcomes (Maciel et al., 2022).

The principal gap in both research and practice lies in the lack of integration between TB spatial clustering prediction models and the management evaluation of community-based case-finding programs. Most existing studies stop at TB hotspot mapping or risk factor analysis, without linking these results to program performance indicators such as case detection outcomes, health cadre performance, screening effectiveness, and referral pathways at the community level. Additional challenges include limitations in data quality and integration, variability in field-level human resource capacity, and social dynamics such as stigma and low community participation in certain areas. These conditions have hindered the full utilization of spatial analysis outputs as strategic tools for contextual program evaluation and management improvement. If this gap remains unaddressed, TB case-finding programs may continue to suffer from low efficiency and effectiveness, as reflected in undetected cases, delayed diagnoses, and persistent performance disparities across regions. Conversely, the development of a TB Spatial Clustering Prediction Model as a foundation for program management evaluation has the potential to generate strategic impacts, including more targeted interventions, optimized utilization of health cadres, and improved resource allocation aligned with area-specific risk levels. Ultimately, this approach not only strengthens the technical aspects of TB control but also promotes a more adaptive, evidence-based, and sustainable transformation of community-based program management.

This study is compelling because it offers a comprehensive solution to a long-standing challenge in TB control, namely the misalignment of intervention targeting and the weak foundation for program evaluation at the community level. The research responds to the need for an evidence-based approach by developing a clustering-based prediction model capable of accurately identifying high-risk areas and subsequently utilizing these results as an instrument for evaluating the management of community-based TB case-finding programs. The proposed solution is not merely technical, through the mapping and prediction of TB distribution, but also strategic, as it links spatial information with program performance, the role of health cadres, and community participation. Accordingly, this study is of particular interest due to its novelty, policy relevance, and strong potential for tangible impact in enhancing the effectiveness, efficiency, and sustainability of community-based TB control programs.

3. Methodology

This study employs a quantitative approach with a spatial analytic–predictive design, integrated with an evaluation of public health program management. The approach aims to develop a TB spatial clustering prediction model through spatial pattern analysis and predictive modeling, while simultaneously utilizing the model outputs as a basis for evaluating the Community-Based TB Case Finding Program. The study adopts an observational design with spatial units of analysis, enabling the examination of relationships between the spatial distribution of TB cases, area-level contextual factors, and the performance of case-finding programs at the community level. The dependent variable in this study is the spatial distribution of reported TB cases, which is analyzed spatially and grouped into area-based risk clusters. Independent variables include demographic and environmental indicators at the area level (such as population density, housing characteristics, and access to health services), as well as management indicators of the Community-Based Case Finding Program, including screening coverage, intensity of health cadre outreach, referral proportions, and levels of community participation. In addition, an intermediate variable in the form of area risk categories derived from clustering results is employed as the basis for evaluating the alignment and effectiveness of program implementation across different clusters.

This study applies a census sampling strategy, encompassing all villages/urban wards in Baubau City that are covered by the Community-Based TB Case Finding Program (through primary health centers and cadre networks) as the spatial units of analysis. Furthermore, the case data sample includes all reported/notified TB cases (e.g., suspected and/or confirmed pulmonary TB, depending on program data availability) recorded in the TB surveillance system and/or health center and health office registers in Baubau City over the most recent two-year period with complete data (e.g., January 2023–December 2024 or January 2024–December 2025, subject to final data availability). Under this design, no partial sampling is conducted; all villages/urban wards and all reported cases within the specified period are analyzed to generate risk clusters (hotspots–coldspots) and to examine the association between program performance indicators—such as screening coverage, referral rates, case detection yield, and community participation—across each spatial cluster.

Data collection in this study was conducted using an integrated secondary data approach, drawing on official registers and reports of the Tuberculosis Program at the primary health center and local health office levels. The data collected included reported/notified TB case data by village/subdistrict area, time period, and basic case characteristics, as well as management data of the Community-Based TB Case Finding Program, such as screening coverage, activities of community health volunteers, referral processes for diagnostic examination, and case detection outcomes. All data were compiled, verified for completeness, and aligned with administrative boundary units to support spatial and cluster analyses, resulting in a consistent database that was ready for predictive modeling and evaluation of program performance at the community level.

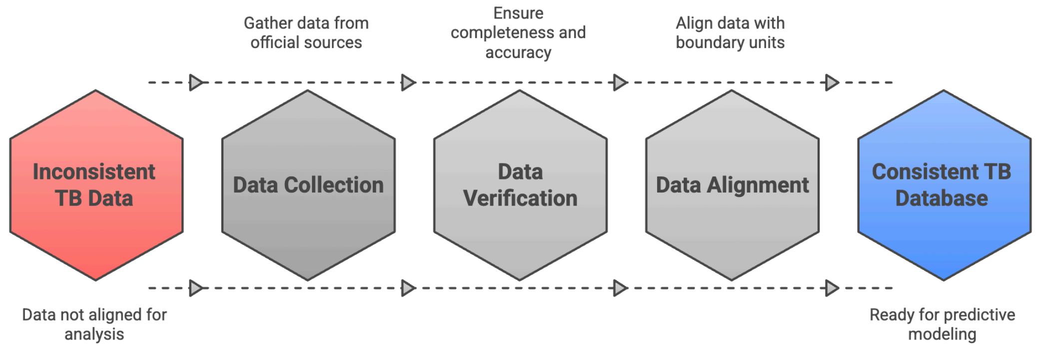

Figure 1. Integrated Data for TB Program Analysis

Data analysis was conducted in a staged and integrated manner to develop a TB spatial clustering prediction model and to evaluate the management of community-based TB case-finding programs. The initial stage involved descriptive analysis to illustrate the distribution of TB cases and program indicators across geographic areas. This was followed by spatial analysis and clustering to identify patterns of high- and low-risk areas, which was subsequently extended through predictive modeling to estimate TB risk levels for each area. The resulting clustering and risk predictions were further analyzed by comparing them with the achievement of program management indicators within each spatial cluster. This approach enabled the identification of alignment, gaps, and overall effectiveness in the implementation of Community-Based TB Case Finding Programs, based on contextual and evidence-driven evaluation.

4. Results and Discussion

4.1 Results

The findings of this study were derived from a series of spatial analyses, predictive modeling, and evaluations of community-based TB case-finding program management conducted in an integrated manner across all study areas. The analysis focused not only on mapping the spatial distribution of TB cases but also on examining the relationship between area-level TB risk and the implementation performance of community-based programs. Through this approach, the study was able to identify TB clustering patterns, develop area-level risk prediction models, and assess the alignment and effectiveness of case-finding program management. In summary, the main findings of this study can be outlined as follows:

Identification of Spatial TB Clusters

The results of the spatial analysis indicate that tuberculosis incidence in the study area exhibits a clear pattern of geographic clustering, confirming that the distribution of TB cases across villages/urban wards is not random. The identification of hotspot clusters indicates the presence of specific areas with high concentrations of TB cases, which may serve as centers of sustained transmission if not adequately addressed. Conversely, the presence of coldspot clusters reflects areas with relatively low TB incidence, which may be attributable to a combination of protective factors such as better environmental conditions, more proactive health-seeking behaviors, or the effectiveness of local TB control programs.

The heterogeneity of TB risk across areas revealed through this clustering analysis underscores that the burden of TB is concentrated in specific locations and is strongly influenced by contextual area-level characteristics. This pattern has important implications for TB control, as it suggests that uniform intervention strategies across all areas may be suboptimal. By understanding the spatial distribution of hotspots and coldspots, community-based TB case-finding programs can be designed in a more targeted and proportionate manner, prioritizing high-risk areas for intensified screening, enhanced health cadre outreach, and strengthened transmission prevention efforts, while simultaneously maintaining achievements in lower-risk areas.

The clustering results indicate that TB hotspot areas tend to be located in densely populated settlements with high population mobility, whereas coldspot areas are generally found in locations with lower population density or relatively better access to health services. These findings suggest that area-level contextual factors play a crucial role in shaping TB distribution patterns, making place-based control approaches more relevant than uniform interventions. The identification of these clusters enables more precise TB risk mapping down to the village/urban ward level.

Table 1. Area Characteristics by TB Risk Cluster

Factor	Description of Area Conditions	Implications for TB Risk
Population Density & Urbanization	Urban areas with high population density and intensive population mobility	Facilitates close interpersonal contact and increases the potential for TB transmission
Health Facilities (Primary Health Centers/Hospitals)	Availability of health services is relatively adequate, but distribution and access are uneven across areas	Plays a greater role in case detection and treatment than in early transmission prevention
Role of Field Health Workers (Cadres/Health Promoters)	Levels of activity among cadres and health promoters vary across areas	Strongly determines the success of active case finding and community education
Clean and Healthy Living Behavior (PHBS)	Low awareness of cough etiquette, personal hygiene, and maintenance of physical resilience	Increases the risk of TB transmission within households and communities
Environmental Conditions & Sanitation	Settlements with inadequate ventilation and poor environmental sanitation	Supports the persistence and spread of TB bacteria in the environment
Socioeconomic Factors	Relatively high poverty levels and low nutritional status	Increases individual vulnerability to TB infection and disease progression

Source: Regional Medium-Term Development Plan (RPJMD) of Baubau City 2025–2029

The table illustrates various area-level contextual factors that contribute to the formation of TB risk clusters. High population density and urbanization in urban areas increase the intensity of interpersonal contact, thereby elevating the likelihood of TB transmission in public spaces and residential environments. In addition, suboptimal environmental and sanitation conditions—such as poor household ventilation and inadequate waste management—create settings that support the persistence of TB bacteria. Behavioral factors, particularly the low adoption of Clean and Healthy Living Behaviors (PHBS), also play a significant role in increasing transmission risk at both household and community levels.

Health system and socioeconomic factors exert a structural influence on TB risk. The availability of health facilities, such as primary health centers and hospitals, plays a more prominent role in case detection and treatment than in primary prevention, particularly when access to services is uneven across areas. The role of field health workers—especially community health cadres and health promoters—emerges as a key determinant of successful active case finding and community education, such that areas with higher levels of cadre activity tend to achieve better case detection outcomes. Meanwhile, socioeconomic conditions, including poverty and poor nutritional status, increase individual vulnerability to infection and disease progression, which cumulatively reinforces the formation of TB risk clusters in specific areas.

The findings presented in the table confirm that TB risk clusters are formed through complex interactions among environmental, behavioral, and health system factors at the area level. No single factor operates independently; rather, a combination of population density, socioeconomic conditions, environmental quality, and service capacity—including the effectiveness of community health cadres—collectively determines the level of TB risk in a given area. Consequently, the TB clustering map generated in this study reflects a dynamic and contextual reality, providing a more accurate representation of area-level vulnerability than approaches relying solely on case counts. The implication of these findings is the need for more adaptive, area-based management of Community-Based TB Case Finding Programs. High-risk clusters require intensified outreach strategies, strengthened roles of health cadres, and integrated cross-sectoral efforts to promote clean and healthy living behaviors and improve environmental conditions. In contrast, lower-risk areas still require sustained achievements through strengthened early detection and continuous education. By incorporating the factors outlined in the table as key considerations, the TB spatial clustering prediction model functions not only as an epidemiological analysis tool but also as a strategic instrument for planning, evaluation, and strengthening the management of community-based TB control programs.

A Well-Established Cluster-Based TB Risk Prediction Model

The development of a cluster-based tuberculosis (TB) risk prediction model in this study demonstrates strong performance in identifying variations in TB risk across geographic areas. By integrating spatial clustering results of TB cases with area-level characteristics and indicators from community-based TB case-finding programs, the model moves beyond simple case enumeration to a more nuanced understanding of spatial risk dynamics. This integration allows the model to reflect not only where TB cases are concentrated, but also how contextual factors—such as program implementation intensity and community engagement—interact with underlying transmission patterns. Consequently, the model provides a more sensitive and geographically responsive representation of TB risk distribution. Moreover, the use of spatial clustering as the foundation of the predictive framework enables the model to capture the inherent heterogeneity of TB risk between areas that may appear similar when assessed through conventional descriptive statistics alone. By incorporating area-level contextual indicators, the model is better equipped to identify subtle risk gradients and transitional zones that have the potential to evolve into future hotspots. This comprehensive approach enhances the model's value for program planning and evaluation, as it supports targeted interventions, risk-based prioritization, and adaptive management of community-based TB case-finding programs. Ultimately, the model offers a robust evidence-based tool for improving the effectiveness and efficiency of TB control strategies at the local level.

The modeling results indicate that the study areas can be clearly classified into high-, moderate-, and low-risk categories based on the predicted risk values generated by the model. High-risk areas largely overlap with previously identified TB hotspot clusters, while low-risk areas tend to coincide with TB coldspot clusters. Moderate-risk areas represent transitional zones that may experience increasing TB incidence if adequate interventions are not implemented. This classification provides a more refined spatial depiction of area-level vulnerability to TB.

Table 2. Area Classification Based on the TB Risk Prediction Model

TB Risk Category	Spatial Characteristics of the Area	Association with TB Clusters	Programmatic Implications
High Risk	Areas with the highest TB prediction values and relatively dense case concentrations	Overlapping with TB hotspot clusters	Top priority for intensified screening, active case finding, and strengthening the role of community health cadres
Moderate Risk	Transitional areas with moderate TB prediction values and potential for increasing cases	Located around or adjacent to TB hotspot clusters	Require close monitoring, strengthened health education, and early preventive interventions
Low Risk	Areas with low TB prediction values and limited case numbers	Overlapping with TB coldspot clusters	Focus on maintaining program achievements and sustained early detection

The classification of areas based on the TB risk prediction model shows that the study area can be systematically grouped into three risk categories: high, moderate, and low. This grouping is derived from prediction values generated by the cluster-based model, which integrates spatial TB case distribution with contextual area-level characteristics. Through this approach, TB vulnerability at the area level can be described more comprehensively than descriptive mapping that merely presents actual case counts. Areas categorized as high risk exhibit the highest TB prediction values and spatially overlap with previously identified TB hotspot clusters. This condition indicates that these areas not only carry a high disease burden but also face a sustained risk of transmission if intensive interventions are not implemented. Consequently, high-risk areas represent the primary priority for planning and implementing Community-Based TB Case Finding Programs.

Moderate-risk areas represent transitional zones characterized by intermediate prediction values and are generally located around identified hotspot areas. Although the number of TB cases in these areas has not yet reached the levels observed in high-risk clusters, the potential for an increase in TB incidence remains substantial, particularly if contextual risk factors are not properly managed. From a prevention perspective, the identification of moderate-risk areas is critical, as timely and appropriate interventions at this stage offer the opportunity to prevent these areas from evolving into future TB hotspots. Meanwhile, low-risk areas are characterized by low TB prediction values and overlap with TB coldspot clusters. These areas reflect conditions in which transmission risk is relatively well controlled and community-based case-finding program achievements have been reasonably effective. Nevertheless, a low-risk classification does not imply the absence of TB threats; therefore, sustained efforts in early detection and continuous health education remain necessary to maintain program achievements. Overall, this classification table underscores the strategic value of the cluster-based TB risk prediction model in supporting more targeted, area-based program management decision-making.

The primary strength of this cluster-based prediction model lies in its ability to project potential TB occurrence rather than merely describing past or existing conditions. As such, the model provides an early warning function for program managers, enabling them to anticipate rising risks in specific areas. Compared with purely descriptive mapping, this predictive approach is more relevant for program planning, as it allows the prioritization of interventions before case surges occur. Overall, the establishment of a robust cluster-based TB risk prediction model reinforces the role of spatial analysis in community-based TB control. The model functions not only as an analytical tool but also as a strategic instrument for program evaluation and management decision-making. By leveraging area-level risk classification results, program managers can allocate resources more efficiently, intensify outreach in high-risk areas, and sustain TB control efforts in lower-risk areas.

Effectiveness of the Clustering Model as a Program Management Evaluation Tool

The study findings indicate that the TB clustering and risk prediction model can be effectively utilized as an instrument for evaluating the management of Community-Based TB Case Finding Programs. The integration of spatial risk cluster maps with program performance indicators enables a more comprehensive assessment of the alignment between area-level TB risk and the intensity of interventions implemented. Through this approach, areas with high TB risk can be clearly identified and subsequently compared with screening coverage, cadre activity, and case detection outcomes, thereby providing an objective assessment of the appropriateness of program management strategies. Furthermore, the area-based evaluation generated by this model is able to reveal variations in program performance across sub-districts that are not visible through aggregate-level analysis alone. Differences in performance across areas reflect variations in local planning, implementation, and resource support. Thus, clustering and risk prediction models function not only as epidemiological analytical tools but also as a foundation for more targeted managerial decision-making aimed at improving the effectiveness and efficiency of Community-Based TB Case Finding Programs.

The application of clustering results in this study reveals important gaps in program planning, particularly in the prioritization of intervention areas. Several geographic areas identified as high-risk clusters were not consistently prioritized in outreach and screening strategies, while some lower-risk areas received comparatively greater program attention. This mismatch indicates that program planning has not yet been fully guided by spatial risk mapping, leading to a less optimal allocation of resources and efforts. As a consequence, opportunities to intensify case detection in areas with the highest TB burden may be missed, thereby limiting the overall effectiveness of community-based TB case-finding initiatives. At the implementation stage, the clustering model further highlights substantial variations in both the intensity and quality of program execution across different risk clusters. High-risk areas show notable disparities in screening coverage, cadre engagement, and referral effectiveness, suggesting inconsistencies in how the program is operationalized at the field level. By systematically comparing program achievements across high-, moderate-, and low-risk clusters, the model offers a more objective and evidence-based assessment of implementation performance. This approach helps identify specific clusters that require strengthened support, improved coordination, or strategic adjustment, thereby enhancing the responsiveness and impact of TB control efforts.

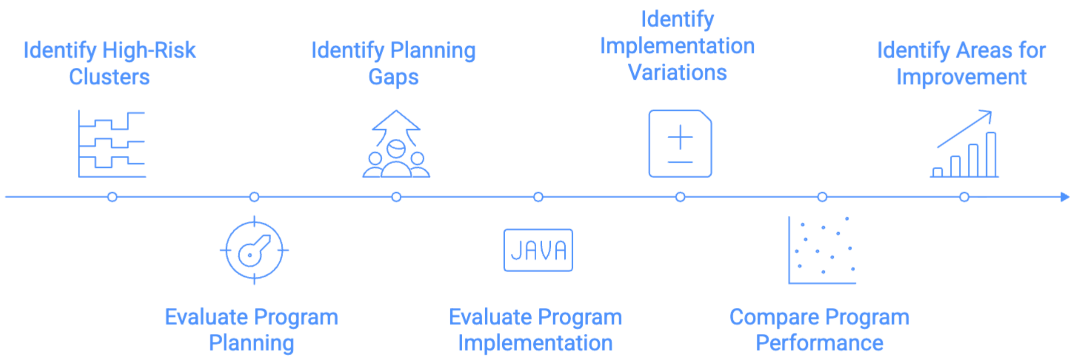

Figure 2. Tuberculosis Program Analysis and Improvement

The figure illustrates a systematic and evidence-based framework for analyzing and improving Tuberculosis (TB) programs. The initial stage begins with the identification of high-risk spatial clusters, which serves to map areas with significant concentrations of TB cases. These results are then used to evaluate program planning, particularly to assess whether high-risk areas have been appropriately prioritized in outreach and screening strategies. The analysis subsequently focuses on identifying planning gaps, namely mismatches between area-level risk and program planning priorities, thereby providing an early indication of potential managerial weaknesses in intervention targeting. The next stage emphasizes the evaluation of program implementation by identifying variations in field-level execution, including differences in screening coverage, cadre activities, and referral processes across areas. These variations are further examined through comparisons of program performance across different risk clusters to assess the effectiveness and consistency of implementation. The entire analytical process ultimately leads to the identification of areas requiring improvement, whether in planning, implementation, or resource allocation. Accordingly, the figure highlights that the use of spatial clustering and area-based evaluation enables community-based TB programs to be improved in a more targeted, adaptive, and sustainable manner.

The clustering and risk prediction results also reveal gaps in program resource allocation, encompassing both human resources and operational support. High-risk areas do not consistently receive a level of cadre deployment, outreach intensity, or logistical support proportional to their vulnerability. These findings underscore that resource allocation not informed by risk stratification may hinder the optimal performance of Community-Based TB Case Finding Programs. Overall, the effectiveness of the clustering model as a management evaluation tool lies in its ability to link epidemiological information with program planning, implementation, and resource management. The model not only identifies high-risk areas but also provides an analytical basis for more precise managerial adjustments. Consequently, the application of TB clustering and risk prediction has strong potential to drive more efficient, adaptive, and evidence-based improvements in the management of community-based TB case-finding programs.

4.2 Discussion

The results of the spatial analysis indicate that tuberculosis (TB) incidence in the study area forms a statistically significant pattern of geographic clustering, confirming that the distribution of TB cases across villages/urban wards is not random. The presence of hotspot clusters indicates areas with high concentrations of cases that may serve as centers of sustained transmission if not appropriately addressed. In contrast, coldspot clusters reflect areas with relatively lower TB incidence, which may be influenced by a combination of protective factors such as better environmental conditions, more proactive health-seeking behavior, and the effectiveness of local TB control interventions. These findings reveal marked heterogeneity in TB risk across areas, indicating that the disease burden is concentrated in specific locations and is strongly shaped by contextual area-level characteristics.

The identified clustering patterns have important strategic implications for community-based TB control. Hotspot areas are commonly associated with high population density, intensive population mobility, inadequate environmental and sanitation conditions, and low adoption of Clean and Healthy Living Behaviors (PHBS), all of which increase opportunities for TB transmission at both household and community levels. Conversely, coldspot areas tend to have lower population density or relatively better access to health services, along with stronger support from community health cadres. These patterns underscore that uniform intervention approaches across all areas are likely to be suboptimal. Therefore, the use of clustering results enables more targeted planning of Community-Based TB Case Finding Programs, prioritizing intensified screening, cadre outreach, and transmission prevention efforts in high-risk areas while maintaining achievements in lower-risk areas.

The findings of this study are consistent with previous research emphasizing that TB exhibits strong spatial distribution patterns influenced by environmental and socioeconomic factors. The World Health Organization (2023) reports that TB clusters commonly emerge in areas characterized by high population density, unhealthy housing conditions, and inequitable access to health services, thereby increasing the risk of sustained community transmission. Similarly, Moonan et al. (2018) demonstrated that the application of spatial analysis to identify TB hotspots enhances the effectiveness of active case finding and community-targeted interventions. In addition, Tatem et al. (2014) highlighted that integrating spatial risk mapping with contextual area characteristics provides a stronger foundation for planning and evaluating TB control programs than approaches relying solely on aggregate indicators. Collectively, these findings reinforce the empirical evidence that spatial clustering of TB is a critical instrument for supporting more adaptive, area-based, and risk-oriented TB control strategies.

The cluster-based TB risk prediction model developed in this study has proven effective in identifying variations in tuberculosis risk levels across geographic areas in a more refined and meaningful manner. By integrating the results of spatial clustering of TB cases with area-level characteristics and indicators of the Community-Based TB Case Finding Program, the model is able to capture the complexity of TB risk that cannot be explained solely through mapping case counts. This approach strengthens the analysis by combining actual distribution patterns with local contextual factors, thereby conceptualizing TB risk as a spatial–dynamic phenomenon shaped by environmental, social, and programmatic performance factors. Consequently, the model is not merely descriptive but also predictive, making it highly relevant for supporting evidence-based decision-making in TB control.

The classification of areas into high-, moderate-, and low-risk categories provides a systematic spatial depiction of TB vulnerability. High-risk areas, which overlap with TB hotspot clusters, indicate concentrated case burdens and the potential for sustained transmission, justifying their prioritization for intensified active screening, case finding, and strengthened roles of community health cadres. Meanwhile, moderate-risk areas function as transitional zones with the potential for increased TB incidence if early and sustained preventive interventions are not implemented. Low-risk areas, although overlapping with TB coldspot clusters, still require the maintenance of program achievements through continued early detection and community education. Overall, these findings confirm that cluster-based prediction models offer a more precise foundation for area-based TB program planning and evaluation compared to conventional approaches.

The findings of this study are consistent with recent advances in TB research highlighting the advantages of spatial clustering approaches in TB risk modeling. Adegboye et al. (2020) demonstrated that spatial cluster-based TB mapping identifies high-risk areas more precisely than conventional incidence analyses, particularly in the context of area-targeted intervention planning. Furthermore, Kang et al. (2021) emphasized that integrating spatial clusters with contextual area-level factors provides strong predictive value for detecting TB transition zones that may evolve into future hotspots. Similar conclusions were reported by Tadesse et al. (2022), who found that cluster-based TB prediction models are highly effective as early warning systems for supporting resource allocation and the evaluation of community-based TB case-finding programs.

The findings of this study confirm that the TB clustering and risk prediction model functions effectively as a management evaluation tool for Community-Based TB Case Finding Programs. The integration of spatial risk cluster maps with program performance indicators enables a more precise assessment of the alignment between area-level TB risk and the intensity of interventions implemented. Through this area-based approach, program managers are able not only to identify areas with a high TB risk burden but also to evaluate whether outreach strategies, screening coverage, and cadre activities have been directed proportionally. Consequently, this model provides a more objective depiction of planning accuracy and program management effectiveness compared to conventional aggregate-based evaluations. Furthermore, the study reveals significant variations in program performance across spatial risk clusters, particularly within high-risk TB areas. Differences in screening coverage, intensity of cadre activities, and the effectiveness of referral processes reflect inconsistencies in program implementation at the local level. These conditions indicate that program planning and execution have not been fully informed by spatial risk mapping, thereby potentially reducing the effectiveness of case detection in the most vulnerable areas. Therefore, the clustering model serves not only as an epidemiological analytical tool but also as a managerial instrument for identifying planning gaps, implementation weaknesses, and the need for more targeted strategic adjustments and resource allocation.

These findings are consistent with recent studies emphasizing the importance of risk-based and spatial approaches in TB program management. The World Health Organization (2023) highlights that the use of risk mapping and spatial analysis is critical for improving the effectiveness of community-based TB case finding, particularly in resource-limited settings. A study by Tadesse et al. (2023) demonstrates that integrating spatial clustering with program performance indicators can reveal implementation gaps that are not detectable through aggregate evaluations. Meanwhile, Kasaie et al. (2023) emphasize that resource allocation not guided by risk stratification contributes to suboptimal TB intervention impacts in high-risk areas. Collectively, these findings strengthen the empirical evidence that clustering and risk prediction models represent a relevant, evidence-based, and strategic approach to enhancing the quality of management in Community-Based TB Case Finding Programs.

5. Conclusion

This study concludes that the distribution of tuberculosis in the study area forms statistically significant spatial clustering patterns, confirming that TB risk is heterogeneous and concentrated in specific areas. The presence of hotspot and coldspot clusters indicates that area-level contextual factors—including population density, population mobility, environmental and sanitation conditions, clean and healthy living behaviors, and access to health services—play a critical role in shaping TB vulnerability. The development of a cluster-based TB risk prediction model has proven effective in classifying areas into high-, moderate-, and low-risk categories with greater precision than conventional descriptive approaches. Accordingly, TB risk can be understood as a spatial–dynamic phenomenon influenced by interactions among epidemiological, social, environmental, and contextual factors. Furthermore, this study demonstrates that TB clustering and risk prediction models function effectively as management evaluation tools for Community-Based TB Case Finding Programs. The integration of spatial risk cluster maps with program performance indicators enables a more objective assessment of the alignment between area-level TB risk and the intensity of interventions implemented, while also revealing variations in program performance across areas. These findings indicate that program planning and implementation not fully informed by spatial risk mapping may reduce the effectiveness of case detection in high-risk areas. Therefore, the application of cluster-based prediction models provides a strong foundation for strengthening TB program management in a more targeted, efficient, and evidence-based manner, and is highly relevant for supporting adaptive and sustainable community-based TB control strategies.

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