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Investigating the geographic linkage between airborne pollutants and tuberculosis rates in India

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Abstract

Recent satellite observations indicate sustained deterioration in ambient air quality across Indian urban and rural regions. In India, nearly 30 people die from tuberculosis every day, a toll that exceeds the average daily COVID-19 deaths observed during the first wave of the pandemic. This study investigates the spatial associations among airborne pollutants, eco-hydrological driver and tuberculosis (TB) incidence and mortality across India's states based on remote sensing and health data. High-resolution Sentinel-5P satellite quantified concentrations of air pollutants (PM_{10}, NO_2, SO_2, O_3, and HCHO), alongside MODIS-derived NDVI, LST, and precipitation data for 2022 as well as TB data collected from report of MFHW 2022. Spatial distribution analysis revealed pronounced geographic clustering, with northern and central states (Uttar Pradesh, Madhya Pradesh, and Bihar) exhibiting the highest convergence of elevated TB burden, poor air quality, and reduced vegetation cover. Statistical analyses found TB incidence was positively linked to air pollution (coefficient 1.98, $p < 0.002$), formaldehyde ($r = 0.286$), and land surface temperature ($r = 0.218$). More vegetation cover was strongly protective against both TB incidence (coefficient -5.73, $p < 0.002$) and mortality (coefficient -4.62, $p < 0.02$). Population density significantly predicted TB mortality (coefficient 1.72, $p < 0.001$). These findings establish a compelling environmental epidemiological framework linking air quality degradation to TB transmission and outcomes in India. The results suggest that environmental remediation strategies, including air pollution control and urban vegetation enhancement should be integrated with conventional biomedical TB control programs. This integrated approach aligns with India's National TB Elimination Programme goals while contributing to broader respiratory health improvements and environmental sustainability objectives.

Keywords Air pollution, LST, Vegetation, Tuberculosis, Spatial analysis

1 Introduction

Air pollution is a significant public health issue, causing millions of premature deaths worldwide each year [1–3]. The World Health Organization estimates that 1.3 million deaths globally are related to ambient air pollution, which has an impact on most organs

and systems of the human body [2]. Particulate matter (PM) is a significant contributor to air pollution and has been linked to adverse health effects and ecosystem damage [4–7]. Urbanization in India has led to a rise in population density, which has further worsened the problem of indoor and outdoor air pollution [8, 9].

The WHO air quality guidelines identify several pollutants indices of air pollution, it includes PM2.5, PM10, NH_3, SO_2, NO, NO_2, CO, Ozone, and Benzene. These pollutants are found both indoors and outdoors, but their concentrations vary depending on the source and environment. Indoor air pollution is caused by a range of factors, including the combustion of solid fuels for cooking and heating, tobacco smoking, emissions from construction materials and furnishings, and poor ventilation [10]. These sources release pollutants such as carbon monoxide, nitrogen oxides, volatile organic compounds, and particulate matter, which can have significant impacts on human health [5, 11].

Air pollution is a major problem in India, and it has a significant impact on public health, including tuberculosis (TB) [3, 12]. When these pollutants are present in high concentrations, they can have harmful effects on human health, including weakening the immune system and increasing the risk of respiratory infections such as TB.

TB is an airborne disease caused by the bacteria Mycobacterium TB, which primarily affects the lungs. When a person with active TB coughs, sneezes, or speaks, they release the bacteria into the air, which can be inhaled by others. Air pollution can affect rate of TB in two ways, firstly by increasing the risk of transmission and secondly by worsening the symptoms or slowing down the recovery process. When a person is exposed to air pollution, their respiratory system can become inflamed and damaged, making it easier for the TB bacteria to take hold and cause an infection. Furthermore, air pollution can worsen the outcomes of TB treatment. When a person with TB is undergoing treatment, it is crucial that they receive enough oxygen to help their body fight off the infection. However, exposure to air pollution can reduce the amount of oxygen in the air, making it more difficult for TB patients to recover. Air pollution can also cause respiratory symptoms such as coughing and shortness of breath, which can make it harder for TB patients to take their medication and follow their treatment plan.

Emerging literature increasingly emphasizes the complex and multifactorial interactions between environmental stressors and infectious disease burdens in low- and middle-income countries, particularly India [13–15]. Studies have shown that chronic exposure to ambient air pollutants, especially fine PM2.5, disrupts pulmonary immune defenses, reducing the lung's ability to clear pathogens and making individuals more susceptible to infections such as TB [16–19]. Recent advancements in environmental epidemiology have adopted a spatial lens to examine how urban form, land use, and microclimatic conditions interact with airborne health risks [20, 21]. For instance, cities with high vehicular density and limited green cover often experience urban heat island effects, which, combined with stagnant air masses, intensify pollutant concentrations [22, 23]. These environmental exposures are not randomly distributed; rather, they disproportionately affect socioeconomically disadvantaged populations residing in marginalized or poorly planned settlements [24–26]. Consequently, there is a growing demand for integrative spatial models that can map and predict disease vulnerability zones by overlaying environmental indicators with public health data. In the Indian context, such spatial epidemiological approaches are essential to designing targeted interventions for TB control that are both environmentally and socially contextualized.

India has the largest number of TB cases globally. This disease is a significant public health concern and requires attention and resources to prevent and treat it effectively. It's catalytic to diagnose TB early and begin treatment as soon as possible to prevent the spread of the disease and avoid TB converting into drug resistant. The treatment for TB usually involves taking several antibiotics for six to nine months. In some cases, drug-resistant TB may require longer and more complicated treatment regimens. Preventing the transmission of TB involves taking precautions such as covering your mouth and nose when coughing or sneezing, wearing a mask, ventilating indoor spaces, and avoiding close contact with people who have TB [27]. Additionally, people who are at high risk of contracting TB, such as healthcare workers and people living in close contact with infected individuals, can receive a TB vaccine or take preventive medication to reduce their risk of infection. Several studies have shown a correlation between airborne TB spread and air pollution from PM, carbon monoxide, sulphur dioxide, and other pollutants. However, the reason for this correlation is likely multifactorial [4]. In addition, air pollution can increase the survival of TB bacteria in the air, allowing them to persist for longer periods and increasing the likelihood of transmission. The quality of air is an important factor in the transmission of TB.

To reduce the burden of TB in India, it is essential to address the issue of air pollution and work towards improving air quality. This can include measures such as reducing emissions from vehicles and factories, promoting cleaner energy sources, and improving indoor air quality through better ventilation and filtration systems. However, air pollution levels in India are consistently high and have been worsening over the past decade [28–30]. According to the Health Effects Institute Report (2020), India had the highest concentration of PM2.5 particles (particulate matter with a diameter of 2.5 microns or less) of any country in the world in 2019. These particles can penetrate deep into the lungs and cause respiratory and cardiovascular problems. Abbafati [1] found that air pollution is responsible for 1.67 million deaths in India, or 17.8% of all deaths. This makes air pollution the second leading risk factor for mortality in India, after high blood pressure.

Against this background the research aims to analyze the spatial distribution and variation of air pollution and TB across the states of India. Geographic analysis is used to explore the spatial distribution of TB, death due to TB and different particles of air pollution, air quality index, Land Surface Temperature (LST) and Vegetation in India. The aim is to identify areas where the incidence of TB, is associated with the environmental factors, particularly air pollution.

2 Methodology

The present study investigates the spatial variation of air pollution and TB distribution across Indian states using a robust set of secondary data sources and spatial analytical tools. The study integrates multi-source datasets, combining Sentinel-5P air quality observations at 0.01° × 0.01° resolution, MODIS-derived NDVI at 1000 m resolution, and tuberculosis data from the TB India Report 2022. This spatially integrated framework allows for precise mapping and statistical assessment of environmental exposure and health outcomes.

State-level shapefiles were sourced from Survey of India to ensure geographic consistency across datasets. Air pollution variables $PM_{2.5}$, PM_{10}, NO_2, SO_2, and O_3 were

retrieved via Google Earth Engine (GEE) for the year 2022. NDVI values were extracted from MODIS data on GEE, representing vegetation cover as a proxy for urbanization or ecological resilience. The TB incidence and mortality data were obtained from the India TB Report 2022, published by the Ministry of Health and Family Welfare. Population density figures were integrated from national census data.

Satellite datasets (Sentinel-5P, MODIS) were pre-processed using cloud masking, gap filling, and QA filtering, then resampled to a uniform grid. Air pollution estimates were cross-validated with CPCB ground station data, and all environmental indicators were temporally aligned with TB statistics from the TB India Report 2022. These steps ensured consistency, minimized errors, and improved confidence in the results.

$$\text{NDVI} = \frac{(NIR - RED)}{NIR + RED} \tag{1}$$

Where:

- NIR = Near-Infrared reflectance.
- RED = Red band reflectance.

NDVI values range from −1 to +1, with higher values indicating denser vegetation. Lower NDVI often corresponds to urban areas, where pollution concentration tends to be higher and vegetation lower.

Quality control and data attribution procedures, data cross-validation, temporal alignment, and spatial harmonization, were applied to ensure accuracy and consistency across Sentinel-5P, MODIS, and TB datasets.

A correlation matrix was first used to evaluate linear relationships between TB cases and environmental variables. The Pearson correlation coefficient (r) was computed as:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \tag{2}$$

Where x_i and y_i are observed values of the two variables and $\bar{x}$, $\bar{y}$ are their means. This allowed us to identify which pollutants or variables had the strongest associations with TB indicators.

Next, we conducted simple linear regression analyses to predict the relationship between TB outcomes and environmental variables. The model is expressed as:

$$Y = \beta_0 + \beta_1 X + \epsilon \tag{3}$$

Where:

- Y = Dependent variable (number of TB patients or TB deaths).
- X = Independent variable (e.g., AQI, NDVI, population density).
- β_0 = Intercept.
- β_1 = Coefficient of independent variable.
- ϵ = Error term.

Two regression models were used:

1. Model 1: TB incidence = f(AQI, NDVI, population density).

2. Model 2: TB mortality/death = f(AQI, NDVI, population density).

This allowed us to quantify the effect of environmental stressors on TB burden across Indian states.

The spatial and statistical approach adopted in this study ensures a multidimensional understanding of how environmental exposures, especially air pollutants like $PM_{2.5}$, affect respiratory health outcomes like TB. The open-access nature of the data (Sentinel, GEE, TB Reports) promotes transparency, scalability, and policy relevance.

The study is structured into four parts: Introduction, Results, Discussion, and Conclusion, each contributing to an integrated assessment of spatial health vulnerability in India. The findings are crucial for environmental health policy, especially under India's National TB Elimination Programme and ongoing efforts to mitigate air pollution impacts.

3 Results

This study analysed the spatial distribution of air quality index and vegetation environmental indicator (NDVI), population density and TB patients as well as other critical air pollutant over India. Also, statistical analysis and the interlinkage among these indicators explicitly shows the related with TB patients.

3.1 Spatial distribution of TB patients, air quality index and population density

The spatial analysis highlights distinct geographic clustering patterns of air quality, population density, and TB outcomes across India (Fig. 1). Air quality exhibits a pronounced north–south gradient, with the Indo-Gangetic Plain including Delhi, Punjab, Haryana, and western Uttar Pradesh recording the most severe concentrations (AQI > 200).

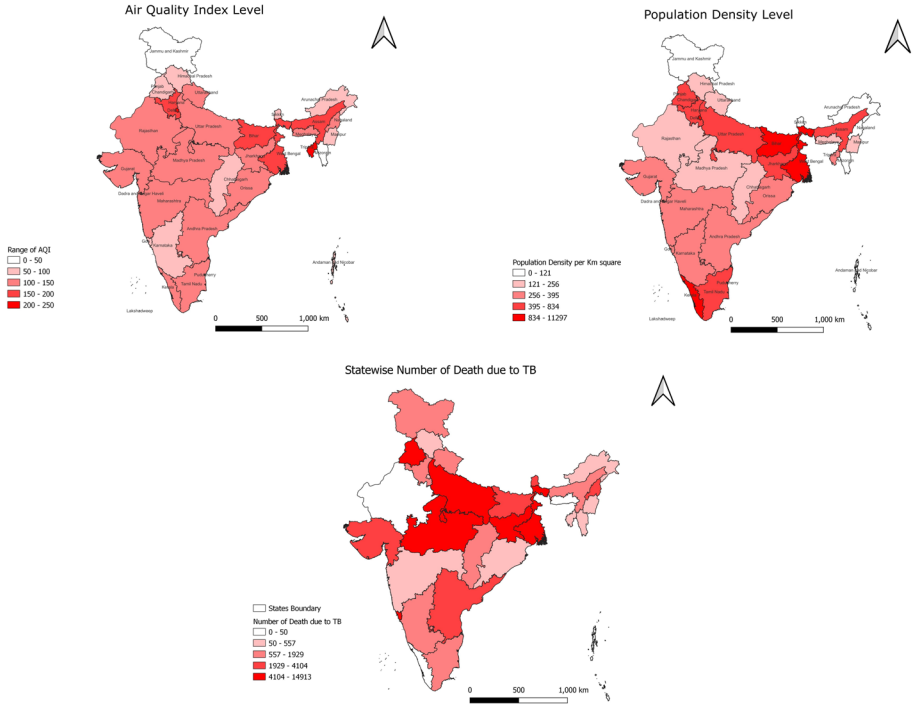

Fig. 1 Distribution of AQI across States of India (**a**), Population Density (**b**), and Spatial Distribution of Deaths due to TB (**c**)

Moderately elevated levels (150–200) are observed in Madhya Pradesh, Chhattisgarh, and eastern Maharashtra, whereas the southern states (Karnataka, Kerala, Tamil Nadu, and Andhra Pradesh) and most northeastern states display comparatively better conditions (AQI 50–150) (Fig. 1a). Population density demonstrates a polycentric distribution (Fig. 1b), with Delhi (11,297 persons/km^2) and Chandigarh (9,252 persons/km^2) at the highest levels, followed by Kolkata, Bihar, Punjab, and Kerala. Moderate densities are seen in Madhya Pradesh, Rajasthan, and Chhattisgarh (200–400 persons/km^2), while the Himalayan belt and northeastern states maintain low densities (< 200 persons/km^2). TB mortality is concentrated in northern and central India (Fig. 1c), where Uttar Pradesh reports the highest deaths (14,913), followed by Maharashtra (6,988) and Madhya Pradesh (4,795). Bihar and West Bengal also contribute substantially, forming a distinct "TB mortality belt." In contrast, Himachal Pradesh, Kerala, and the northeastern states exhibit relatively low TB deaths (< 800).

3.2 Correlation analysis of air pollution and TB burden

Case notification data (Fig. 2a) highlight that Uttar Pradesh bears the highest TB burden with 363,664 notified cases, followed by Maharashtra (147,420) and Madhya Pradesh (135,759). Vegetation patterns derived from NDVI (Fig. 2b) reveal that Mizoram (0.54), Arunachal Pradesh (0.46), and Sikkim (0.44) record the highest vegetation levels, while heavily industrialized and urbanized states in the north and west show substantially lower values. Pollution distribution (Fig. 2c) indicates that Tripura, Delhi, and Bihar suffer the worst conditions, with AQI values exceeding 190, closely overlapping with zones of high TB incidence and mortality.

Correlation analysis (Table 1) demonstrates that TB patient counts are positively associated with HCHO ($r = 0.29$), LST ($r = 0.22$), and SO_2 ($r = 0.15$), while a moderate correlation exists with respiratory symptoms ($r = 0.60$). Precipitation shows a strong positive relationship with NDVI ($r = 0.48$) but a slight negative association with SO_2 ($r = -0.06$). Regression results (Tables 2 and 3) indicate that air pollution is strongly associated with TB incidence ($\beta = 1.98$, $p = 0.002$), vegetation plays a protective role ($\beta = -5.73$, $p = 0.002$), and population density has a weaker negative effect ($\beta = -0.55$, $p = 0.049$). For mortality, population density emerges as the strongest predictor ($\beta = 1.72$, $p < 0.001$), while air pollution shows a weaker association ($\beta = 0.12$, $p = 0.063$), and vegetation again displays a protective effect ($\beta = -4.62$, $p = 0.02$).

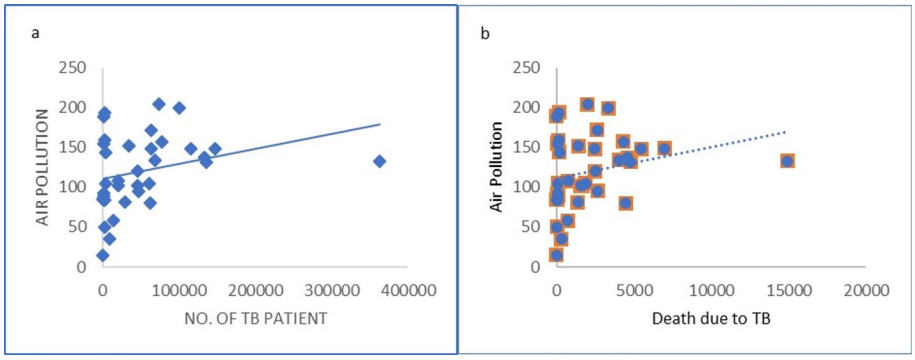

Fig. 2 **a** Scatter plot of no of air pollution and no. of TB patient. **b** Scatter plot of no of air pollution and death due to TB

Table 1 Correlation between TB patients and air pollutants

	SO_2 Mean	Precipitation Mean	O_3	NO_2	NDVI	LST	HCHO	Cough Sneezing	TB Patients
SO_2_Mean	1								
Precipitation Mean	-0.06	1							
O_3	0.01	0.21	1						
NO_2	-0.07	-0.36	-0.13	1					
NDVI	-0.09	0.48	0.01	-0.12	1				
LST	-0.02	0.06	0.35	-0.24	-0.07	1			
HCHO	0.27	0.04	0.03	-0.07	0.19	0.20	1		
Cough Sneezing	0.08	0.30	-0.05	-0.08	0.08	0.05	0.16	1	
TB Patients	0.15	0.17	-0.09	0.05	-0.08	0.22	0.29	0.60	1

Table 2 Number of TB patient and environmental factors

No. of TB patient	Coefficient	Standard error	*P* Value	95% confidence interval	
Air pollution	1.98	0.58	0.002	0.80	3.17
Enhance vegetation	−5.73	1.73	0.002	−9.25	−2.21
Population density	−0.55	0.27	0.049	−1.09	−0.003
Constant	−1.13	1.17	0.342	−3.50	1.25

Prob > F 0.0002

R-squared 0.47

Adj R-squared 0.41

Table 3 Death due to TB and environmental factors

Death due to TB	Coefficient	Standard error	*P* Value	95% confidence interval	
Air pollution	0.12	0.065	0.063	−0.007	0.256
Population density	1.72	0.17	0	1.37	2.06
Enhance vegetation	−4.62	1.86	0.02	−8.42	−0.84
Constant	−0.67	1.74	0.70	−4.23	2.88

Prob > F 0.0627

R-squared 0.10

Adj R-squared 0.07

Scatter plot analysis (Fig. 2a) illustrates a positive association between air pollution levels (10–210 μg/m^3) and TB mortality (500–15,000 deaths). The regression explains 6.1% of variance (R^2 = 0.0614), indicating a weak but significant relationship. States with low pollution (< 50 μg/m^3) consistently exhibit mortality exceeding 2,000 deaths, while states with severe pollution (> 150 μg/m^3) show highly variable mortality outcomes, suggesting that confounding factors such as healthcare access and socioeconomic conditions also play a role. In contrast, the association between air pollution and TB incidence (Fig. 2b) is stronger, with the regression explaining nearly 40% of variance (R^2 = 0.3982). The pattern shows a curvilinear trajectory: states with pollution below 50 μg/m^3 consistently report fewer than 100,000 cases, whereas states above 150 μg/m^3 consistently record more than 200,000 cases, with incidence exceeding 350,000 in the most polluted regions. The pattern shows a curvilinear trajectory of states with pollution below 50 μg/m^3 consistently reporting fewer cases, whereas states above 150 μg/m^3 consistently record more cases, with incidence exceeding more in the most polluted regions.This suggests a stronger and potentially nonlinear influence of air pollution on TB transmission compared to mortality outcomes (Fig. 3).

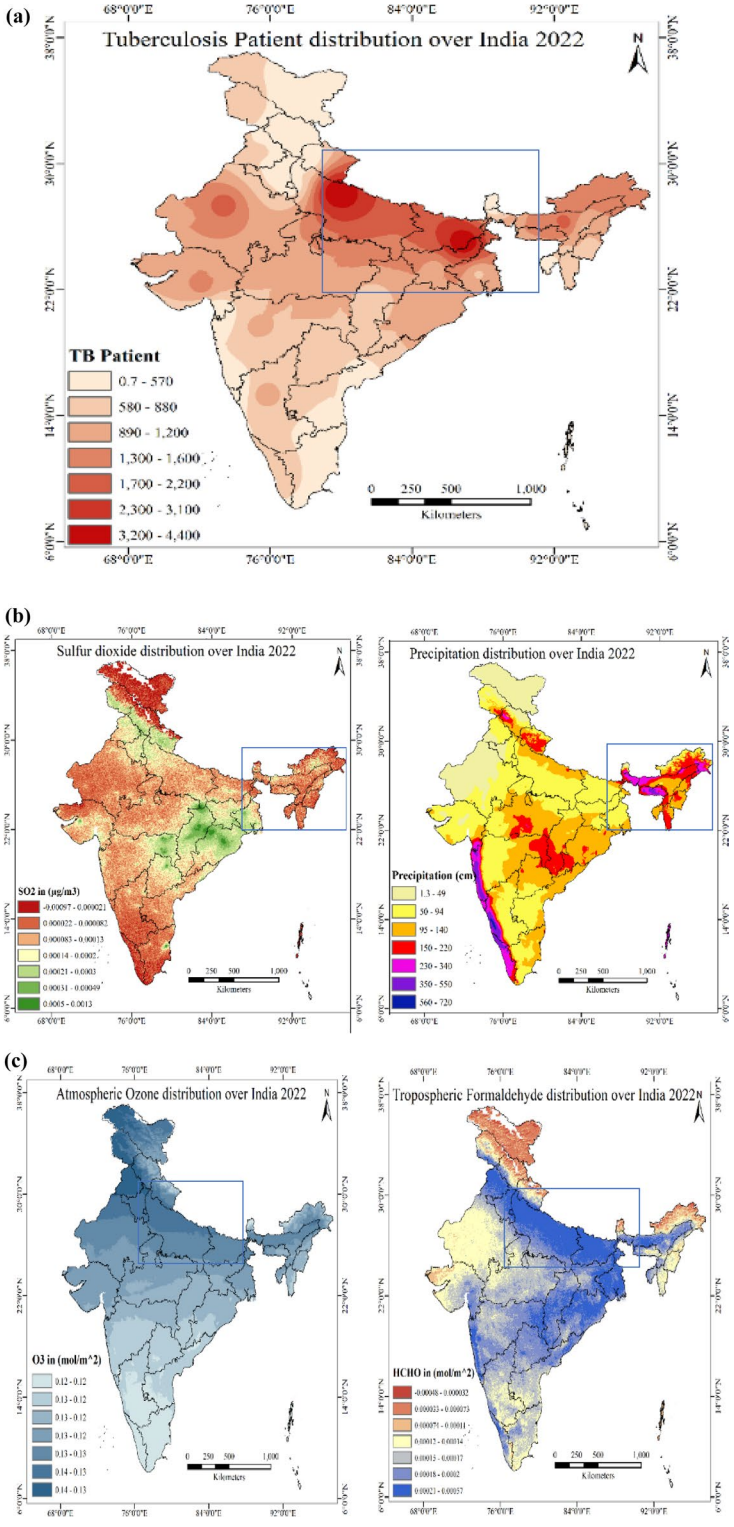

Fig. 3 **a** Spatial distribution of TB patients. **b** Spatial distribution of TB patients, vegetation, land surface temperature, and distribution of air pollutants across states of India. **c** Spatial distribution of TB patients, Vegetation, land surface temperature, and distribution of air pollutants across states of India. **d** Spatial distribution of TB patients, vegetation, land surface temperature, and distribution of air pollutants across states of India. e Spatial distribution of TB patients, vegetation, land surface temperature, and distribution of air pollutants across states of India. **f** Spatial distribution of TB patients, vegetation, land surface temperature, and distribution of air pollutants across states of India

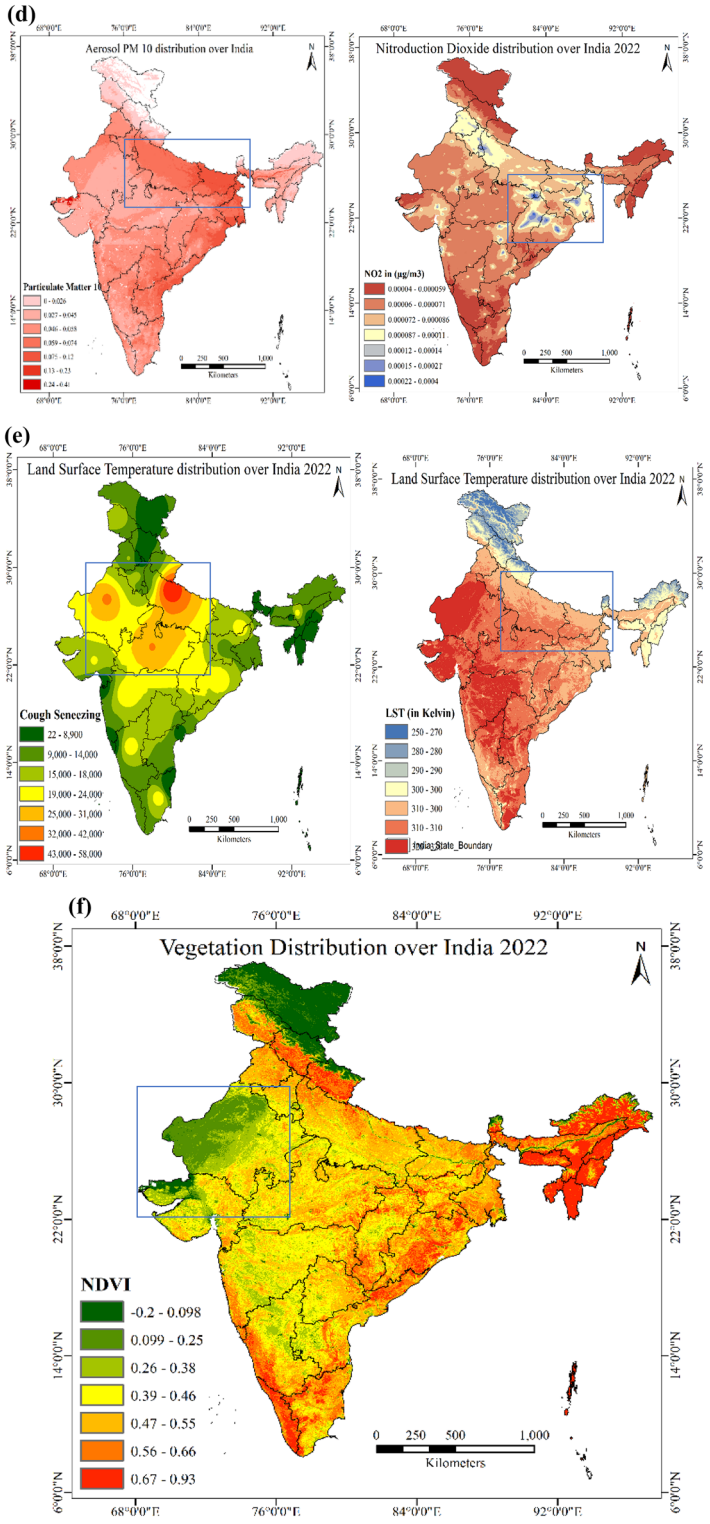

Fig. 3 (continued)

Table 1 presents a correlation matrix displaying the relationships among SO2, HCHO, NDVI, NO2 environmental variables and health-related variables like TB. Each cell in the table represents the correlation coefficient between the corresponding pair of variables, ranging from – 1 to 1.

The diagonal elements represent the correlation of each variable with itself, which is always 1. Looking across the Table 3, we observe interesting patterns. For instance, there is a positive correlation between SO_2 and HCHO, suggesting a potential link between these air pollutants. Precipitation shows a negative correlation with SO_2, implying that higher precipitation is associated with lower SO_2 levels. Additionally, NDVI exhibits a positive correlation with precipitation, indicating a potential relationship between vegetation and rainfall.

However, moving to the health-related variables, TB Patients show a moderate positive correlation with HCHO, indicating that areas with higher formaldehyde levels may also have more reported TB cases. Cough Sneezing, on the other hand, has a positive correlation with NO_2, which may suggest a potential respiratory impact associated with higher NO_2 levels.

These correlations provide valuable insights into potential associations between environmental factors and health outcomes, contributing to our understanding of the complex interplay between air quality, weather conditions, and public health. It is important to note that correlation does not imply causation, and further analyses and considerations are needed to establish causal relationships and draw meaningful conclusions.

Based on the results of the regression analysis between TB patients and air pollution and enhanced vegetation, we can draw the air pollution has a positive and statistically significant relationship with the number of TB patients. The coefficient value of 1.98 indicates that for every unit increase in air pollution, there is a corresponding increase of 1.98 TB patients. The p-value being less than 5% indicates that this relationship is statistically significant. Enhanced vegetation has a negative and statistically significant relationship with the number of TB patients. The coefficient value of –5.73 indicates that for every unit increase in enhanced vegetation, there is a corresponding decrease of 5.73 TB patients. The p-value being less than 5% indicates that this relationship is statistically significant.

Further, we examined the relationship between the number of deaths due to TB and three independent variables - air pollution, population density and enhanced vegetation. The regression coefficients for air pollution, population density and enhanced vegetation are 0.12, 1.72 and – 4.62, respectively.

The positive coefficient value for air pollution indicates that an increase in air pollution is associated with an increase in deaths due to TB. The magnitude of the coefficient (0.12) suggests that for every unit increase in air pollution, the number of deaths due to TB increases by 0.12 units. This relationship is statistically significant (p-value less than 5%). On the other hand, the negative coefficient value for enhanced vegetation (–4.62) suggests that an increase in enhanced vegetation is associated with a decrease in deaths due to TB. This means that for every unit increase in enhanced vegetation, the number of deaths due to TB decreases by 4.62%. This relationship is also statistically significant (p-value less than 5%).

4 Discussion

The present analysis underscores a compelling spatial and statistical association between air pollution, vegetation cover, population density, and the epidemiology of TB in India. While TB has long been viewed through the lens of socio-economic and healthcare access disparities, the findings of this study suggest that environmental determinants

particularly air quality and vegetative cover play a critical, and often underappreciated, role in shaping the disease burden across Indian states. This perspective represents a departure from conventional TB analyses, which predominantly emphasise demographic, behavioural, and biomedical factors, and moves towards a more integrated environmental health framework.

One of the most striking patterns emerging from the spatial mapping is the overlap between high TB incidence and elevated air pollutant concentrations in specific geographic belts, particularly the northern and central states. This co-location is unlikely to be coincidental. Airborne particulate matter and gaseous pollutants are known to exacerbate respiratory vulnerability by impairing clearance, inducing oxidative stress, and triggering chronic inflammation in the respiratory tract [16, 31]. Such physiological changes can weaken host defences, thereby facilitating both the acquisition of Mycobacterium TB infection and the progression from latent to active disease. The regression results, showing a statistically significant positive association between air pollution and TB patient numbers, further validate this environmental risk pathway. The magnitude of the coefficient suggests that even moderate increases in pollution could translate into substantial increments in TB burden, especially in densely populated states with already strained public health systems.

The positive, albeit smaller, association between air pollution and TB-related mortality observed in the model also deserves attention. While the effect size here is lower compared to incidence, it nonetheless reflects a plausible link between pollutant exposure and poorer clinical outcomes. Chronic exposure to pollutants such as fine $PM_{2.5}$ and nitrogen dioxide has been associated with diminished lung function and compromised immune response during TB treatment, potentially prolonging recovery times or increasing vulnerability to treatment failure [32, 33]. Moreover, pollutants like ozone and formaldehyde may exacerbate comorbid respiratory conditions such as chronic obstructive pulmonary disease or asthma which in turn could worsen TB prognosis. These indirect pathways emphasise the need to consider environmental remediation as a complementary strategy to biomedical interventions in reducing TB mortality.

Equally important is the inverse association between enhanced vegetation cover and TB outcomes, which emerges consistently for both incidence and mortality. Vegetation can influence TB epidemiology through multiple mechanisms. From an ecological standpoint, higher vegetation is often associated with better air quality, as trees and plants act as natural filters that absorb gaseous pollutants and trap airborne particulates [34]. This "ecosystem service" reduces pollutant exposure in human populations, potentially lowering respiratory vulnerability. From a climatic perspective, vegetated areas tend to have lower ambient temperatures and better humidity regulation, which may indirectly affect bacterial survival and transmission dynamics in the environment. Furthermore, regions with higher vegetation are frequently less urbanised, and therefore less likely to experience the intense crowding and air quality deterioration common in densely populated cities both of which are known risk factors for TB spread [35, 36].

The protective effect of vegetation observed in this study also raises broader socio-environmental considerations. Many of the north-eastern states, which display the highest vegetation indices in our dataset, also have lower TB incidence and mortality despite limited healthcare infrastructure compared to more industrialised states. This suggests that environmental quality may serve as a "buffer" against certain health risks, mitigating

the full impact of other structural disadvantages. Such a pattern aligns with research in environmental epidemiology that links green space exposure to improved respiratory health and reduced risk of chronic diseases [37]. The implication is clear: public health strategies targeting TB should not only focus on biomedical treatment and contact tracing but also incorporate urban planning and environmental conservation measures that preserve and expand green cover.

Population density, another significant predictor in our models, appears to influence TB mortality more strongly than TB incidence. This may be due to the compounded effects of crowding on healthcare access, treatment adherence, and transmission risk. In densely populated urban settings, TB patients may face greater delays in diagnosis due to overburdened health systems, leading to more advanced disease stages at presentation. High density can also amplify within-household and community transmission, particularly in socio-economically deprived areas where ventilation is poor and air pollution is common. Additionally, high-density regions may serve as hubs for multidrug-resistant TB (MDR-TB) due to the challenges in ensuring consistent treatment adherence in transient or highly mobile populations [38]. The strong mortality association found here suggests that population management through decentralisation of urban settlements and improved housing design could be an indirect but impactful TB control strategy.

When considering the joint spatial patterns, a notable "syndemic" zone emerges across Uttar Pradesh, Bihar, and Madhya Pradesh, where high TB incidence, elevated air pollution, lower vegetation cover, and substantial population density converge. This clustering effect is consistent with the ecological concept of "multiple stressors" in public health, wherein co-existing environmental and social hazards interact to produce disproportionately high disease burdens [39]. Addressing TB in such regions will likely require multi-sectoral interventions that go beyond conventional health department mandates, involving environmental ministries, urban development authorities, and community-based organisations.

The finding that Gujarat and Rajasthan show relatively high TB incidence despite having better air quality and vegetation levels compared to the central-northern cluster introduces an interesting nuance. This pattern may point to other region-specific drivers such as migrant labour patterns, occupational exposures (e.g., silica dust in mining), or differences in case detection and reporting systems. It also underscores that while environmental factors are critical, they operate within a broader socio-economic and occupational health context. Future research should examine these state-specific variations to disentangle the relative contributions of environmental, occupational, and healthcare system factors.

From a methodological perspective, the observed correlations between pollutants (e.g., the positive link between SO_2 and formaldehyde, and the inverse relationship between precipitation and SO_2) also hold relevance for TB epidemiology. Such co-pollutant dynamics could have compounding or antagonistic effects on respiratory health. For instance, precipitation can temporarily reduce airborne pollutant concentrations through wet deposition, which might explain its negative association with SO_2 levels. Conversely, areas with high industrial emissions may emit multiple pollutants simultaneously, resulting in co-exposures that are more harmful than the sum of their parts [40]. In this light, TB prevention efforts could benefit from monitoring multi-pollutant indices rather than focusing narrowly on single pollutants.

The public health implications of these findings are substantial. First, environmental monitoring should be integrated into TB surveillance systems to enable real-time assessment of environmental risk factors in high-burden regions. This could involve partnerships between the health ministry, meteorological departments, and environmental agencies. Second, air pollution control policies such as stricter vehicular emission standards, industrial emission caps, and the promotion of cleaner fuels should be explicitly recognised as TB prevention measures in national strategic plans. Such framing could attract cross-sectoral funding and strengthen political commitment to pollution reduction. Third, vegetation enhancement programmes, including urban afforestation and green belt development around industrial zones, should be prioritised not only for climate and biodiversity goals but also for their potential to reduce TB and other respiratory diseases.

It is also critical to address the temporal dimension of TB environment interactions. The current study uses cross-sectional data for 2022, which limits causal inference. However, TB is a chronic condition with a long latency period, and pollutant exposure over preceding years may be as important as current levels in influencing disease outcomes. Longitudinal studies tracking both environmental changes and TB incidence over time would provide stronger evidence for causality. Similarly, incorporating seasonal variation into future analyses could shed light on whether pollution peaks during certain months correspond to spikes in TB diagnoses, which might inform targeted public health interventions.

The observed relationships also invite discussion on the intersection of TB control and climate change. Climate change is expected to influence air quality through changes in temperature, precipitation patterns, and the frequency of extreme events such as dust storms and wildfires all of which could alter TB transmission dynamics. Additionally, climate-related migration may increase population density in certain urban areas, further compounding TB risks. Integrating TB control strategies into broader climate adaptation plans could therefore yield synergistic benefits [41].

Another limitation of this analysis is the absence of indoor air pollution data. In India, biomass cooking fuels remain a major source of household air contamination, particularly in rural and socioeconomically disadvantaged settings. Prolonged exposure to indoor smoke is linked to higher risk of active TB and adverse treatment outcomes [42, 43]. Future research should incorporate household-level metrics, as indoor exposures such as biomass fuel use, overcrowding, poor ventilation, and socioeconomic deprivation significantly contribute to TB transmission, especially in rural and low-income households [44, 45], interacting with ambient pollution to exacerbate vulnerability.

Findings challenge the siloed approach to TB control that focuses narrowly on diagnosis, treatment, and socio-economic determinants. While these remain essential, they must be complemented by strategies that address the environmental contexts in which TB transmission and progression occur. In the Indian context, this means that ministries responsible for environment, urban development, forestry, and public health should work collaboratively towards shared targets that simultaneously improve environmental quality and reduce TB burden.

5 Conclusion

The analysis demonstrates that TB patterns in India are strongly shaped by environmental and spatial conditions. States such as Uttar Pradesh, Madhya Pradesh, and Bihar show overlapping zones of high TB burden and severe air pollution, revealing concentrated areas of risk. Statistical findings indicate that pollution levels substantially elevate TB incidence, while vegetation cover plays a mitigating role by lowering case numbers. Population density, in contrast, emerges as the most consistent factor influencing TB-related mortality, underlining the effects of overcrowding and uneven healthcare access. These insights broaden the understanding of TB beyond medical determinants, highlighting the interplay of ecological stressors and demographic pressures. Cleaner air and greater vegetation density appear to create healthier environments that slow TB transmission and improve patient outcomes. Policy measures must therefore integrate environmental health with TB control. Pollution reduction, expansion of green cover, and sustainable urban development can serve as effective preventive strategies. Strengthening health systems in high-density regions is equally important to reduce deaths. Embedding these environmental dimensions into India's National TB Elimination Programme will not only support progress toward TB eradication but also contribute to long-term goals of climate resilience and public health improvement.

6 Limitation of study

An important limitation of this study is the reliance on state-level secondary data, which may mask intra-state heterogeneity and overlook individual-level determinants. Additionally, the analysis did not control for potential confounders such as socioeconomic status, healthcare access, and indoor air pollution, all of which may substantially influence TB outcomes. While this study primarily focused on environmental determinants, future research should integrate finer spatial data and individual-level socioeconomic and healthcare indicators to strengthen causal understanding of TB environment interactions.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12982-025-01049-9.

Supplementary material 1

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Author contributions

Vijay Kumar: conceptualization, methodology, software, formal analysis, investigation, writing-original draft preparation and writing, review and editing; Tulika Tripathi: conceptualization, methodology, formal analysis, investigation, writing-original draft preparation and writing, review and editing; Alok Raj: software, formal analysis, investigation, review and editing; Pradeep Kumar: software, formal analysis, investigation, review and editing.

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Data availability

In this study, we used freely available secondary data from the public domain. No new datasets were generated or analysed during the study. The dataset access links are provided in the Reference section.

Declarations

Ethics approval and consent to participate

This study used publicly accessible data from Survey of India, Sentinel-5P, Google Earth Engine, and the Ministry of Health and Family Welfare and did not involve any human subjects or procedures necessitating ethical approval. The research relied on aggregated, anonymized data from a public database, with no participation of individual subjects. Not applicable. The study uses de-identified secondary data with no direct involvement of human participants.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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