RESEARCH PAPER

EXPLORING GEOSPATIAL CLUSTERS OF FIVE PRIMARY RESPIRATORY DISEASES IN SOUTH PUNJAB, PAKISTAN: AN EPIDEMIOLOGICAL EXAMINATION

Munazza Fatima[1*], Ibtisam Butt[2], Neda Firouraghi[3], Behzad Kiani[4]

[1] Department of Geography, The Islamia University of Bahawalpur, Bahawalpur, Punjab Pakistan

[2] Institute of Geography, University of the Punjab Lahore, Pakistan

[3] Centre de Recherche en Santé Publique (CReSP), Département de Médecine Sociale et Préventive, École de Santé Publique, Université de Montréal, Montreal, Quebec, Canada

[4] University of Queensland Centre for Clinical Research, The University of Queensland, Brisbane, Australia

*Corresponding author: munazza.fatima@iub.edu.pk

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ABSTRACT. Respiratory diseases constitute a significant burden of morbidity and mortality in developing nations such as Pakistan. This study aims to analyze five prevalent respiratory ailments - acute respiratory infections (ARI), tuberculosis (TB), pneumonia, asthma, and chronic obstructive pulmonary diseases (COPD) - within South Punjab, Pakistan. Utilizing the tehsil level (the administrative sub unit of district), case data spanning five years (2016-2020) were collected from 1,487 government health centers across the study area. Spatial analysis techniques including Local Moran's I and Getis Ord Gi* statistics were employed to identify clusters and outliers. The results revealed spatial heterogeneity in respiratory disease prevalence, delineating both high-intensity (hotspots) and low-intensity (cold spots) clusters across the region. Specifically, ARI hotspots were observed in northeastern and central regions, asthma hotspots in central and north-central areas, COPD hotspot areas in the north and northeast, pneumonia hotspots in the central region, and TB hotspots predominantly in the central region. These findings offer critical insights for targeted public health interventions, facilitating resource allocation for disease prevention and control efforts. Additionally, this study presents recommendations addressing local environmental and socio-economic factors to mitigate respiratory disease incidence through administrative environmental management and community engagement strategies.

KEYWORDS: respiratory diseases, spatial analysis, hotspots, public health interventions, South Punjab

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INTRODUCTION

Respiratory diseases profoundly influence public health and contribute significantly to global morbidity and mortality rates. Whether they manifest acutely or chronically and exhibit communicable or non-communicable characteristics, respiratory diseases impose a substantial global burden, affecting millions of individuals (ERS 2021). The spectrum of respiratory diseases includes a range of conditions, each with distinct characteristics and impacts on pulmonary health (John Hansen-Flaschen et al., 2023). ARI, a transient affliction lasting less than 30 days, may affect various respiratory components, including the lungs, trachea, bronchioles, or nasal cavity (Jolliffe et al., 2013). Pneumonia, a more severe lower respiratory infection, not only shares the respiratory domain with ARI but also poses a threat to lung functionality by filling alveoli with pus and fluid, resulting in breathing difficulties (EPI 2018). COPD, an incurable yet manageable condition, introduces a chronic dimension to respiratory health, impacting airways and lung structures with persistent airflow blockage and associated breathing challenges (CDC 2022a). The chronicity of COPD contrasts with the transient nature of ARI and the severity of pneumonia. However, asthma, characterized by airway inflammation and muscle constriction, contributes to the complexity of respiratory diseases, affecting individuals of all age groups with symptoms such as coughing, wheezing, shortness of breath, and chest tightness (WHO 2021). While asthma and COPD share certain symptoms, the underlying mechanisms and triggers often differ. TB, caused by mycobacterium tuberculosis, presents another facet of respiratory health, primarily targeting the lungs but also capable of affecting organs beyond the respiratory system, such as the kidneys, spine, and brain (CDC 2016). TB introduces an infectious dimension, distinct from the acute and chronic respiratory conditions previously discussed. Each respiratory disease has its own set of factors.

Lung cancer, asthma, acute respiratory infections, tuberculosis (TB), and chronic obstructive pulmonary disease (COPD) are the five main respiratory diseases that place a significant burden on society (Marciniuk et al., 2014; Wisnivesky & De-Torres, 2019). It is estimated that globally around a billion people suffer from seasonal influenza annually (WHO, 2023b), 488.9 million people from lower respiratory infections (Safiri et al., 2022), 454.6 million people from COPD (Momtazmanesh et al., 2023), 262 million people from asthma (WHO, 2023a), and 10.6 million from TB (WHO 2020b). In addition, on a global scale, four million individuals experience premature mortality due to chronic respiratory diseases (Ferkol & Schraufnagel, 2014; WHO, 2007; Wisnivesky & De-Torres, 2019). A recent study stated that during the year 2019 there were approximately 454.6 million reported cases of chronic respiratory diseases worldwide (Momtazmanesh et al., 2023). Young children and infants are particularly vulnerable. Nearly three million children, the majority of whom were under five, lost their lives to lower respiratory tract infections and pneumonia, particularly in developing and underdeveloped regions (Lim et al., 2012).

Respiratory diseases also contribute significant disease burden in Pakistan. In 2019, the country reported over 200 million cases of upper respiratory infections (Liu et al., 2022) and annually witnesses around half a million new TB cases, with approximately 15 thousand evolving into drug-resistant strains (WHO 2022). Pneumonia, claiming the lives of over one million children each year, stands as the leading cause of death among children in Pakistan (EPI 2018). COPD ranks as the seventh major cause of death in the country, contributing to nearly 5% of total mortality (CDC 2022b). Moreover, there is a growing concern that this percentage may rise in the coming years (Amir Khan et al., 2019). Also, asthma has a substantial impact on the population in Pakistan, with an estimated fifteen million children and 7.5 million adults living with the condition (Khan; Noman et al., 2016). As per the District Health Information System (DHIS), ARI stands as the primary contributor to morbidity in the Punjab Province. The calculated mean index of the top ten diseases spanning the years 2015 to 2018 revealed that ARI, with a prevalence of 12.67%, ranks as the foremost ailment within the province (DHIS 2019). Likewise, in South Punjab, Pakistan, acute respiratory infections constitute a substantial burden, comprising 24% of all reported diseases and a staggering 77% of all respiratory diseases within the region. (DHIS 2019). Some factors responsible for these high respiratory diseases rates are indoor (Rabbani et al., 2022) and ambient air pollution (Fatima et al., 2023a), smoking (Cinar & Dede 2010), adult crowding, increased family size, poor ventilation and use of biofuels, illiteracy, and unawareness of the disease (Khaliq et al., 2015).

Numerous investigations conducted in Pakistan have employed spatial clustering techniques to explain the distribution patterns of diverse diseases. Notable examples include studies on polio (Ahmad et al. 2015), malaria (Fatima, Butt, et al., 2022; Umer et al. 2018), dengue (Khaliq et al., 2023; Naqvi et al. 2021) and cutaneous leishmaniasis (Zeb et al. 2021). However, the existing literature reveals a scarcity of studies focusing on the spatial cluster analysis of respiratory diseases. Only few studies has been identified such as those on TB (I. Fatima et al. 2021; Fatima et al. 2024; Miandad et al. 2014), asthma (Khan et al. 2020) and ARI (Fatima, Khattak, et al. 2022). These studies focused either on one disease at a time or covered a small region. Hence, against this backdrop, we set out to investigate clusters and hotspots of all major respiratory diseases in South Punjab at the tehsil level as the finest geographical scale to identify high-risk areas and provide a foundation for more scientific investigation into the etiology of each respiratory disease.

Literature review

The global prevalence of respiratory disease varies regionally. The WHO estimates that respiratory infections cause 6% of all diseases in the world. Throughout the globe, 6.6 million children under the age of five die every year because of respiratory infections out of which 95% are from low-income nations (Ghimire et al. 2022). Similarly, South Asia exhibited the most elevated mortality rates associated with chronic respiratory disease, whereas sub-Saharan Africa recorded the lowest (Labaki & Han 2020). In 2021, TB caused 1.6 million deaths, making it the second leading cause of death after COVID-19 (WHO 2020b). Asthma has been associated with one in every 250 deaths globally, ranking 26th among causes contributing to years of life lost in South Asia (Burney et al., 2015; Masoli et al. 2004). Based on the most recent data from the WHO published in 2020, the incidence of lung disease-related fatalities in Pakistan escalated to 86,968 constituting 5.96% of the total mortality rate (WHO 2020a). The age-adjusted death rate stands at 77.79 per 100,000 individuals, positioning Pakistan at the eighth rank globally in this regard (WHO 2020a). Hence, there is a multifactorial difference in the mortality rate of respiratory diseases globally that is linked to various etiological agents, available therapeutics, exposure frequencies, and host immunity (Ho et al., 2018).

Spatial analysis of respiratory diseases involves using geographic information system (GIS) and spatial analytic techniques to study the distribution and patterns of respiratory diseases in specific regions (Rex et al. 2020). When it comes to geographical surveillance for geographically dispersed diseases, the main obstacles are identifying areas with markedly higher prevalence rates, carrying out statistical analyses to determine their importance, and explaining the factors that contribute to the higher disease prevalence in these areas (Tiwari et al., 2006). Spatial clustering and hotspot detection techniques using the Anselin Local Moran's I statistic and the Getis-Ord Gi* statistic play a vital role in ensuring accurate examination of such areas (M. Fatima et al. 2021; Kiani et al. 2023; Laohasiriwong et al. 2017). This spatial clustering technique has been employed to only Bahawalpur district of South Punjab in analyzing ARI during 2010-2015 (Fatima, Khattak et al. 2022). However, the current study appears to be the first of its type in that it provides fine-grained spatial patterns of all the main respiratory diseases across 11 districts in South Punjab, especially at the tehsil level. This degree of detail may provide insightful information on the distribution and incidence of respiratory diseases in the area, which might help better guide public health initiatives and the distribution of resources. The study's coverage of several districts may also make it possible to compare and identify regional differences in the frequency and distribution of respiratory diseases. All things considered, this kind of research has the potential to greatly advance our knowledge of respiratory health in the concerned region and support the creation of focused preventative and management plans.

METHODS

Study area

The focus of this research is an area called South Punjab, which is the most populous province in Pakistan. It is situated in the southern part of the larger Punjab region. South Punjab spans across a total area of 99,579 square kilometers and is located between coordinates 69.5–74°E and 27.6–31.4°N. It shares borders with India to the east, Sindh Province to the south, a portion of Baluchistan Province to the west, and North Punjab to the north. South Punjab is made up of three divisions: Bahawalpur, Dera Khazi Khan (D.G. Khan), and Multan. These divisions are further divided into 11 districts and 46 Tehsils, as shown in Fig. 1. For this study, all tehsils within South Punjab have been included for spatial analysis.

The environmental risk factors, including indoor and outdoor air pollution and frequent dust storms in summer, which are coupled with high density and low socio-economic conditions could increase vulnerability to respiratory diseases. The climate in South Punjab is characterized by intense heat and aridity during the summer months and dust storms are common throughout the season (GOP 2021). High values of particulate matter (30 - 70$PM_{2.5}$ μg/m^3) making this region's air quality unhealthy and sometimes very unhealthy according to the WHO air quality standards (Fatima et al. 2023b). In addition, almost 87.6% population rely on solid fuel for cooking and heating (Sajid Rasul et al. 2021).

This region is one of the poor regions of Pakistan with multi-fold environmental and socio-economic issues. The prevalence of multi-dimensional poverty significantly surpasses that observed in other regions of the province, characterized by high rates of stunting growth, extensive undernourishment, incomplete access to clean water and hygiene, and a great number of out-of-school children (UNDP 2022). The literacy rate in the region is notably deficient, averaging at 46.2% across the entire population (Sajid Rasul et al. 2021; UNP 2022). Additionally, the area exhibits a substantial dependency ratio of 79.6%, highlighting a considerable portion of the population dependent on adults for support (GOP 2018). All of these make South Punjab a good choice for this study.

Disease Data

The respiratory disease data was spatially aggregated at the tehsil level, while temporally it spanned monthly records as reported cases from January 2016 to December 2020. Primary disease data collection was conducted through the District Health Information System (DHIS) of respective districts, utilizing consolidated reports of cases from each health facility within the district. A comprehensive network of healthcare facilities in the South Punjab region, comprising 102 hospitals, 383 dispensaries, 110 rural health centers, 762 basic health centers, 6 TB centers, 56 sub-health centers, and 68 maternity health centers, facilitated the acquisition of disease data. Fig. 2 represents the steps of methods and results.

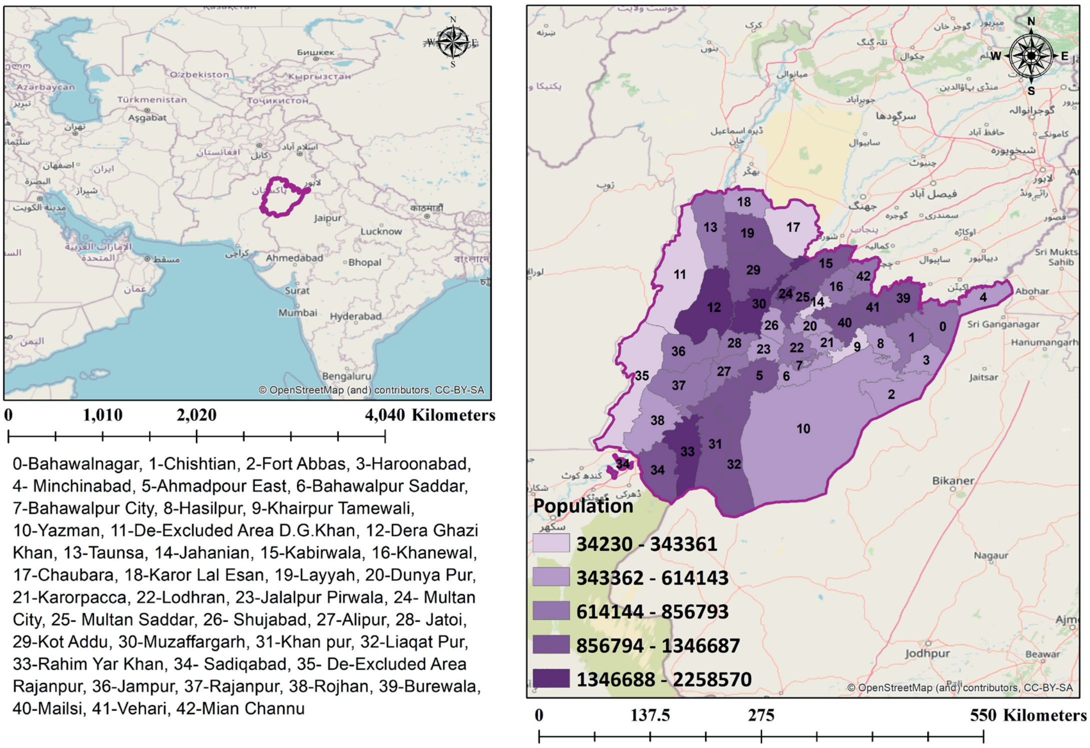

Fig. 1. Map of the study area including the population at the Tehsil level in South Punjab

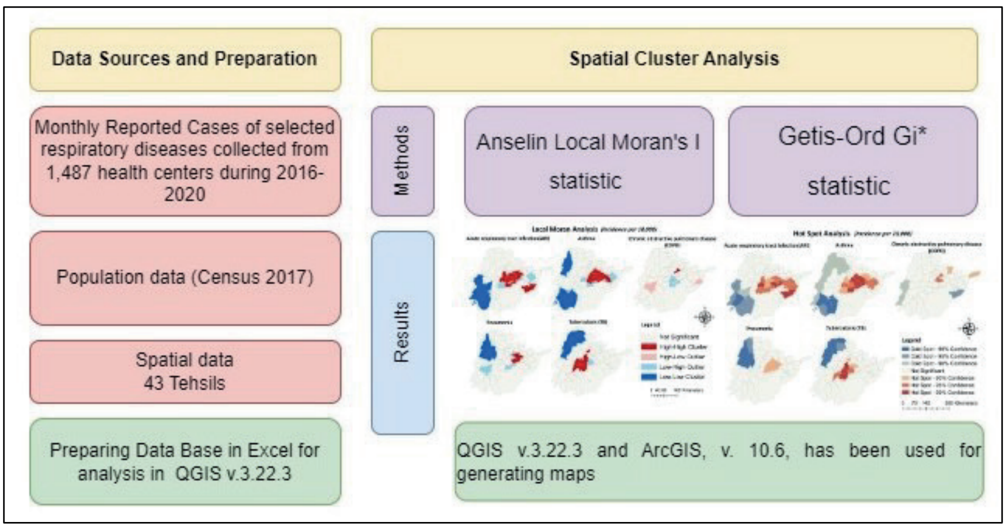

Fig. 2. Methodological Steps

Spatial analysis

This study incorporated two local spatial methods, specifically Local Moran's I and Getis-Ord Gi*. Both the Anselin Local Moran's I statistic and the Getis-Ord Gi* statistic were employed to analyze the clustering patterns of respiratory disease incidence and identify areas with high incidence (hotspots) (Anselin, 1995; Getis & Ord 1992; Ord & Getis 1995). The primary aim was to assess the spatial patterns in the observed data values for each location. In both instances, the null hypothesis assumed the absence of spatial clustering or patterns in the distribution of the observed data values. Essentially, it signifies that the data values are randomly dispersed across the study area without any significant clustering or spatial interrelation.

Spatial autocorrelation and cluster outlier analysisGlobal and local Moran's I statistics is applied on incidence rates of respiratory diseases. Global Moran's I provide an overall measure of spatial autocorrelation for an entire dataset, indicating whether there is a general clustering or dispersion of similar values across the study area. In this study, we employed the Euclidean distance method to calculate spatial relationships. However, Local Moran *I*, also known as Local Indicators of Spatial Association (LISA), is a spatial method extensively used for assessing spatial autocorrelation in geospatial data sets. It plays a key role in spatial analysis. The Local Moran *I* calculation involves comparing the value of each observation with the values of its neighboring observations. This analysis aims to determine if there is a relationship between the value of a specific location and its neighboring values. The spatial association is measured by employing a standardized z-score formula. Positive values indicate positive spatial autocorrelation, which signifies the presence of clusters with similar values. Conversely, negative values indicate negative spatial autocorrelation or spatial outliers. Clusters and outliers offer a deeper understanding of how certain areas or locations relate to their surrounding neighbors (Anselin, 1995). The clusters indicate that similar values tend to be spatially clustered together. There are two types of local Moran clusters (Anselin, 1995):

- High-High (HH): High-High clusters represent areas with high respiratory disease incidence that are surrounded by other high-value areas. These clusters indicate the presence of spatially concentrated regions of high values.
- Low-Low (LL): Low-Low clusters represent areas with low disease incidence that are surrounded by other low-value areas. These clusters indicate the presence of spatially concentrated regions of low values.

Local Moran outliers, also known as spatial outliers, are locations that exhibit values significantly different from their neighboring areas. They represent locations with values that do not conform to the spatial pattern observed in the surrounding regions. There are two types of local Moran outliers:

- High-Low (HL): High-Low outliers represent areas with high values that are surrounded by low-value areas. These outliers indicate the presence of areas with unusually high values in regions where low values are predominant.
- Low-High (LH): Low-High outliers represent areas with low values that are surrounded by high-value areas. These outliers indicate the presence of areas with unusually low values in regions where high values are predominant.

Local Moran I statistic is calculated using equation 1:

$$I_i = \frac{\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2},\ i \neq j \qquad (1)$$

In this formula, "x_i" and "x_j" represent observed values at two different locations *i* and *j*, "$\bar{x}$" is the average of these observed values, "n" is the total number of assessed locations, and "w_{ij}" represents the spatial weight associated with observations (Anselin, 1995).

Hot-spot analysis (Getis-Ord Gi* statistic)

Another spatial approach is hot-spot analysis, which calculates the Getis-Ord Gi* statistic, as a spatial measure that is used to identify local clusters of high or low values for a specific phenomenon within a geographical dataset (Getis & Ord 1992). It utilizes spatial weights to define the neighborhood relationships between spatial units. The spatial weights matrix defines the proximity and strength of interaction between neighboring units. The Getis-Ord Gi* statistic calculates a z-score, p-value, and confidence level (CI) bin for each individual location in a study area, indicating the degree of spatial clustering and the significance of that clustering. Statistical significance can be determined by comparing the z-scores to critical values obtained from a normal distribution or through permutation methods. In this study, permutation methods were used in conjunction with the Getis-Ord Gi* statistic (Anselin, 1995; Ord & Getis, 1995). The number of permutations was 499, which indicates that 499 random shuffling of attribute values were performed to establish the reference distribution.

Eq. 2 is used to calculate the Getis-Ord Gi* statistic:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} - \bar{x}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}} \qquad (2)$$

The given expression suggests that x_j represents the observed value for a specific region *j*. w_i, *j* indicates the spatial weight between two regions, *i* and *j*. The total number of regions is represented by *n*. $\bar{x}$ denotes the average value of the observed values, and s represents the standard deviation (Getis & Ord, 1992).

RESULTS

Global Moran's *I*

Global Moran's I was employed to assess the spatial autocorrelation for each disease, determining whether similar values were clustered, randomly distributed, or dispersed across the study area. The Euclidean distance method was used to compute spatial relationships between geographic units. The results revealed varying patterns of spatial distribution (Fig 3). For pneumonia, the Moran's I value (0.0073) indicated no significant clustering, suggesting a random spatial pattern (p = 0.599). In contrast, ARI displayed a strongly clustered pattern, with a Moran's I of 0.2652 and a z-score of 3.7268, meaning there is less than a 1% likelihood that the clustering occurred by random chance (p = 0.0001). Similarly, asthma showed significant clustering (Moran's I = 0.1057), with a z-score of 2.2861, indicating less than a 5% probability of this pattern arising randomly (p = 0.022). However, for COPD, the Moran's I value of -0.1106 suggested no significant departure from randomness (p = 0.227). Lastly, tuberculosis exhibited the strongest clustering, with a Moran's I of 0.3054 and a z-score of 4.1643, indicating a less than 1% likelihood that the clustering is due to chance (p = 0.000031) (Table 1).

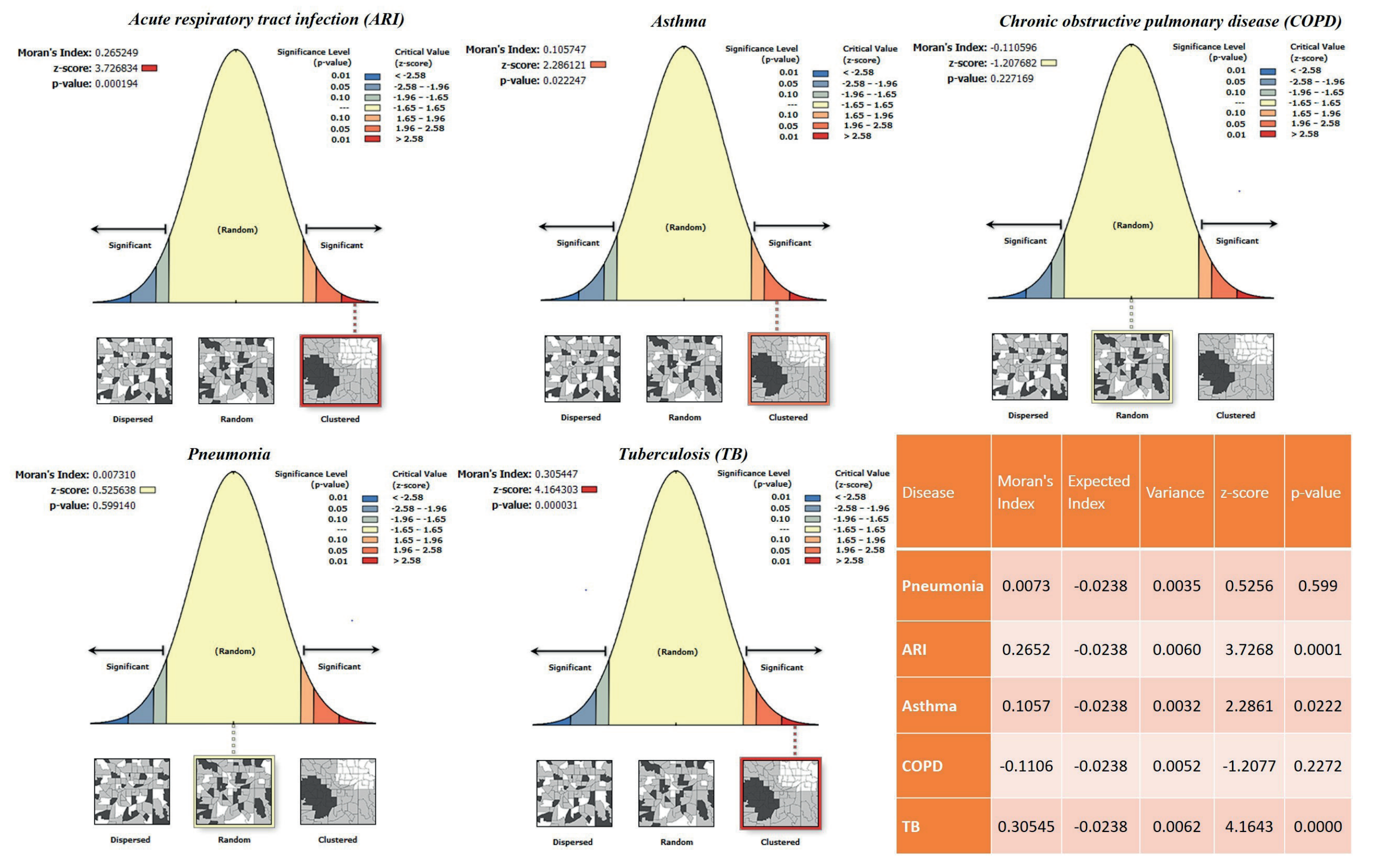

Fig. 3. Global Moran's I result for respiratory diseases incidence rates in South Punjab during 2016-2020

Table 1. Global Moran's I Summary by Disease

Disease	Moran's Index	Expected Index	Variance	z-score	p-value
Pneumonia	0.0073	-0.0238	0.0035	0.5256	0.599
ARI	0.2652	-0.0238	0.0060	3.7268	0.0001
Asthma	0.1057	-0.0238	0.0032	2.2861	0.0222
COPD	-0.1106	-0.0238	0.0052	-1.2077	0.2272
Tuberculosis	0.30545	-0.0238	0.0062	4.1643	0.0000

Anselin Local Moran I

Clusters and outliers identified by Anselin local Moran's I are detected and presented in Fig. 4. These results reveal the spatial variation patterns of common respiratory diseases.

Acute respiratory infection (ARI)

For ARI, the HH clusters were located in Fort Abbas, Bahawalpur Saddar, Dunya Pur, Karorpacca, Lodhran, Jalalpur Pirwala, Shujabad, Mailsi and the southwest part of South Punjab displayed LL cluster. According to Moran I statistics, Chishtian, Ahmadpour East, and Khairpur Tamewali were LH areas that were surrounded by areas with high ARI incidence.

Asthma

In terms of asthma, Bahawalpur City, Hasilpur, Khairpur Tamewali, Jahanian, Dunya Pur, Karorpacca, Lodhran, and Mailsi exhibited high-high clusters. Conversely, De-excluded areas D.G.Khan, Khan pur, Rahim Yar Khan, Sadiqabad, Rojhan were concentrated in low-low clusters. Chishtian, Bahawalpur Saddar, and Jalalpur Pirwala had a lower incidence of asthma but were surrounded by areas with higher incidence rates.

Chronic obstructive pulmonary disease

COPD is predominantly associated with a high-risk cluster in Jahanian, low-high areas in Bahawalpur Saddar and Lodhran, as well as high-low clusters in Haroonabad and Rajanpur.

Pneumonia

In terms of Pneumonia, Karorpacca and Mailsi were identified as high-risk clusters, while the areas of De-excluded, D.G.Khan and Dera Ghazi Khan, were found to be low-risk clusters. Additionally, Bahawalpur Saddar, Jahanian, and Rajanpur displayed characteristics of low-high areas in relation to Pneumonia.

Tuberculosis

When it comes to tuberculosis, there is a high-risk cluster that encompasses Ahmadpur East, Jalalpur Pirwala, Multan City, Shujabad, Alipur, and Jatoi. However, De-Excluded Area D.G.Khan, Taunsa, Karor Lal Esan, and Layyah have been identified as low-risk clusters. Although Lodhran itself is a low-risk area, with an increased risk of the disease in the surrounding regions.

Hot-spot analysis (Getis-Ord Gi* statistic)

The utilization of hotspot analysis allows us to identify locations where there is a statistically significant incidence of diseases and create maps highlighting these hotspots and cold spots. This is accomplished through the calculation of z-scores, with negative values indicating cold spots and positive values indicating hotspots (Fig 5).

Acute respiratory tract infection

The current study revealed the existence of distinct spatial clusters in certain locations, suggesting the presence of hotspots for ARI in the northeastern and central regions of the study area. Conversely, the southwestern area was identified as a cold spot, indicating a lower incidence of ARI cases in that specific region.

Asthma

The figure displays the spatial distribution of asthma hotspots, which are primarily situated in the central and north-central regions. Conversely, cold spots, where the incidence of asthma is relatively lower, are concentrated in the southern and southwestern areas.

Chronic obstructive pulmonary disease

Regarding COPD, the high-risk areas are primarily located in the north and northeast, whereas the cold spot with a 95% confidence interval is situated in the eastern part of the study area.

Pneumonia

The map demonstrates that when it comes to pneumonia, the central part of the study area has hotspots, while the cold spots are mainly located in the northwestern region.

Tuberculosis

In terms of TB, the map illustrates that the central part exhibits a greater number of hotspots with high z-score values, while the cold spots are concentrated in the northwestern region.

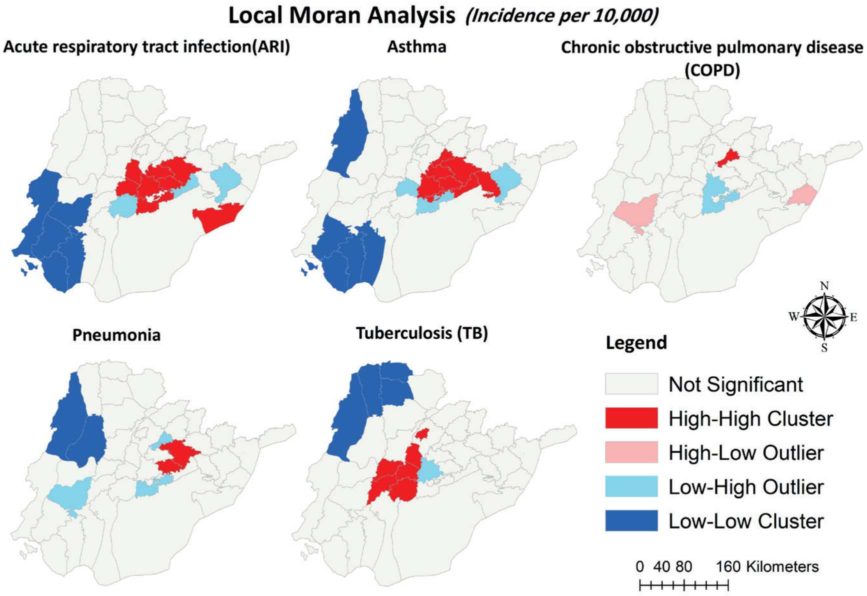

Fig. 4. Spatial clusters and outliers of respiratory diseases incidence rates, using local Moran I statistics, in South Punjab during 2016-2020

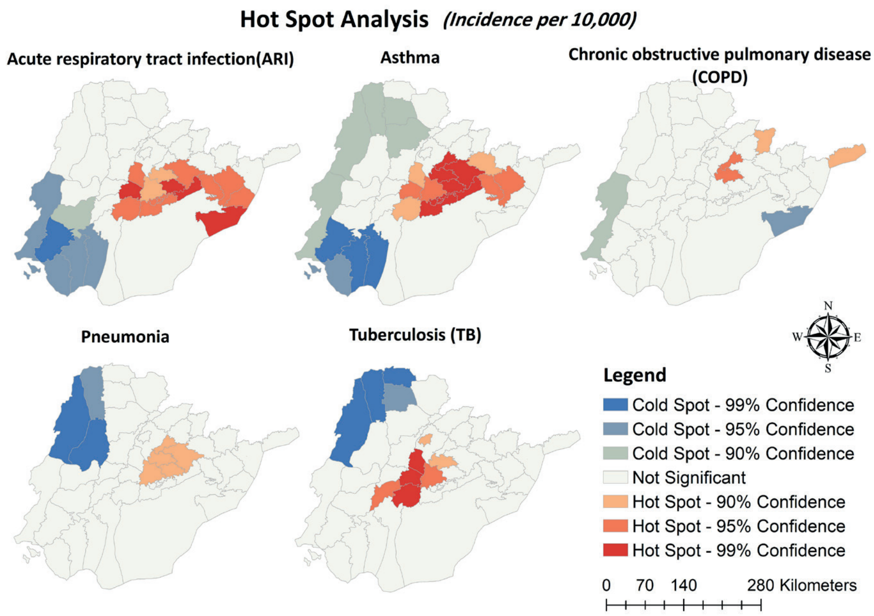

Fig. 5. Spatial hotspots and cold spots of respiratory diseases incidence rates, using Getis-ord Gi statistics, in South Punjab during 2016-2020

DISCUSSION

The geospatial epidemiological analysis conducted in South Punjab, Pakistan, revealed complex patterns in the spatial distribution of five major respiratory diseases. Using Anselin Local Moran's I and hotspot analysis (Getis-Ord Gi* statistic), the study identified distinct clusters and hotspots, offering valuable insights into the epidemiological dynamics of these diseases within the region. Specifically, the analysis highlighted significant clustering patterns for ARI, asthma, COPD, pneumonia, and tuberculosis.

The findings indicated the prevalence of HH clusters across multiple tehsils, alongside the presence of LL clusters in specific regions. Moreover, areas exhibiting LH characteristics were surrounded by elevated disease rates, suggesting localized factors influencing disease transmission. Hotspot analysis further validated these clusters, identifying statistically significant disease incidence areas.

The environmental and socio-economic conditions prevalent in South Punjab create an environment that is highly favorable for the occurrence of respiratory diseases. While each respiratory disease may have its unique risk factors, there are shared elements that impact the respiratory health of individuals in the region.

The climate of this region is of extreme type with January and December being the coldest months in the region with temperatures usually lower than 15^{0}C(PMD, 2020). Influenza as the most prevalent infection among the Pakistan population is found to be high in the spring and winter seasons (Naz et al., 2019). A previous study by Fatima et al. (2022) also supports the fact that during 2010-2012 ARIs were widely reported during winter seasons in the Bahawalpur district. Fog similarly promotes influenza transmission and causes respiratory problems. In foggy weather, aerosol inhalation, as noted by Song et.al (2022), is frequent, particularly during the winter season in South Punjab (Song et al. 2022). The number of foggy days increased up to an average of 7 days/month during December and January in this region (PMD 2020). Furthermore, it is proved through literature that dust storms affect respiratory health by direct inhalation of particles (Sadeghimoghaddam et al. 2021). In this context, South Punjab is an arid and semi-arid region, with frequent dust storms with an average of 10 to 20 dust storms from April to August (PMD 2020). While these dust storms are prevalent across the entirety of South Punjab, they are particularly pronounced in the southeastern area, which comprises the Cholistan Desert (Britannica 2010).

Ambient air pollution is one of the prime factors affecting the respiratory health of the population of this region, as South Punjab exhibits, high values of particulate matter (30 - 70PM2.5 µg/m^3) making this region's air quality unhealthy and sometimes very unhealthy according to the WHO air quality standards (Fatima et al. 2023a). Similarly, 87.6% of households rely on solid fuel for cooking and heating making the indoor air quality bad and making respiratory health vulnerable (Sajid Rasul et al. 2021). Pakistan is one of the most polluted countries in the world, and COPD has the highest mortality and morbidity burden attributed to air pollution. In 2019, COPD represented the greatest burden, accounting for 57% of total deaths attributed to air pollution (Fatima et al. 2023a). Apart from air pollution, smoking is recognized as a primary risk factor for COPD (Leberl et al. 2013; Liu et al. 2015). In this region, nearly 24% of males and 3.3% of females are reported to be tobacco smokers (UNICEF 2019) making them vulnerable to respiratory diseases.

The spatial patterns of respiratory diseases showed that the central part of South Punjab is a hotspot of almost all respiratory diseases. Therefore, multiple factors can be relatable to these respiratory diseases. For instance, the tehsils showing hotspots of respiratory diseases include mainly high-density such as Multan city (7903 persons per km^2) and Bahawalpur city (2773 persons per km^2) (Sajid Rasul et al., 2021). Lai et al. (2013) explored that high-density residential structures increase the risk of TB. The same is the case with South Punjab where on average, there are 6.6 persons per household, with a room density of 3.9 persons per room (UNICEF 2019). Besides, the poor structure of the house also contributes to the risk of respiratory disease (Fakunle et al., 2018), this region is characterized by 32% of households having mud as their primary building material, indicative of the region's low socioeconomic status (Nawab et al. 2022). Illiteracy was found to be positively related to respiratory infections such as COVID-19 (Mohammadi et al. 2023), thus, the literacy rate is as low as 46.6% in South Punjab (GOP 2018) increasing the risk of respiratory infections such as ARI, TB, and pneumonia.

Hence, a multitude of environmental factors including severe weather conditions, frequent dust storms, and ambient air pollution, alongside socioeconomic determinants such as low literacy rates, substandard living conditions, increased transmission risk due to overcrowding, reliance on solid fuels for cooking, smoking habits, elevated levels of ambient air pollution, and constrained access to healthcare services may collectively contribute to the prevalence of respiratory diseases in the region.

The primary strength of this study lies in its comprehensive analysis of the spatial clustering of respiratory diseases within South Punjab, employing commonly utilized methods in epidemiological research. These findings offer potential insights for further exploration of these respiratory disease dynamics concerning additional variables. However, this study also possesses certain limitations. It relied solely on disease data and did not incorporate other relevant factors such as environmental, socio-economic, and behavioral variables in the context of these diseases. Consequently, building upon our results, we suggest future investigations employing spatial regression modeling to investigate deeper into the patterns of each disease within South Punjab, Pakistan.

CONCLUSION

In conclusion, the geospatial epidemiological analysis conducted in South Punjab, Pakistan, has unveiled intricate patterns in the spatial distribution of five major respiratory diseases, shedding light on the epidemiological dynamics within the region. These findings highlight the multifaceted nature of respiratory disease prevalence in South Punjab, which may be influenced by a multitude of environmental and socio-economic factors. Among the studied diseases, asthma is more likely to spread in the region due to its association with air pollution and other environmental factors prevalent in South Punjab. Furthermore, there is a notable interdependence among the diseases, with areas showing high cases of COPD also experiencing increased rates of bronchitis, indicating shared environmental and socio-economic vulnerabilities. While this study provides valuable insights into the spatial epidemiology of respiratory diseases, future research endeavors should consider integrating additional variables and employing spatial regression modeling to further explain the complex dynamics and inform targeted interventions aimed at mitigating the burden of respiratory diseases in South Punjab, Pakistan.

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