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Geospatial intelligence and health analitycs: Its application and utility in a city with high tuberculosis incidence in Brazil

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ABSTRACT

Background: Geospatial Intelligence and Health Analysis have been used to identify tuberculosis (TB) hotspots and to better understand their relationship to social and economic factors. The purpose of this study was to use geospatial intelligence to assess the distribution of TB and its correlations with Human Development Index (HDI) in a city with high TB incidence in Brazil.
Methods: We conducted an ecological study, using National System of Information on Noticeable Disease (SINAN) to identify TB cases. Geocoding was performed using QGIS 2.0 software and Google Maps API 3.0. We applied geospatial intelligence to detect where in the city clustering of TB cases occurred, and assessed the association of an area's HDI (each one of the components — longevity, education, and income) with TB spatial distribution.
Results: During the study period (2011–2013), there were 737 TB cases. TB cases showed heterogeneity across the 29 neighborhoods. The neighborhoods with HDI-income lower than the mean had higher TB incidence ($p = 0.036$).
Conclusions: We found several hotspots of TB across the 29 neighborhoods, and an inverse association between HDI-income and TB incidence. These findings provide useful information and may help to guide TB control programs.

Introduction

Despite increasing treatment success rates, tuberculosis (TB) continues to spread worldwide. The World Health Organization (WHO) estimates that, in 2015, 10.4 million people developed TB and more than 1 million died by the disease [1]. Brazil is ranked 18th among the 22 high-TB burden countries, accounting for 33% of the estimated cases in Americas [2]. This scenario is due to several factors, most of them related to economic and social issues such as poverty, drug addiction and a lack of access to health programs [1,2].

TB epidemiology is influenced by geographic and social factors. The social and economic dimensions of a country are based on the health of people, their level of education attainment and their standard of living, which are the components of Human Development Index (HDI). Spatial analytics in epidemiology is useful in identifying vulnerable populations and geographic areas of TB [3–6]. Understanding the variations in TB prevalence across geographic regions is effective to plan interventions focused on TB control [7].

In recent years, Web technologies and spatial data infrastructures (SDI) have emerged as useful tools to visualize and analyze the spatial patterns of several diseases, including TB [7–12]. Techniques of geospatial intelligence [8,13,14], for example, spatial analytics, have been used to identify geospatial hotspots of TB and to better understand its relationship with social and economic factors [7,11,12]. Little attention has been paid to geographic variation

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of TB prevalence in Brazil. The objective of this study was to use geoprocessing Web Services to evaluate TB distribution and its correlations with HDI components in a city with high TB incidence in Brazil.

Methods

Study design and location

We conducted an ecological study, using geospatial intelligence techniques [8,13,15], to assess the correlation between TB incidence rates and the HDI in the city of Canoas during three years (2011–2013). Canoas is located in the metropolitan area of Porto Alegre, a city in Southern Brazil; Porto Alegre has the fourth highest TB incidence in Brazil (80.4 cases/100,000 inhabitants) [2]. Canoas has a population of 323,827 inhabitants, and is the 17th city with the highest TB incidence in Brazil. The city is comprised of 29 municipalities (neighborhoods), with a population density of 2613.59 inhabitants/km^2 [16]. Canoas is considered a commuter town (or bedroom town), that is, many Canoas' residents work in Porto Alegre (the capital), but live and sleep in Canoas. Given the geographical proximity with a city with a high incidence of TB and the fact of being a commuter town, we think it is important to conduct this study in Canoas, once those two cities have interchangeable characteristics. This study was approved by the research ethics committee of Lutheran University of Brazil (Universidade Luterana do Brasil – ULBRA) (number 2011-340H).

TB information

We used the information contained in the National System of Information on Noticeable Disease (SINAN) to identify the cases of TB. SINAN is a database of the Brazilian government which stores information concerning all notifiable infectious and contagious diseases. TB is a compulsory notification disease is Brazil. So that, for all patients starting TB treatment, doctors, including those from the Department of Tisiology, Canoas Secretariat of Health, should complete the SINAN form, which is then typed in SINAN database. To avoid under-reporting (data that are in SINAN form but not already on SINAN database), we reviewed both SINAN form (from Department of Tisiology, Canoas Secretariat of Health) and SINAN database.

For the incidence calculation we selected all new cases of TB. Readmissions after treatment abandonment and relapses were not included. The following data were collected from patient records using a standardized data extraction tool: demographic data (sex, age, and years of schooling), clinical form of TB (isolated pulmonary, isolated extra pulmonary, and pulmonary + extra pulmonary), HIV status, acid-fast bacilli smear, culture, chest X-ray, and treatment outcomes (cure, default, death).

Human Development Index (HDI)

The Human Development Index (HDI) is a composite statistic of health, education and income indicators created in 1990 for the Human Development Report of the United Nations Development Programme. The HDI was created to emphasize that people and their capabilities should be the ultimate criteria for assessing the development of a country, not economic growth alone. The health dimension is assessed by life expectancy at birth; the education dimension is measured by mean of years of schooling for adults aged 25 years and more and expected years of schooling for children of school entering age. The standard of living dimension is measured by gross national income per capita. The index ranges between 0 (minimum value) and 1 (maximum value), and are calculated according to technical notes [17,18].

Geospatial intelligence

Geospatial intelligence is the ability to solve problems through spatial relations, which support spatial analysis techniques such as geocoding [13–15]. Geocoding is a computational technique of transforming a description of textual information as addresses to a location on the Earth's surface, that is, spatial representation in numerical coordinates. Geographic information systems (GIS) can be defined as a set of tools for collecting, processing, managing and presenting spatial information technologies [19].

Participants were geocoded using their postal address (geographical coordinates of place of residence). We used demographic data from Brazilian Institute of Geography and Statistics (IBGE, *Instituto Brasileiro de Geografia e Estatística*) [16]. Geocoding was performed using the free software QGIS 2.0 (Quantum GIS Development Team, 2013) with the extension MMQGIS (http://michaelminn.com/linux/mmqgis/) containing a Python geocoding plugin making it easy to use the Google Maps API. We applied GIS technology to detect where in the city clustering of TB cases may be occurring [8,13–15]. We also evaluated the association of an area's HDI (each component — longevity, education and income) with the spatial distribution of TB. The maps were made using kernel density measurements (KDE). KDE is a non-parametric way, described by Silverman [20], to estimate the probability density function of a random variable. This spatial method is one of the most widely used techniques for generating hotspot maps as smooth continuous surfaces. The technique has been shown to have advantages over other methods of aggregating point data, such as spatial clustering [21–23].

For the hotspot map, we used adaptative radial quadratic kernel algorithm; this was performed using TerraView 5.3.2. Software (National Institute of Space Research — *Instituto Nacional de Pesquisas Espaciais*, INPE). According to the developers of this soft-

Table 1
Characteristics of study population.

Variables	Year 1 n = 326	Year 2 n = 218	Year 3 n = 193	Total n = 737(%)
Demographic characteristics				
Male sex	199	142	123	464 (63)
White	276	176	164	612 (83.1)
<8 years of schooling	143	127	112	382 (51.8)
Input type				
New case	265	178	169	612 (83)
Relapse	28	23	18	69 (9.4)
Retreatment	33	17	6	56 (7.6)
Radiographic pattern				
Typical of TB	306	209	192	707 (95.9)
Forms of TB				
Isolated pulmonary TB	242	166	166	574 (77.9)
Isolated extra pulmonary TB	79	44	28	151 (20.5)
Pulmonary + extra pulmonary TB	5	6	1	12 (1.6)
Laboratory tests				
Smear-negative sputum	87	42	34	163 (22.1)
Culture-positive sputum	2	2	6	10 (1.4)
Comorbidities				
HIV positive	31	52	34	177 (24.0)
Outcome				
Cure	257	172	154	586 (79.5)
Dropout of treatment	34	18	6	59 (8.0)
Deaths from other causes	10	4	4	18 (2.4)
Deaths from TB	5	6	4	15 (2.0)

ware, adaptative quadratic kernel takes into account the distance variation and area. Therefore, it is not necessary to predefine a distance threshold or a number of nearby neighbors, because the algorithm itself makes these settings.

Spatial patterns of disease prevalence were compared using the spatial clustering statistics Moran's I. Moran's I is a global index of spatial autocorrelation that is used to assess the similarity (or spatial dependence) observed among a neighborhood and its neigh-

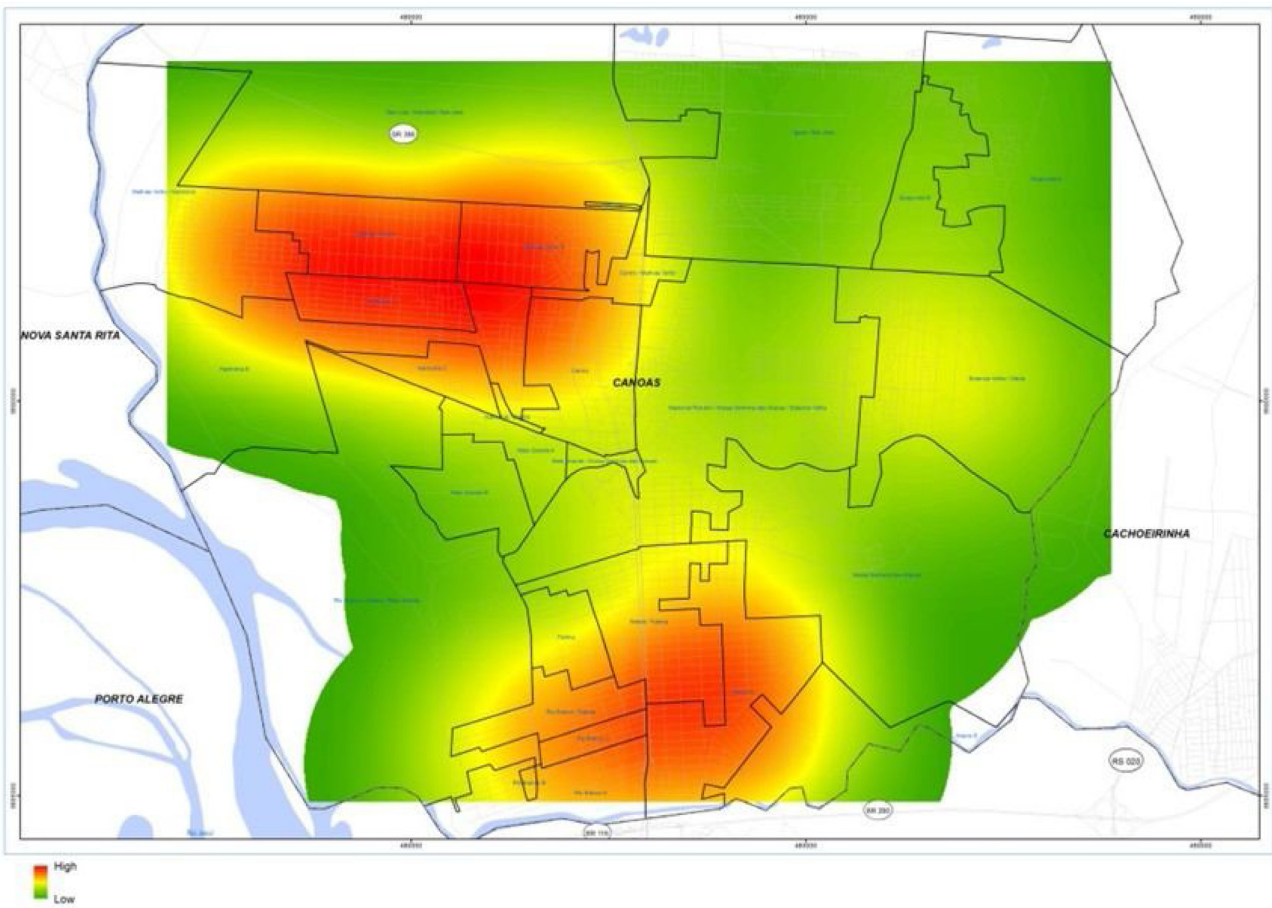

Fig. 1. Distribution of tuberculosis cases, 2011–2013. Hotspots are identified in red.

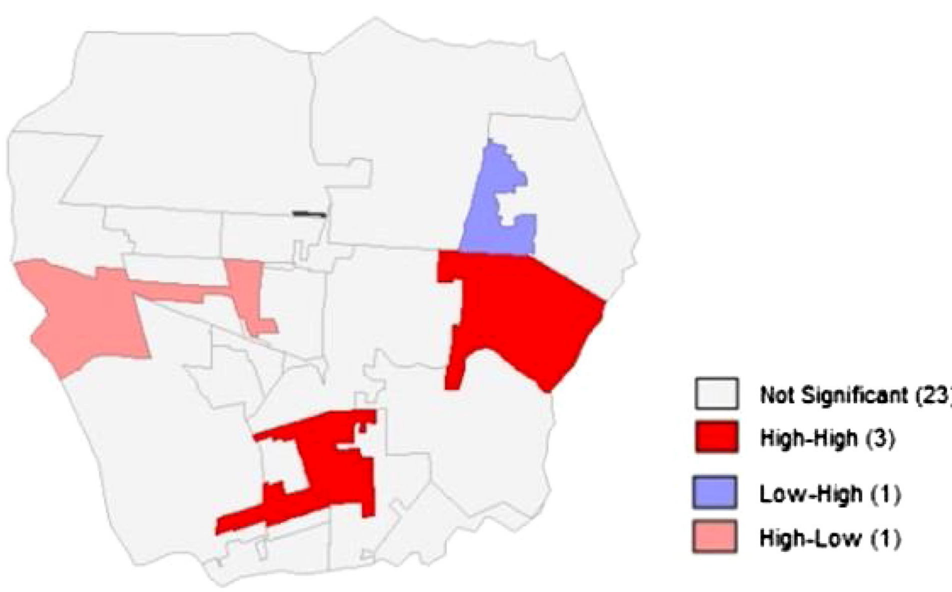

Fig. 2. Spatial autocorrelation of TB incidence. Not significant: not a part of a cluster; high–high: hotspots — neighborhoods with high TB incidence surrounded by a cluster of high TB incidence; low–high: spatial outlier — neighborhoods with low TB incidence surrounded by a cluster of high TB incidence; high–low: spatial outlier — neighborhoods with high TB incidence surrounded by a cluster of low TB incidence.

Table 2
Characteristics of the 29 neighborhoods.

Neighborhood	Population	Demographic density	TB cases	TB incidence/ 100,000 hab	TB/HIV (%)	HDI total	HDI income	HDI education	HDI longevity
1.Niterói A	23,395	8011.81	81	346	28.16	0.75	0.744	0.651	0.87
2.Estância Velha/Olaria	33,142	4626.53	68	205	15	0.719	0.719	0.619	0.836
3.Mathias Velho B	15,414	6636.24	62	402	20.96	0.725	0.719	0.635	0.834
4.Mathias Velho/Harmonia	21,312	10,392.96	61	286	29.09	0.595	0.64	0.424	0.775
5.Mathias Velho A	17,371	3119.10	42	242	23.07	0.693	0.703	0.583	0.812
6.Rio Branco A	11,113	9028.56	32	288	21.87	0.729	0.73	0.625	0.85
7.Harmonia A	14,254	160,564.14	30	210	17.24	0.654	0.664	0.535	0.788
8.Harmonia B	13,552	10,120.28	27	199	33.3	0.765	0.739	0.699	0.865
9.Rio Branco/Fátima/Mato Grande	11,550	25,109.77	24	208	8.69	0.615	0.648	0.461	0.777
10.Marechal Rondon/Nossa Senhora das Graças/Estância Velha	23,414	2467.24	24	103	22.72	0.893	0.897	0.866	0.918
11.Niterói/Fátima	13,925	5414.41	22	158	15	0.817	0.819	0.731	0.911
12.Niterói B	6,642	1901.79	22	331	15.79	0.615	0.648	0.461	0.777
13.Igara/São José	20,863	1125.83	18	86	18.75	0.85	0.841	0.8	0.912
14.Centro	13,158	5324.97	15	114	23.07	0.896	0.91	0.859	0.921
15.Nossa Senhora das Graças	7,800	772,47	15	192	42.85	0.846	0.854	0.776	0.915
16.São Luís/industrial/São José	4,634	218,26	15	324	0	0.729	0.73	0.625	0.85
17.Guajuviras B	24,933	10,890.50	14	56	27.27	0.713	0.699	0.642	0.809
18.Rio Branco/Fátima	7,823	114,996.13	12	153	30	0.729	0.73	0.625	0.85
19.Mato Grande A	3,329	13,540.58	9	270	0	0.729	0.73	0.625	0.809
20.Guajuviras A	14,027	1686.75	7	50	50	0.6	0.618	0.464	0.85
21.Centro/Mathias Velho	3270	4192.31	6	183	33.3	0.777	0.767	0.687	0.85
22.Fátima	4042	4055.41	5	124	0	0.777	0.767	0.687	0.754
23.Harmonia C	5029	787,00	5	99	0	0.846	0.854	0.776	0.891
24.Mato Grande B	4,278	4,679.24	3	70	0	0.777	0.767	0.687	0.891
25.Rio Branco B	681	44,01	2	294	0	0.846	0.854	0.776	0.915
26.Rio Branco C	3,020	1,452.14	1	33	0	0.846	0.854	0.776	0.891
27.São Luís	377	12,465.05	0	0	0	0.6	0.618	0.464	0.915
28.Harmonia/Centro	817	966,85	0	0	0	0.6	0.618	0.464	0.754
29.Mato Grande/Nossa Senhora das Graças	662	432,05	0	0	0	0.777	0.767	0.687	0.891

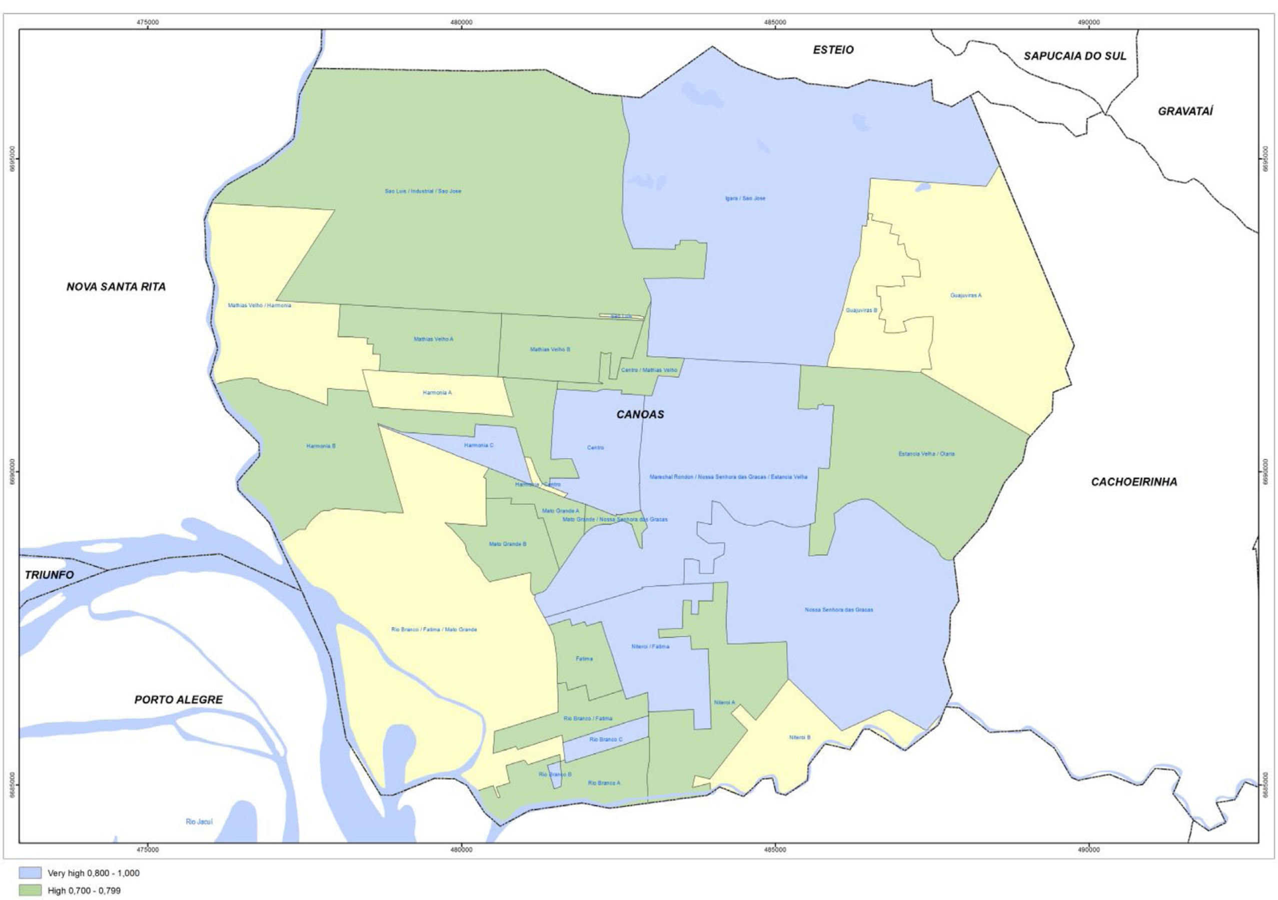

Fig. 3. Tuberculosis incidence according to HDI-income.

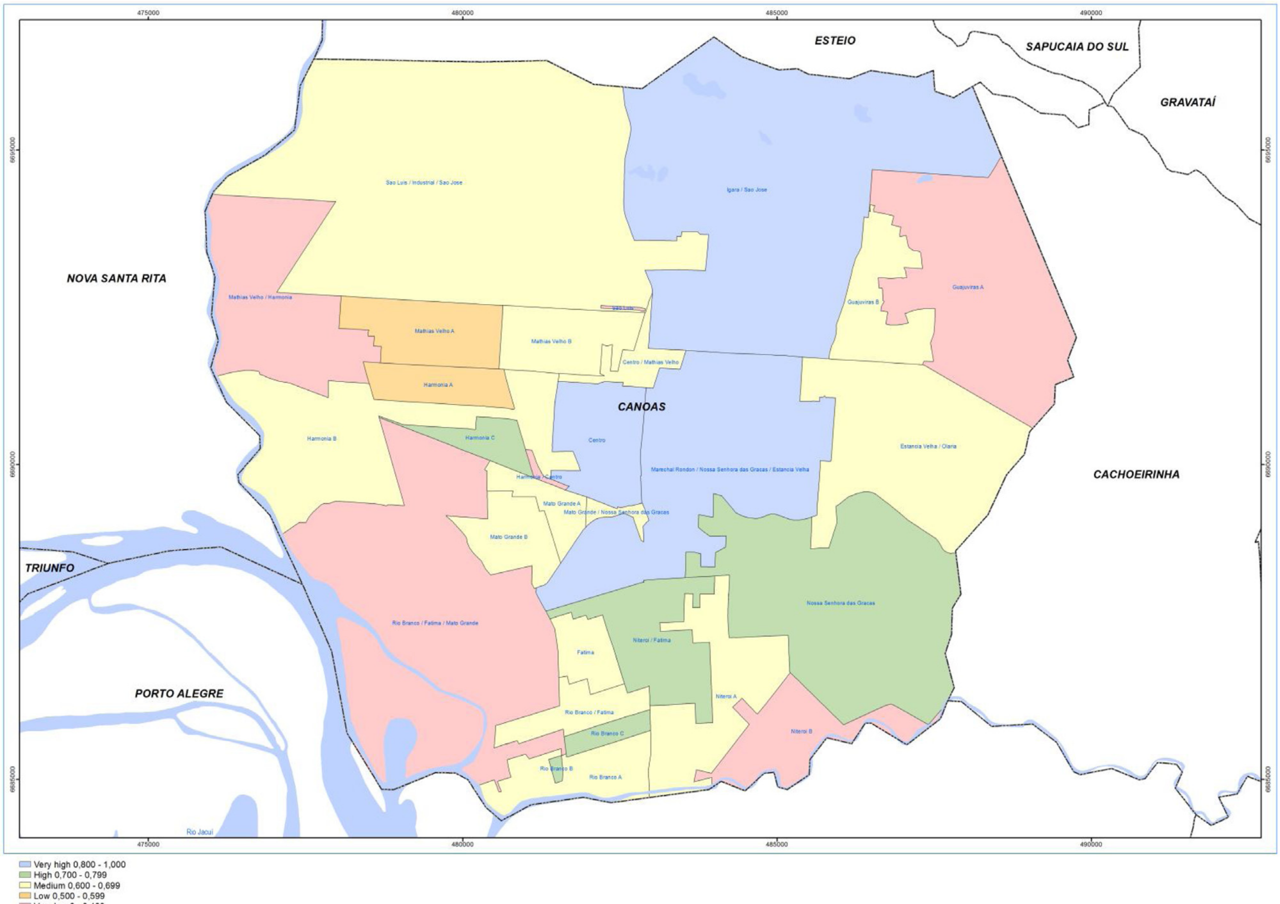

Fig. 4. Tuberculosis incidence according to HDI-education.

boring units [24]. A Moran's I value >0 indicates that there are neighborhoods with similar TB incidence located close together. Moran's I < 0 indicates that neighboring areas have dissimilar values. $p < 0.05$ indicates the presence of spatial autocorrelation. This can identify hotspots, cold spots, and spatial outliers. Spatial outliers represent neighborhoods with TB incidence that is discrepant from the neighboring areas. Using this analysis, neighborhoods will fall into one of 5 categories: (1) not significant (not a part of a cluster); (2) hotspot: neighborhoods with high TB incidence surrounded by a cluster of high TB incidence (high-high); (3) cold spots: neighborhoods with low TB incidence surrounded by a cluster of low TB incidence (low-low); (4) spatial outlier: neighborhoods with high TB incidence surrounded by a cluster of low TB incidence (high-low); and (5) spatial outlier: neighborhoods with low TB incidence surrounded by a cluster of high TB incidence (low-high).

Statistical analysis

Data analysis was also performed using SPSS 18.0 (Statistical Package for the Social Sciences, Chicago, Illinois). Data were presented as number of cases, mean ± standard deviation (SD), or median with interquartile range (IQR). The correlation between HDI-longevity, education, and income and TB incidence were evaluated by Spearman correlation test. For comparative analysis of TB incidence, we considered the mean of each component and categorized them as lower as or higher than the mean. A p-value <0.05 was considered statistically significant.

Results

During the study period, there were 737 TB cases (326 in 2011, 218 in 2012 and 193 in 2013). However, only 633 TB cases were found after geocoding. Out of these patients, 11 were excluded because they were out of Canoas' geographic limits. Then 622 TB cases were included in the analyses. The characteristics of the study population were shown in Table 1. The TB incidence in the city for the three years was 58.36 cases/100,000 inhabitants (75.4 cases/100,000 inhabitants in 2011, 49.1 cases/100,000 inhabitants in 2012, and 50.95 cases/100,000 inhabitant in 2013).

The TB cases showed heterogeneity across the 29 neighborhoods. In the hotspot map (Fig. 1) we can identify that the areas of high TB incidence rate (in red) were located in the neighborhoods NiteróiA, Estância Velha/Olaria and Mathias VelhoB. There was positive spatial autocorrelation in TB incidence (Moran's I: 0.15; $p < 0.05$). Fig. 2 shows statistically significant clustering of neighborhoods into hotspots and spatial outliers.

Table 2 shows the demographic density, TB incidence, TB/HIV coinfection rate, and the HDI (total, income, education, and longevity) of the 29 neighborhoods. The demographic density was not significantly correlated with TB incidence ($r = 0.183$; $p = 0.341$).

The mean HDI-income, -education, and -longevity were 0.75 ± 0.09, 0.65 ± 0.13, and 0.85 ± 0.05, respectively. Figs. 3–6 show the HDI maps (income, education, longevity, and total) according to TB incidence. The neighborhoods with HDI-income lower than the mean had higher TB incidence (210.0 ± 122.6 cases/100,000 hab. vs 121.3 ± 78.2 cases/100,000 hab.; $p = 0.036$). The neighborhoods with HDI-education lower than the mean had

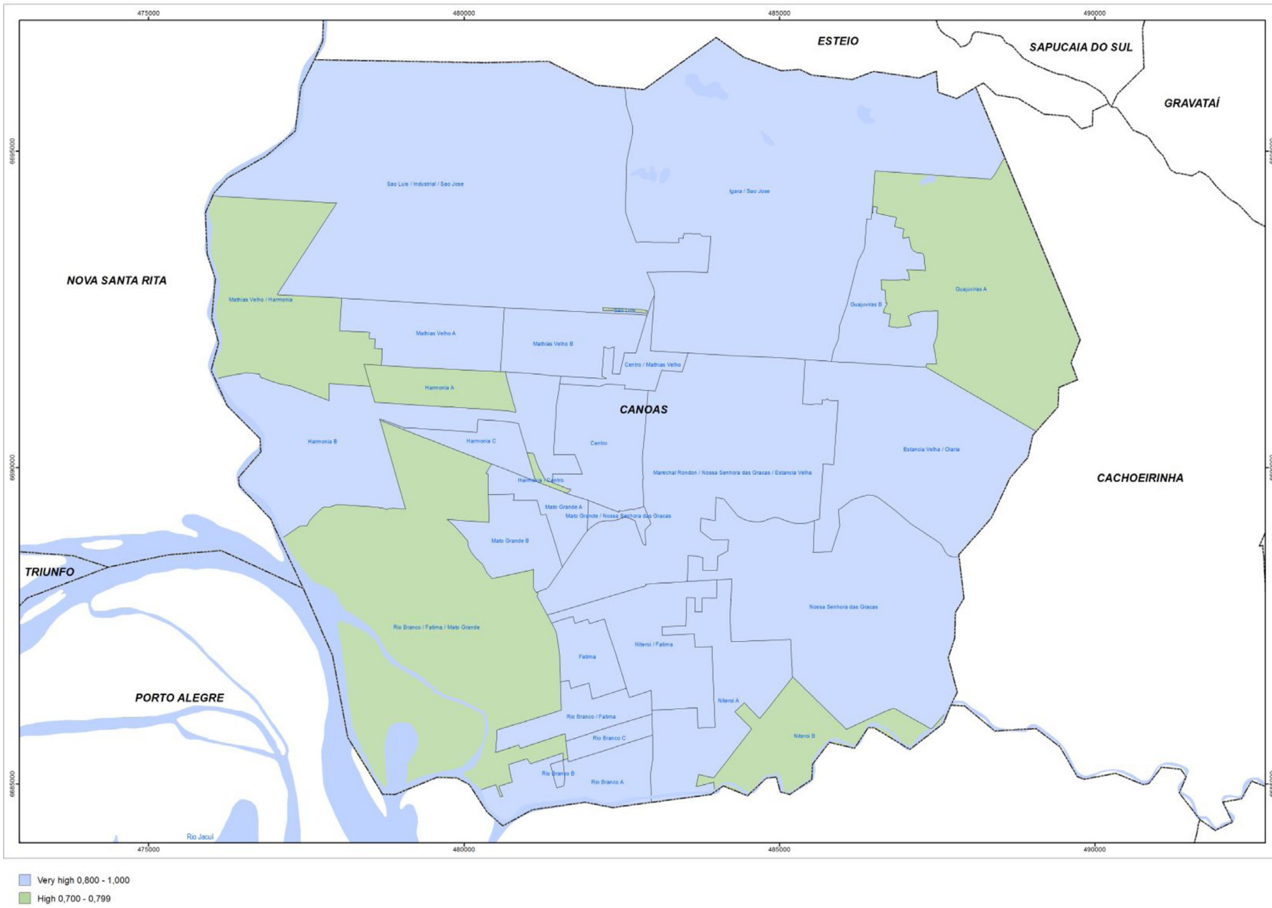

Fig. 5. Tuberculosis incidence according to HDI-longevity.

also a higher TB incidence (125.6 ± 32.4 cases/100,000 hab. vs 94.9 ± 25.4 cases/100,000 hab.), although this difference was not statistically significant (p = 0.169). In addition, the neighborhoods with HDI-longevity lower than the mean tended to have higher TB incidence (212.2 ± 117.1 cases/100,000 hab. vs 149.6 ± 108.2 cases/100,000 hab.); however, this difference was not statistically significant (p = 0.154). Fig. 7 shows the box plots of TB incidence by categories of HDI (total, education, income, and longevity).

Discussion

In this ecological study, we evaluated, using geospatial intelligence, the association between TB incidence rates and the HDI in a city with high incidence of TB.

We found that TB cases showed heterogeneity across the 29 neighborhoods. In addition, the neighborhoods with HDI-income lower than the mean had higher TB incidence.

The use of geospatial data in health is not a novelty. However, recent developments in geospatial intelligence might add to the findings of previous studies, making it possible, for example, to geocode incidence cases. The creation of GIS software in particular allows recognizing geographic patterns in population. Health geography and the application of geospatial data and techniques continue to expand its influence and use to support more accurate and timely decision-making in the healthcare market. Comprehensive location-based information is essential to define priorities and in decision-making process [25,26].

Geospatial intelligence has been applied to analyze and visualize the spatial patterns of TB. Geospatial intelligence, when integrated with surveillance information data, can be used to identify hotspots of TB [3,4,27]. Understanding such spatial variations in TB incidence is effective to plan TB control and can be useful for health managers to formulate targeted interventions [5,27]. In the present study, we identified heterogeneity among the 29 neighborhoods, with several hotspots of TB, as shown in Fig. 1. Is was not surprising that the population in these areas all share common risk factors for TB, like low socioeconomic level, and agglomeration of population, and this was already demonstrated in previous studies [5,28]. In a retrospective study [28] aimed to evaluate the spatial and non-spatial determinants of successful tuberculosis treatment outcomes, the authors found that the spatial clusters of TB cases were concentrated in older, impoverished and outskirts areas. In another study [5], the proportion of minorities and per capita gross domestic product were strong predictors of TB hotspots in some regions.

Also, we identified two spatial outliers: one neighborhood with high TB incidence surrounded by a cluster of low TB incidence (high–low); and one neighborhood with low TB incidence surrounded by a cluster of high TB incidence (low–high) (Fig. 2). One study conducted in China [29], to evaluate the meteorological determinants of TB incidence, also demonstrated spatial outliers (low–high and high–low). The identification of spatial outliers can help to develop future researches to better understand why and what factors could be related to those differences in TB incidence in neighboring areas.

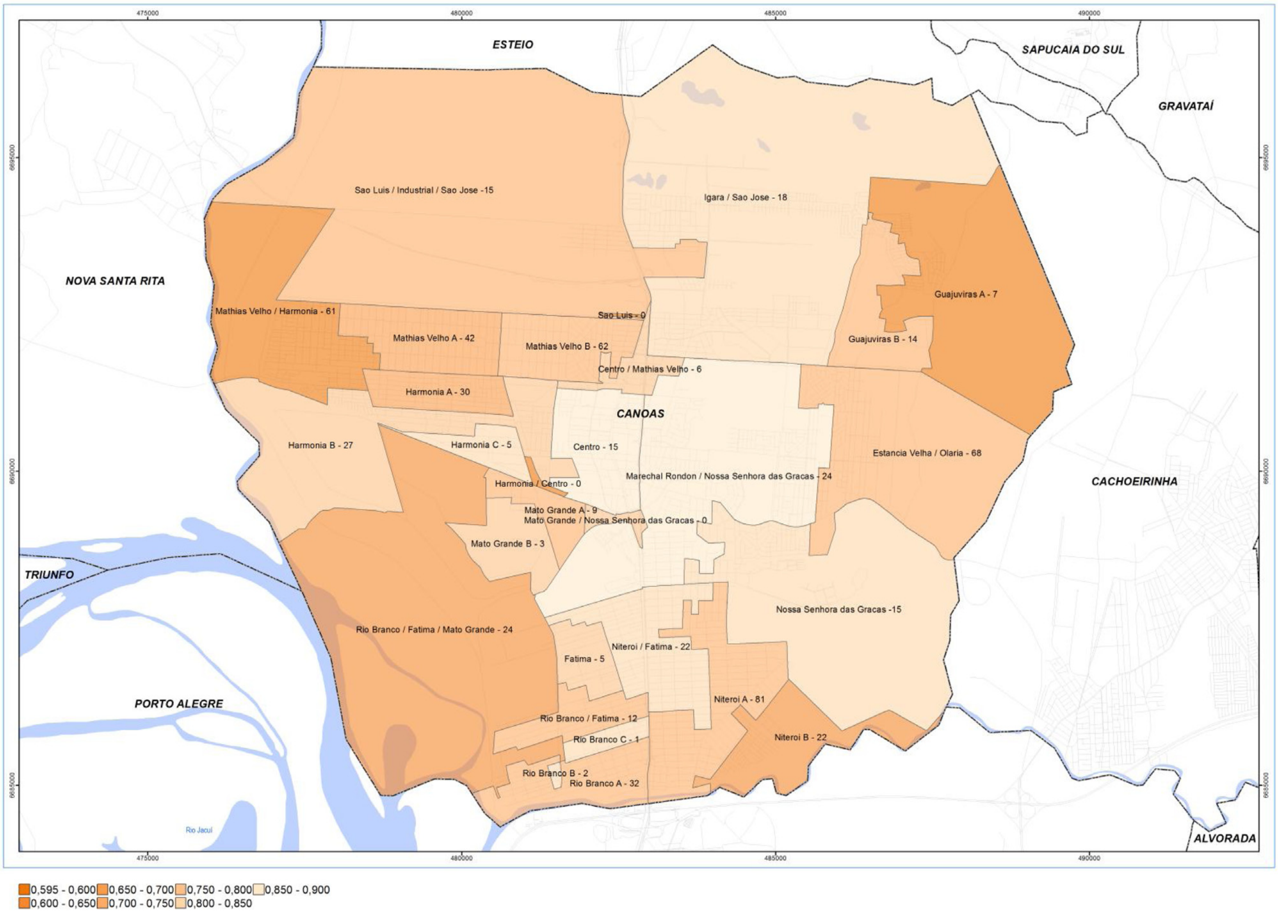

Fig. 6. Tuberculosis incidence according to total HDI.

Neighborhoods with HDI-income lower than the mean had higher TB incidence in our study (Figs. 3 and 7). Tuberculosis is known to be a marker of social inequities due to precarious living conditions [30,31]. In a study conducted in the low-income South African township of Rhini, social capital, overcrowding, and poor housing quality were associated with TB prevalence [32]. Other authors demonstrated that TB patients with lower household income were at greater risk of poor TB treatment outcomes [33]. Previous studies have also shown that low income may increase the risk of treatment default among TB patients [34,35].

The neighborhoods with HDI-education lower than the mean had also a higher, although not statistically significant, TB incidence (Figs. 4 and 7). Poor educational level is negatively correlated with health in general [32]. However, inequalities in TB are driven by the unequal distribution of several social determinants not only education, such as nutrition, adequate housing, environmental conditions, employment, etc [36,37]. In addition, we found that those neighborhoods with HDI-longevity lower than the mean tended to have higher TB incidence, although the difference was not significant (Figs. 5 and 7). In fact, the more disadvantaged a country is in terms of life expectancy at birth, the higher its TB incidence rate would be in Ref. [31]. On the other hand, one of the physiological systems most affected by aging is the immune system. The clinical expression of so-called immunosenescence depends on the presence of comorbidities and exposures to other environmental factors or infections. It results from limited T-cell clonal expansion and involution of the thymus, with consequent T-cell dysfunction. In some regions, the designation of the group at the highest risk for developing active TB has shifted to the elderly [38,39].

Our study has some methodological limitations. First, this is an ecological study in which the variables were measured in groups rather than at the individual level, therefore we cannot make inferences on the individual level from data collected on an aggregate level. Second, we cannot exclude the possibility of missing cases or underreport of TB cases from the data obtained from government's surveillance system database. Also, due to the small sample size, the study findings that only neighborhood differences in HDI-income were associated with TB incidence may not accurately reflect the true picture of TB incidence in Canoas, where HDI-education and HDI-longevity may also be significant neighborhood risk factors for TB incidence. In addition, the study period was short. Furthermore, we did not determine the degree to which the context of each small area in relation to neighboring areas, affected the local rate of TB incidence. Nevertheless, despite these limitations, this spatial density study reaches its goal to detect "risk" areas with high concentrations of TB cases (hotspots), and relate them to HDI components.

In conclusion, we found several hotspots of TB across the 29 neighborhoods of a city with high TB incidence. The neighborhoods with HDI-income lower than the mean had higher TB incidence. These findings provide useful information and may help to guide TB control programs.

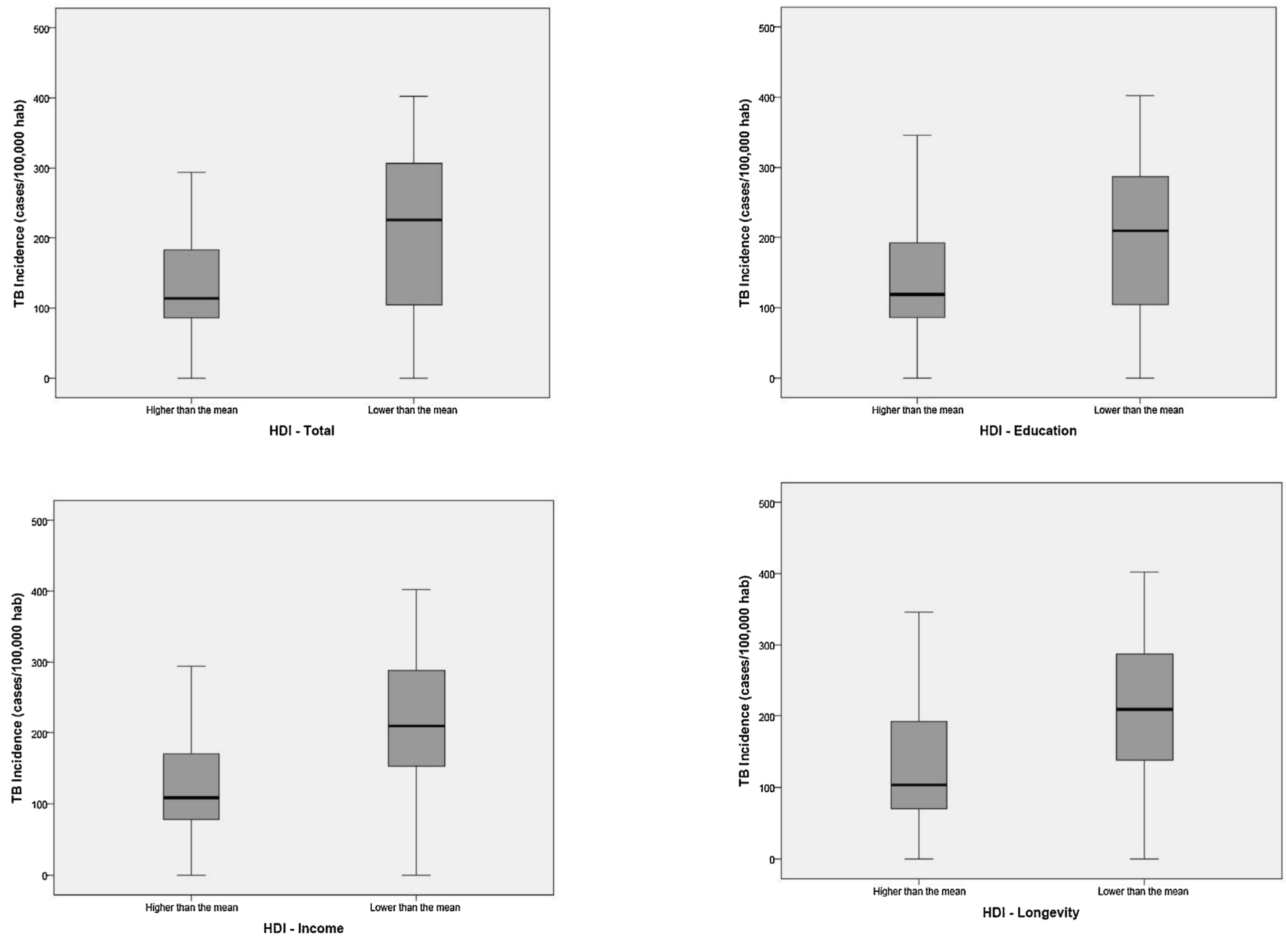

Fig. 7. Box plots of TB incidence by categories of HDI (total, education, income, and longevity).

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Competing interests

None declared.

Ethical approval

Not required.

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