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Spatio-temporal analysis of leptospirosis in Brazil and its relationship with flooding

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Abstract

Leptospirosis is a serious public health problem in Brazil, which can be observed after flooding events. Using an exploratory mixed clustering method, this ecological study analyzes whether spatial-temporal clustering patterns of leptospirosis occur in Brazil. Data from the Brazilian Unified Health System (SUS) were used to calculate the prevalence of leptospirosis between 2007 and 2017 in all counties of the country. Clustering techniques, including spatial association indicators, were used for analysis and evaluation of disease yearly spatial distribution. Based on Local Indicators of Spatial Association (LISA) with Empirical Bayesian rates detected spatial patterns of leptospirosis ranging from 0.137 ($p = 0.001$ in 2009) to 0.293 ($p = 0.001$ in 2008). Over the whole period, the rate was 0.388 ($p = 0.001$). The main pattern showed permanence of leptospirosis clusters in the South and emergence and permanence of such clusters in northern Brazil. The municipalities with leptospirosis cases and at least one flood occurrence registered in the Brazilian Integrated Disaster Information System were incorporated into the LISA cluster map with Empirical Bayesian rates. These counties were expected to exhibit clustering, not all did. The results of the cluster analysis suggest allocation of health resources in areas with leptospirosis clustering.

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Introduction

Leptospirosis is a bacterial disease transmitted through contact with infected rodent urine. Its incidence can be observed after the occurrence of extreme events, flooding in particular. Other factors, such as poor sanitation services, garbage accrual and water accumulation can also trigger leptospirosis outbreaks (Londe *et al.*, 2016; Silva *et al.*, 2020). According to the World Health Organization (WHO), the number of cases of human leptospirosis worldwide is not precise, but the incidence in humid tropical climates is estimated to range between 10 and 100 per 100,000 people, numbers that increase in high-exposure risk groups during outbreaks (WHO, 2003). In addition, the disease is underreported because of the difficulty in distinguishing clinical signs from other endemic diseases (Luenam and Puttanapong, 2019).

Leptospirosis is a serious public health problem in Brazil where registration of cases, like in several parts of the world, is required (Londe *et al.*, 2016). The highest prevalence is found in the southern and northern regions of the country. Of its 5,570 counties, 2,600 had confirmed cases of leptospirosis between 2007 and 2017, with an annual average of 3,846 cases and a prevalence of 1.9 per 100,000 inhabitants (Marteli *et al.*, 2020). Epidemiological studies have explored the use of mapping tools at different scales (Baquero and Machado, 2018; Gutiérrez *et al.*, 2019; Oliveira Filho *et al.*, 2014; Silva *et al.*, 2020). Geoprocessing techniques are applied to collect and treat (spatial) geographic information to generate (usually cartographic) products related to location of cases. Using geographical information systems (GIS), spatial statistics techniques can detect areas where leptospirosis occurs or have occurred, thus providing support for public policies to prevent the disease (Marteli *et al.,* 2020).

Cluster can be detected by various spatial exploratory, analytical techniques. Among them, Moran's *I* stands out and is widely used in research on health (Dhewantara *et al*., 2018; Galan *et al*., 2021; Luenam and Puttanapong, 2019, 2020). For geographical areas delimited by polygons, such as political-administrative divisions, the aim is to detect the existence of spatial conglomerates, i.e. to determine whether the observed events exhibit some systematic, spatial pattern as opposed to random distribution (Chhetri *et al*., 2013). Global and local statistical tests are useful for this kind of investigations as they are complementary (Anselin, 1995). Global tests check for the presence of clusters without identifying their location, while local tests check for the presence of clusters in specific areas, allowing the identification of cluster location and testing of statistical significance (Anselin, 1995).

This study aimed to analyze the presence of clusters of leptospirosis and their spatial and temporal distribution from 2007 to 2017 in Brazil. A first brief description of the global and local autocorrelation of leptospirosis in Brazil is presented as done by Galan *et al.* (2021), who focused on the differentiation between rural and urban patterns based on data from 2000 to 2015. Besides focusing on the relationship with the patterns due to flood disasters, the present study delves more deeply into the presentation, interpretation, and discussion of spatial statistics results concerning leptospirosis.

Material and Methods

Study area

The Brazilian Institute of Geography and Statistics (IBGE) informs that the country has 5,570 municipalities in a land area of 8.5 million km² and an estimated population of 208,494,900 people in 2018 (IBGE, 2019). According to data from the Brazilian Ministry of Health (DATASUS, 2019a), 2,600 municipalities recorded at least one case of leptospirosis between January 2007 and December 2017.

Data sources

The leptospirosis data were obtained from the Brazilian Ministry of Health through its Information System for Notifiable Diseases (Sistema de Informação de Agravos de Notificação - SINAN). This system collects and processes data on diseases on the compulsory notification list, such as leptospirosis, with the information made available by the Department of Informatics of the Brazilian Unified Health System (DATASUS, 2019b) through the SINAN Net website.

In this study, we considered confirmed cases per municipality of residence for each year from 2007 to 2017 (DATASUS, 2019a). These data were tabulated and related to the digital municipal grid of the IBGE in a GIS environment, using a digital shapefile format, with Lat/Long geographic projection in the SIRGAS 2000 Geodetic Reference System. Population data were obtained from the estimate of the resident population by municipality and year (DATASUS, 2019c). For the analysis of the study period (2007-2017), the 2017 population estimate was used. In six municipalities there was no population data until the year 2011, so the population estimate of the nearest year (2012) was used.

Spatial analysis

For Moran's *I* analysis, the leptospirosis and population variables were entered separately. For the subsequent analysis, the prevalence calculation was given by the number of cases of the disease/resident population * 100,000 (P), as commonly used in the literature (Marteli *et al.*, 2020).

For data processing, Quantum GIS (QGIS), version 2.18.16, and GeoDa, version 1.20.0.8, were used. In QGIS, the vector base of polygons of the annual prevalence of leptospirosis over the study period was generated. In GeoDa, spatial autocorrelation techniques were applied to analyze and evaluate its spatial distribution. The spatial statistics methods used were Global and Local Moran's *I*. The former assesses whether attributes associated with spatial locations are random, clustered or dispersed (Moran, 1948). For each value, it subtracts the average, creating a deviation from this mean. The deviation values are multiplied to create a cross product, e.g., such as that for the observation of leptospirosis cases at location *i*:

$$I = \frac{\sum_i \sum_j w_{ij} \, z_i . z_j / S_0}{\sum_i z_i^2 / n} \tag{1}$$

where w_{ij} are elements of the spatial weight matrix of the prevalence of leptospirosis in Brazilian municipalities *i* and *j* ; $S_0 = \Sigma_i \Sigma_j w_{ijis}$ is the sum of all spatial weights; *n* the total number of confirmed cases; and z_i the variance of an attribute for *i* the resource from its average, which is stated as, $z_i = x_i - \bar{x}$ where $\bar{x}$ is the mean of the variable *x* (Anselin, 2020a). In this study, we considered Moran's *I* with empirical Bayesian as a way to correct the conventional Moran's *I* statistic for varying population densities between observational units, i.e. when the variable of interest, in this case, leptospirosis prevalence, is a rate or a proportion (Anselin, 2019).

As spatial weight matrix, the first degree Queen contiguity was used for the Global Moran's *I* with the Empirical Bayes option since it is suitable for irregular polygons (Anselin, 2020b), such as municipal political boundaries. A topological correction was made to ensure contiguity in the construction of the neighbourhood matrix, because some municipalities have two polygons as territorial limits. It was also was necessary to change the matrix for island municipalities*, i.e.* Fernando de Noronha (PE) and Ilha Bela (SP). Test statistical significance was obtained by application of 999 permutations, which calculates a reference distribution for the statistic under the null hypothesis of spatial randomness by randomly permuting the observed values (neighbourhood) over the randomly generated data set (Anselin, 2020a).

As Global Moran's *I* does not indicate the location of the clusters, Anselin (1995) proposed the Local Indicators of Spatial Association (LISA), which provides a statistic for each locality with a significance assessment and establishes a proportional relationship between the sum of the local statistics and the corresponding global statistic. By definition, LISA indicates of significant spatial clustering extent for similar values around that observation for each observation, and the sum of the LISAs for all observations is proportional to an overall indicator of spatial association (Anselin, 1995). For Local Moran's *I*, the sum of local statistics is proportional to Global Moran's *I*, which corresponds to the average of local statistics. Local Moran's *I* identifies local spatial clusters and outliers. Thus, the value product at the location with its spatial lag and the weighted sum of values at neighboring locations is simplified by Anselin (2020b) as:

$$I_i = z_i \sum_j w_{ij} z_j \quad (2)$$

where the sum of all the weights is equal to the total number of observations ($S_{0=n}$).

For the interpretation of Local Moran's *I*, it is necessary to analyze whether the index values return has statistical significance or not. In GeoDa, the spatial autocorrelation tool returns five values: i) the Global Moran's *I* (-1 to +1); ii) the expected *I*; iii) the variance; iv) the z-score; and v) the *p*-value. Both z-scores and *p*-values are statistical significance measures that lead to the refutation or assumption of the null hypothesis of spatial randomness). Here, we consider pseudo-*p*, which is achieved through permutations (non-parametric analysis), instead of using a normal distribution as reference. Moran's *I* is positively clustered if dataset values tend to cluster spatially so that high values are surrounded by other areas with similarly high values (high-high - HH) or low values are surrounded by other areas with similarly low values (low-low - LL). When high values tend to be surrounded by low values or low surrounded by high, the index is negative, *i.e.* representing outliers, such as high-low (HL) or low-high (LH). If positive cross-product values balance out negative cross-product values, Moran's *I* tends towards zero. The numerator is normalized by the variance so Moran's I falls between -1 +1. By including areas with insufficient evidence for a non-random spatial pattern (p-value >0.05), the cluster map (LISA MAP) shows five classes standardized as explained above, *i.e.* HH, LL, HL and LH and an extra class for lacking conclusive evidence (Anselin, 2005; Luenam and Puttanapong, 2020). For leptospirosis spatial analysis, hotspots and coldspots indicate statistically high and low incidence, respectively. Identification of counties with flood records was added to the LISA MAP for the whole study period (2007-2017) as catalogued by the Integrated Disaster Information System (S2ID), monitored since January 2013 (SEDEC, 2017). S2ID has no information about flooded municipalities between 2007 and 2012. From 2013 to 2017, there were 382 flood records in 263 municipalities.

Results

In Brazil, of the 5,570 municipalities, 2,600 had confirmed cases of leptospirosis between 2007 and 2017, totaling 42,310 occurrences. The average annual number was 3,846 cases (Marteli *et al.*, 2020), similar to Thailand in 2014 and 2015, with 3,470 and 3,300 cases, respectively (Luenam and Puttanapong, 2020).

As seen in Table 1, the Global Moran's *I* with Empirical Bayesian statistics for leptospirosis prevalence by year showed values ranging from 0.137 (pseudo *p*-value = 0.001 in 2009) to 0.293 (pseudo *p*-value = 0.001 in 2008). The Global Moran's *I* with Empirical Bayesian for the total evaluated period was 0.388 (pseudo *p*-value = 0.001), and results for each year separately also had pseudo *p*-value = 0.001. Consequently, the z-score ranged from 19.02 (in 2009) to 37.35 (in 2008), and the z-score was 48.04 for the prevalence over the total study period. In the entire historical series (annual and total), the overall spatial association was positive. The overall z-score values by year were positive, indicating similar values for the cluster tendency but, as expected when analyzing each municipality individually for each year, not all of them were positive, *i.e.* they had both positive and negative associations.

Moran's local univariate analysis showed that approximately 29% of all municipalities (1,616 Brazilian municipalities out of the total 5,570) showed clustering with respect to leptospirosis; 2009 had the smallest annual rate of HH municipalities with 2.1%, and the highest annual rate was noted in 2011 with 3.8% of municipalities. For the total period, 5.7% of the municipalities belonged to the HH group. In the years 2008, 2010 and 2017, about 15.7% of the municipalities were of the LL type. On the other hand, in the total prevalence assessment (2007 to 2017), 23.3% of the municipalities were classified as LL.

The total study period revealed 1.3% and 0.5% of municipalities with LH and HL classes, respectively (Table 1), but the spatial distribution of this dataset seemed more spatially dispersed on the maps (Figure 1). Therefore, for these two classes, less than 2% of

Table 1. Spatial autocorrelation of human leptospirosis in Brazil from 2007 to 2017.

Annual and total prevalence	Global Moran's *I*	Z-score	Significance percentage of the municipalities in Moran's Local univariate analysis				
			HH	LL	LH	HL	Not signif.
2007	0.231	30.81	2.59	17.06	3.36	0.72	76.28
2008	0.293	37.35	2.15	15.67	3.11	0.68	78.38
2009	0.137	19.02	2.14	15.73	2.84	0.68	78.62
2010	0.219	27.52	2.42	15.67	3.23	1.04	77.63
2011	0.186	24.58	3.75	15.96	2.64	0.81	76.84
2012	0.199	25.98	2.69	17.18	3.36	0.68	76.09
2013	0.260	34.21	2.60	16.00	3.27	0.70	77.43
2014	0.289	38.09	2.44	16.34	2.84	0.56	77.83
2015	0.269	34.78	2.69	17.61	2.87	0.66	76.16
2016	0.238	29.97	3.34	17.11	3.93	0.72	74.90
2017	0.243	30.58	3.29	15.69	3.43	0.83	76.77
2007-2017	0.388	48.04	5.69	23.32	1.29	0.54	69.16

the municipalities were classified as dispersed. Approximately 3% of Brazilian municipalities were classified as LH, on average, annually, less than 1% of municipalities were classified as HL. Approximately 70% of municipalities in the 2007 to 2017 period were not significant; 75% on an annual rate. Thus, it is not possible to state with 95% confidence that these municipalities present a non-random pattern regarding the spatial distribution of leptospirosis prevalence. Local spatial clusters of leptospirosis prevalence in Brazil by year are presented in Figure 1. The main pattern observed is the permanence of HH clusters in southern Brazil and the emergence and permanence of HH clusters in the southwest, northern region over the study period. In 2014, for example, the state of Acre had HH clusters for all municipalities with records of confirmed leptospirosis cases. From 2007 to 2014, Espírito Santo State had HH clusters in almost all of its territory. In Rio Grande do Sul State, given its larger territorial dimension, prevalence of HH clusters occurred in the central region, with some annual variations of HH and LH clusters. For some years, in the southwest of Rio Grande do Sul, there were LL clusters. In Santa Catarina State, during the period, HH clusters predominated in the far west of the state near to Argentina border and in the far eastern area near the coast. The central region of the state presented non-significant municipalities and LH clusters between classes transition. Figures 2a and 2b present leptospirosis clusters prevalence in Brazil for the total study period. In Figure 2b, municipalities with flood records occurring between 2013 to 2017 and monitored by S2ID (SEDEC, 2017) were added. In Acre State, all municipalities with flooding records were classified with HH clusters, except Cruzeiro do Sul, which had a total prevalence of 522.86 for the period although it was not significant for LISA Cluster Map analysis.

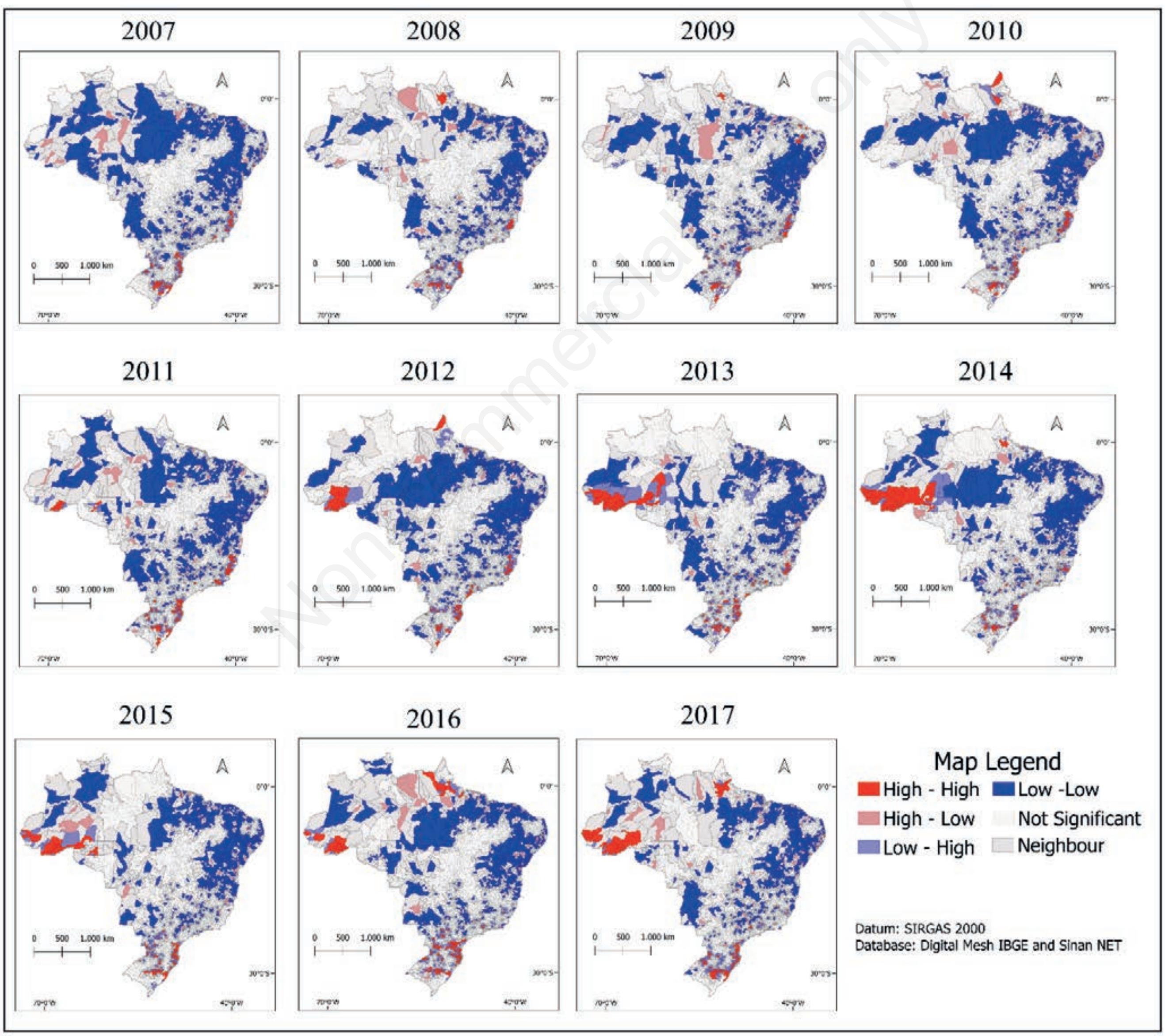


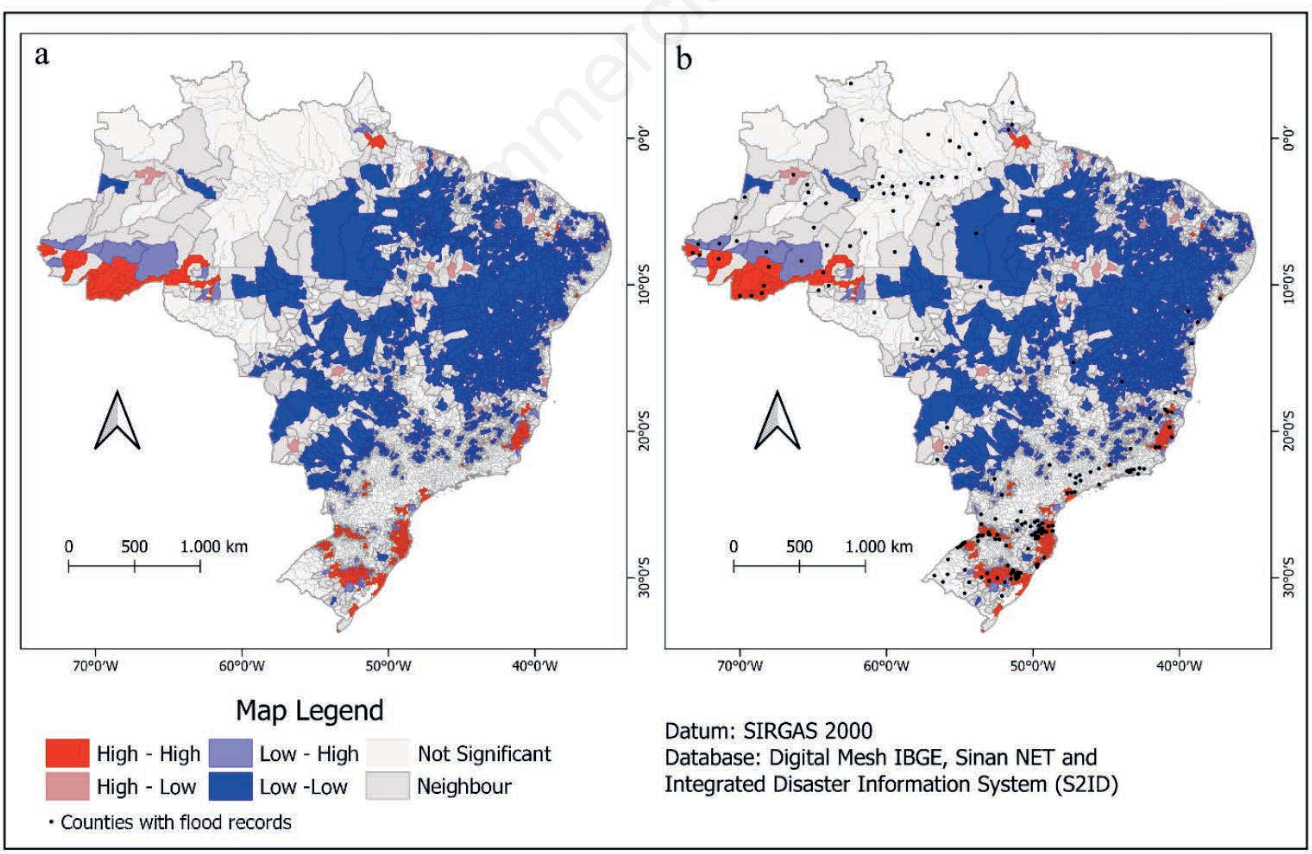
Figure 1. Univariate analyses of leptospirosis in Brazil from 2007 to 2017. Data obtained by local indicators of spatial association (LISA).

Of the 5,570 municipalities, 3,852 had not statistically significant clusters. Of these, 1,963 had records of leptospirosis cases and 132 had at least one record of flooding between 2013 and 2017 and confirmed leptospirosis cases from 2007 to 2017, *i.e.* of the 186 municipalities with flooding and confirmed leptospirosis cases, 71% were not significant. Around 18.8% of the municipalities with flooding records were classified as HH, and 11% of them had flooding records. This may have occurred because many municipalities with flood records and leptospirosis cases did not have statistically significant clusters. However, in Figure 2a, it is possible to see that the areas of flooding occurrence were concentrated in the South, North, and in regions along the coastline of south-eastern Brazil, where leptospirosis outbreaks also occurs. In the Midwest, Northeast, and in the state of Minas Gerais, there were few flooding records and LL areas dominated.

The total prevalence period classified the municipalities in the central and north-eastern regions of Brazil as LL. Table 2 presents the total annual clusters of confirmed leptospirosis cases, the total population of these municipalities, the prevalence rate per 100,000 people and the number of municipalities equivalent to these values. The average number of municipalities with confirmed leptospirosis cases was 813.63 per year, with a total of 892 with confirmed leptospirosis cases in 2011. The annual prevalence rate of HH clusters during the study period ranged from 8.61 to 29.06 per 100,000 people, with the highest rate observed in 2014. For the total period analyzed, there were 317 municipalities with a prevalence of 107.21 of this kind of cluster, while it was non-significant in 1,963 municipalities, with a prevalence of 20.25.

The highest number of non-significant leptospirosis cases on the cluster map appeared in the city of São Paulo, with 2,411 confirmed cases, with a prevalence for the study period of 19.91, while the highest prevalence in this period occurred in Santa Vitória do Palmar (Rio Grande do Sul), with 834.56. This municipality had 261 confirmed cases in an estimated population of 31,274 inhabitants (in 2017). Pacoti (Ceará) and Cruzeiro do Sul (Acre) had prevalence of 576.92 and 522.86, respectively. Pacoti had 69 cases in a population of 11,960 and Cruzeiro do Sul 432 cases in a population of 82,622 (in 2017).

For the HH class, the municipality with the highest number of cases in the period was Rio Branco, the Acre State capital, accounting 2,598 confirmed cases of leptospirosis in an estimated population of 383,443 inhabitants (2017). The prevalence was 677.55. The highest period prevalence for HH was 1,525.16 in Antônio Carlos (Santa Catarina), with 127 cases and an estimated population of 8,327 inhabitants (2017). Capivari do Sul (Rio Grande do Sul) and Iporã do Oeste (Santa Catarina) had prevalences of 1,077.49 and 1,063.83, respectively. Capivari do Sul had 47 confirmed cases of leptospirosis in a population of 4,362 inhabitants and Iporã do Oeste had 95 cases in a population of 8,930 inhabitants (2017).



Figures 2. Cluster map of leptospirosis in Brazil from 2007 to 2017. a) LISA Cluster Map of leptospirosis; b) counties with flood records.

Table 2. Descriptive statistics of human leptospirosis clusters in Brazil (2007-2017).

Year	Cluster type	Case (no.)	Population (no.)	Prevalence (rate per 100,000)	County (no.)
2007	HH	847	9,838,600	8.61	144
	LL	44	6,455,208	0.68	16
	LH	15	1,066,212	1.41	5
	HL	176	4,443,990	3.96	40
	Not sign.	2,219	79,055,251	2.81	482
2008	HH	1,139	7,355,170	15.49	120
	LL	29	5,540,255	0.52	17
	LH	6	454,121	1.32	3
	HL	142	2,739,789	5.18	38
	Not sign.	2,338	88,303,076	2.65	527
2009	HH	854	5,243,277	16.29	119
	LL	25	3,482,972	0.72	18
	LH	5	320,883	1.56	4
	HL	79	1,645,176	4.8	38
	Not sign.	3,033	98,242,722	3.09	643
2010	HH	970	9,715,739	9.98	135
	LL	24	3,835,621	0.63	21
	LH	12	958,508	1.25	6
	HL	124	3,949,830	3.14	58
	Not sign.	2,655	88,279,670	3.01	550
2011	HH	1,8	12,927,037	13.92	209
	LL	48	7,745,121	0.62	29
	LH	11	645,179	1.7	6
	HL	90	1,678,165	5.36	45
	Not sign.	3,058	87,718,932	3.49	603
2012	HH	855	7,078,067	12.08	150
	LL	64	8,963,824	0.71	23
	LH	3	257,471	1.17	2
	HL	93	2,014,612	4.62	38
	Not sign.	2,205	93,074,631	2.37	565
2013	HH	1,293	9,492,542	13.62	145
	LL	44	8,026,018	0.55	21
	LH	16	1,093,338	1.46	5
	HL	108	3,456,779	3.12	39
	Not sign.	2,669	94,917,944	2.81	641
2014	HH	1,783	6,135,581	29.06	136
	LL	53	5,375,239	0.99	28
	LH	8	543,251	1.47	3
	HL	54	1,466,084	3.68	31
	Not sign.	2,857	104,886,113	2.72	657
2015	HH	1,779	8,473,463	20.99	150
	LL	30	3,451,775	0.87	16
	LH	21	1,456,347	1.44	9
	HL	72	1,571,385	4.58	37
	Not sign.	2,435	102,160,315	2.38	656
2016	HH	928	10,843,190	8.56	186
	LL	119	14,467,400	0.82	33
	LH	6	510,728	1.17	6
	HL	63	1,987,244	3.17	40
	Not sign.	1,964	91,828,744	2.14	594
2017	HH	913	9,933,566	9.19	183
	LL	48	8,201,168	0.59	25
	LH	5	531,313	0.94	4
	HL	65	1,960,632	3.32	46
	Not sign.	2,008	95,805,980	2.1	605
2007-2017	HH	13,326	12,429,692	107.21	317
	LL	693	18,204,076	3.81	246
	LH	133	1,159,125	11.47	42
	HL	193	642,747	30.03	30
	Not sign.	27,959	138,070,243	20.25	1,963

Discussion

Luenam and Puttanapong (2019, 2020) applied spatial analysis of leptospirosis in Thailand and, similarly, Dhewantara *et al.* (2018) evaluated LISA in the period from 2005 to 2016 in China. Galan *et al.* (2021) obtained clusters of leptospirosis in Brazil from 2000 to 2015 but did not present any methodological statistical parameters, nor Moran's *I* values, making the analysis unfeasible for comparative purposes. Global Moran's *I* with Empirical Bayesian for the total period evaluated in this study was 0.388 (pseudo *p*-value = 0.001). Similar values were found by Luenam and Puttanapong (2019) in Thailand for the years 2013, 2014, and 2015, with indices of 0.393, 0.361, and 0.453 at $p = 0.05$, respectively. When evaluating the indices obtained for the years 2005 to 2016 in China, Dhewantara *et al.* (2018) found values ranging from 0.316 (for the year 2005) to 0.009 (for the year 2014). Moran's *I* showed statistical significance for global (pseudo *p*-value = 0.001) and local (pseudo *p*-value = 0.05) spatial autocorrelation of the annual leptospirosis prevalence for the total study period (Table 1). Variations in the both annual and total analysis of leptospirosis prevalence in the LISA cluster map occur because of the global average of the spatial autocorrelation statistic, the basis of Moran's *I*.

When applying the LISA method we observed autocorrelation at the local level and spatial clusters (HH and LL) in areas with a high prevalence of leptospirosis (HH) as the South region, part of the Southeast and in the south-western part of the northern region (Figures 1 and 2). LL clusters were detected in Brazil's central region (Figure 2) but the values in more than 70% of the municipalities were not significant (Table1, and Figures 1 and 2). The high frequency of non-significant municipalities for this spatial statistics method was also observed by Galan *et al.* (2021) in Brazil from 2000 to 2015, and from 2005 to 2016 by Dhewantara *et al.* (2018) in China, countries with similar territorial dimensions. A very large variation in prevalence rate was identified among neighbouring municipalities across much of the Brazilian territory, especially in the annual results. Municipalities that had prevalence rates close to the average and where neighbours also had prevalence rates close to the average, ending up in a "gray" non-significant zone. Analyzing the total data (2007 to 2017), there are more consistent patterns of regions with fewer cases.

Another issue to be considered is disease underreporting in Brazil. Several studies show reporting biases on the public health system and difficulties with the clinical diagnosis of other, similar neglected tropical diseases (Costa *et al*., 2015; Picardeau, 2015). Occasionally, high prevalence rates of leptospirosis were identified for some municipalities, but their values did not reach statistical significance so they could not be considered as true spatial clusters. This kind of result was not uncommon in municipalities, such as Roca Sales and Poço das Antas, both in the state of Rio Grande do Sul, with leptospirosis prevalence of 80.6 and 101.21 in 2007, respectively.

When adding spatial flood records from the Integrated Disaster Information System to the municipalities depicted on the LISA leptospirosis cluster map results, it was expected that there would be clusters in all these municipalities reinforcing the weight of neighbourhood in the method. However, the S2ID data did not provide much further useful information. The explanation may be that these records are based on information from the municipalities only when the magnitude of flooding exceeds their capacity to deal with the event in question. For example, flooded floodplains used only for irrigated crops or other flooding that does not cause damages and losses of high magnitude to the municipality are not reported in S2ID. However, both these events can be hotspots for leptospirosis dissemination. In any case, the S2ID record is relevant, as it records the occurrence of extreme events in which flooding affects vulnerable populations and therefore is a potential leptospirosis dissemination event. Still, hydrological records would be needed for a better exploration of the data.

Flood records have a daily time scale, but SINAN Net data are annual and monthly (DATASUS, 2019b). Meteorological variables, such as precipitation, which cause flooding events, should be analyzed in short time scales: daily or weekly, because grouping precipitation in monthly, seasonal, or annual timesteps causes loss of precipitation variability when the objective is to analyze the record of leptospirosis cases caused by the occurrence of flooding (Amilasan *et al*., 2012; Barcellos and Sabroza, 2001; Matsushita *et al*., 2018; Suwanpakdee *et al.*, 2015). No studies with this level of detail of daily and/or weekly precipitation and leptospirosis occurrence were found in the literature. Problems arise when spatial data are annual, while events remain for only short periods. The most effective outcomes for leptospirosis cases and precipitation have been at a weekly time scale for municipal spatial scales (Cunha *et al.*, 2022; Matsushita *et al.*, 2018). At the scale of study at national level there is a great limitation of data, hampering the investigation of the geographical and epidemiological characteristics of leptospirosis. The lack of adequate environmental data is also pointed out in the literature (Luenam and Puttanapong, 2020).

Conclusions

This study explored the main contributions of the LISA method with Empirical Bayesian in detecting spatial clusters of leptospirosis in Brazil with emphasis on the higher prevalence of leptospirosis clustering in the South, Southeast and the south-western regions of the North. The results show the presence of local spatial clusters of leptospirosis prevalence in Brazil by year and identified HH clusters in the northern and southern regions. For the total period prevalence, results showed local spatial HH clusters in the North, South and Southeast, as well as LL clusters in the central part of the country corresponding to the Midwest, Northeast, part of the North, and Southeast. The method of spatial cluster analysis met the objective of this research. We suggest that other variables should still be explored and research in areas consistently identified as HH be further conducted for epidemiological decision-making.

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