Geospatial Health 2025; volume 20:1393

Evaluation of spatial cluster detection methods for dengue fever in the state of Paraiba, Brazil

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Abstract

This study is a quantitative, ecological, descriptive, retrospective, cross-sectional study on dengue in the state of Paraíba in north-eastern Brazil aimed to compare the performance of spatial clustering methods based on epidemiological data. The population consisted of all people residing in the state, and the sample was all dengue fever cases reported annually between 2018 and 2022. The residence localization of people suffering from dengue fever was used to identify the spatial distribution of this infection in the Paraíba State. Scan Statistics, Besag-Newell, Getis-Ord, M-Statistics and Tango were used and it was observed that the methods Getis-Ord, M-Statistic and Tango showed large spatial clusters, which included municipalities with high and low values. Scan Statistics and Besag-Newell's method also showed most of these clusters, with Scan Statistic providing better agreement with the high Standardized Incidence Ratio (SIR) than Besag-Newell's method. In conclusion, Scan statistic outperformed the other methods by identifying significant clusters in greater proportion in all study periods when mapping using Rigorous Impact Evaluation (RIE) was applied. However, it is necessary to consider each method's assumptions to select the most appropriate method for each application. Thus, this study provides relevant elements to help decision makers manage and prevent diseases, such as dengue fever and other vector-borne diseases.

Introduction

Arboviruses pose a growing challenge to global public health due to the pathogens' potential for dispersal and their ability to adapt to new environments and hosts. These viruses have the propensity to cause extensive epidemics due to universal susceptibility, with numerous severe cases, including neurological, articular and hemorrhagic manifestations (Donalisio *et al.*, 2017). Arboviruses are spread by blood-sucking arthropods, such as mosquitoes and ticks, and there are more than a hundred types of arboviruses causing various diseases in humans, *e.g.*, dengue fever, yellow fever (DENV), chikungunya (CHIKV), and Zika (ZIKV). The severity of these infections ranges from asymptomatic to life-threatening, with outbreaks becoming increasingly common in tropical and subtropical regions, making them an issue of international concern (Harapan, *et al.,* 2020).

In the Brazilian epidemiological context, the most widely circulating arboviruses are dengue virus, chikungunya virus and Zika virus – the former is the most prevalent and has the most significant impact in terms of reported cases and outbreaks (Donalisio *et*

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Key words: spatial clustering methods, epidemiology, dengue fever, Brazil.

Conflict of interest: the authors declare no potential conflict of interest, and all authors confirm accuracy.

Contribution: AONV, study conception, data collection and analysis, writing of results and discussion, preparation of the final manuscript; RMM, review and correction of data analysis, methodology, results, discussion, and review the final version; LWL, methodology, results, discussion, and review the final version.

Ethics approval and consent to participate: not applicable.

Availability of data and materials: all data generated or analyzed during this study are included in this published article.

Funding: National Council for Scientific and Technological Development - CNPq (Grant 305914/2021-9) and Fundação de Apoio Pesquisa do Estado da Paraiba (FAPESQ - Grant 64529.997.28469.09042024).

Acknowledgments: this research is supported by the National Council for Scientific and Technological Development - CNPq (Grant 305914/2021-9) and Alline Oliveira do Nascimento Veloso has been supported by Fundação de Apoio Pesquisa do Estado da Paraiba (FAPESQ - Grant 64529.997.28469.09042024).

Received: 27 March 2025.
Accepted: 13 August 2025.

Geospatial Health 2025; 20:1393
doi:10.4081/gh.2025.1393

al., 2017). If i social, economic and environmental factors are taken into account areas with high risk in epidemiological problems can be detected. Therefore, geoprocessing methods, *i.e.* Geographic Information Systems (GIS) that analyzes and manage spatial data, are essential for identifying, locating and monitoring populations vulnerable to a given condition (Lawson, 2006). Spatial statistics, particularly cluster detection, stand out among these techniques. Clusters signify areas where the incidence of a disease is significantly different from the usual situation in the surrounding environment, which can be identified by comparing the incidence of a disease inside and outside the area in question (Kulldorff, 1995). Methods for detecting spatial clusters include Besag-Newell (1991), Ord-Getis (1995), Circular scan (Kulldorff, 1997), M-statistics (Rogerson, 2001) and Tango methods (2010).

The epidemiological literature highlights various applications of methods for detecting spatial clusters emphasizing the importance of these approaches for identifying risk patterns and understanding the geographical distribution of health-related events (Minamisava *et al.*, 2009; Lima *et al.*, 2019; Pinto *et al.*, 2022; Ramos *et al.*, 2022). By detecting spatial disease patterns, this approach contributes to the formulation of explanatory hypotheses regarding the incidence of dengue fever in specific regions (Santos *et al.*, 2022; Melo *et al.*, 2022; Pereira *et al.*, 2024). Several studies have explored methods for detecting spatial clusters on epidemiological data, demonstrating relevance in identifying patterns that are crucial for public health planning. Studies, such as those used by Hashtarkhani *et al.* (2021) in Iran, Huang *et al.* (2022) in the United States and Minamisava *et al.* (2009) and Lima *et al.* (2019), in Brazil illustrate this methodological diversity and reinforce the importance of understanding methodological limitations and potential. Although very useful, these methods have limitations and assumptions that must be considered when interpreting the results, such as variations in population density and spatial distribution of cases, which can influence the sensitivity of different methods. Even if they may be relevant for public health surveillance, some limitations may impact the quality and interpretation of the clusters they detect (Neill, 2009; Pinto *et al.*, 2022). Furthermore, each method is based on different theoretical aspects, that may contribute to different results. Due to the variability of results, the adaptability of each method to the epidemiological problem should be investigated. In particular, the comparisons among different methods could point out the potentialities of them to lead with arboviral disease record data. For the reasons given above, this study aimed to compare the performance of some commonly used spatial clustering methods based on dengue fever data. The results are expected to contribute to developing more robust approaches adaptable to regional and demographic variations and more effective and equitable public policies.

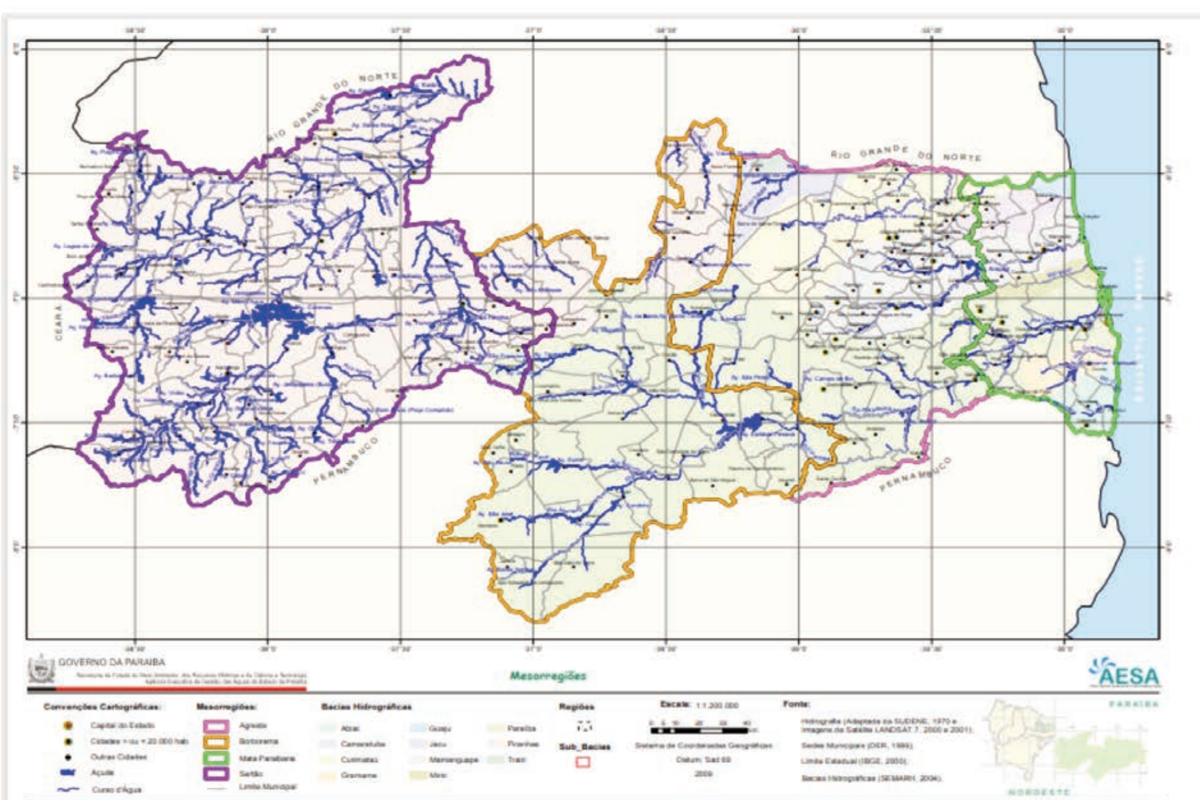

Figure 1. Map of the State of Paraíba, Brazil, with the four different geographic regions. Source: AESA, 2023. Executive Agency for Water Management of The State of Paraíba.

Materials and Methods

The geographic region of the study was the state of Paraíba encompassing 223 municipalities in north-eastern Brazil (Figure 1). It has a population of 4,059,905 inhabitants, distributed over four geographic regions as given by Brazilian Institute of Geography and Statistics (IBGE): the Coast or Forest Zone (marked by a green border on the map), two intermediate sub-regions called Borborema and Agreste (the former marked with a yellow border and the latter with a pink) and Sertão in the western back lands (marked with a purple border (IBGE, 2015, 2021, 2022). We obtained data for all dengue cases reported in 2018, 2019, 2020, 2021 and 2022 from SINANWEB (https://portalsinan.saude.gov.br/sinan-dengue-chikungunya), which is the official Brazilian site for publishing disease notifications.

The municipality of residence of the cases was used to identify their spatial distribution pattern in the state. The other variables present in this study were population estimates per municipality and the municipalities' geographic coordinates. In addition, the incidence of dengue cases was computed for each municipality and for the entire state. The Spatial Incidence Ratio (SIR) was also calculated for each municipality. This measure shows the relationship between two incidences in the occurrence of a phenomenon, i.e. the incidence in the entire geographic area of interest and the incidence in a specific location in this area. The SIR standardizes the study variable, removing the effect of the particular population in large geographic areas, the region in this case. Standardizing information according to the at-risk population is essential, allowing a more consistent comparative analysis between different geographic areas (Lima *et al*., 2019).

To understand the SIR concept, knowledge of the geographical object under study where events of interest occur (the geo-object) as well as the extent of the larger surrounding geographically delimited region (where similar event may also occur) must be known (Goodchild, 1992). SIR is given by the equation described by Lima *et al*. (2019):

$$RIE(gi) = \frac{\frac{x(gi)}{M(gi)}}{\frac{\sum_{i=1}^{n} x(gi)}{\sum_{i=1}^{n} M(gi)}}, \quad \text{Eq. 1}$$

where $x(g)$ is a random variable representing the count of occurrences of an epidemiological event in a given period for each geo-object (gi); i=1, ... , n and $M(gi)$ represents the population at risk in each gi.

The normality of the data was assessed using the Lilliefors test (1967), an adaptation of the Kolmogorov-Smirnov goodness-of-fit test. It verifies the null hypothesis that the data come from a normal distribution. The p-value in this case ($p<0.05$) was lower than the established significance level (5%). Hence, the data did not present a normal distribution, so nonparametric tests were used to perform the spatial analyses. In the theoretical aspect, assumptions of each method must be taken into account in order to select the most appropriate method for each application.

A set of commonly used spatial clustering methods (Scan Statistics, Besag-Newell, Getis-Ord, M-Statistics and Tango) were used to detect significant and non-significant areas of events under study in a geographic region through georeferenced information as described by Homes *et al.* (2015). Scan Statistics searches for areas of high incidence by using circular windows of varying sizes around each geo-object; Getis-Ord identifies significant clusters of high or low values based on spatial dependence between neighbouring regions; Besag-Newell aggregates adjacent spatial units until a fixed number of cases is reached, forming clusters based on absolute frequencies; M-statistic assesses the spatial concentration of events by comparing local incidences with an expected distribution, allowing for the detection of areas with higher or lower cases concentrations; and the Tango method uses case count data adjusted for population to identify regions with incidence above the expected level, highlighting high-density clusters. Thus, statistics are fundamental tools to provide quantitative support for public health actions (Sá *et al.*, 2020).

Table 1. Compatibility matrix between Method and SIR.

Method	High SIR (>1,5)	LowSIR (<1,5)
Significant	HS	LS
Not significant	HN	LN

HS refers to geo-objects with a SIR >1.5 and classified as significant by the method. LS refers to geo-objects with SIR <1.5, but still identified as significant. HN includes geo-objects with SIR >1.5 that were not considered significant by the method, while LN represents geo-objects with SIR <1.5 and not classified as significant.

Using the free softwares *R* (https://www.r-project.org) and Geosurveillance (https://geosurveillance.software.informer.com), the statistical methods mentioned above were applied to give their results on the dengue fever cases reported between 2018 and 2022 in Turkey. These results were subsequently compared using the SIR maps as reference. For this comparison, compatibility matrices were constructed with the aim of identifying which method classified the largest number of geo-objects with SIR values greater than 1.5 as significant. The compatibility matrix assesses the level of agreement between the results produced by each method and the reference SIR values. Its structure is presented in Table 1.

Compatibility was measured by the index based on the *Kappa* coefficient that is a statistical measure that assesses the degree of agreement between calculated values the observed classifications (Ferreira *et al.*, 2025):

$$K = \frac{P0 - Pc}{1 - Pc} \quad \text{Eq. 2}$$

where K is the *Kappa* coefficient, with $P0$ and Pc are given by:

$$P0 = \frac{\sum_{i=1}^{M} m_{ii}}{N} \text{ and } Pc = \frac{\sum_{i=1}^{M} m_{i+}\, m_{+i}}{N^2} \quad \text{Eqs. 3 and 4}$$

where M is the total number of classes; m^{ii} is the sum of the main diagonal of the compatibility matrix; m_{+i} the sum of all values of the line i; m_{+i} the sum of the values of column i; and N is the value of possible decisions present in the compatibility matrix.

This index expresses the proportion of agreement between the results of the method under evaluation and the SIR values and is used to identify the method that shows the highest degree of compatibility with the reference data. Among the spatial clustering methods in the comparison, the biggest compatibility index based on the *Kappa* coefficient is the best one.

Results

According to official data from SINANWEB, Paraíba recorded 81,959 dengue cases between 2018 and 2022. In 2018, 10,977 cases were reported (13.3%). There was a significant increase in 2019, with 18,808 cases (18.9%). In the following year, 2020, there was a reduction to 6,830 cases (6.8%), possibly due to under-reporting resulting from the confinement and restrictive measures during the COVID-19 pandemic (Mascarenhas, 2020). The number of cases increased in 2021, with 16,025 (19.5%) notifications, followed by another increase in 2022, with 29,319 (35.7%) cases.

The maps with the SIR and the results of the different spatial clustering methods are presented in Figure 3-7. Figure 3 refers to the year 2018 and shows a higher incidence (38 municipalities with SIR >1.5) of dengue cases in the Back lands and also in the Agreste and Borborema regions (Figure 3A). The maps generated by spatial cluster methods show that the Scan method (Figure 3B) identified 33 significant clusters compatible with high values of the SIR. M-Statistic (Figure 3E) and Tango Statistic (Figure 3F) methods also identified areas with a high incidence of events compatible with the SIR map (32 and 29, respectively), while Besag-Newell (Figure 3C) and Getis-Ord (Figure 3D) identified significant clusters in a smaller proportions compared to the SIR maps (17 and 13, respectively).

Figure 4 refers to the year 2019 and shows a higher concentration of high SIR in the north of the state, specifically in Agreste (Figure 4A). Figure 5 shows the situation in 2020 with the highest incidence of dengue cases, which are distributed heterogeneously throughout the state (Figure 5A), and Figure 6 in 2021 with the highest incidence of dengue cases, predominantly located in the Agreste and Borborema regions (Figure 6A). Finally, in 2021 Borborema and the Back lands contain municipalities with the highest incidence of dengue (Figure 7), which are evidenced by high SIR values (Figure 7A). In all cases, Besag-Newell provided a lower number of significant municipalities compared with other methods. Table 2 presents the results of the compatibility index based on the *Kappa* coefficient computed for all methods in this comparison, using SIR as reference map. The values in bold are the best indices for each year. It is worth noting the Scan statistics reached the best index in all comparisons.

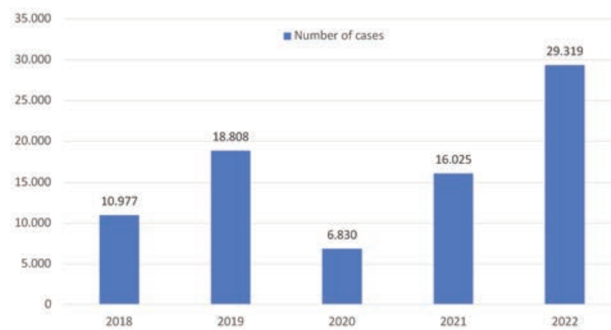

Figure 2. Registered cases of dengue fever in Paraíba (2018-2022).

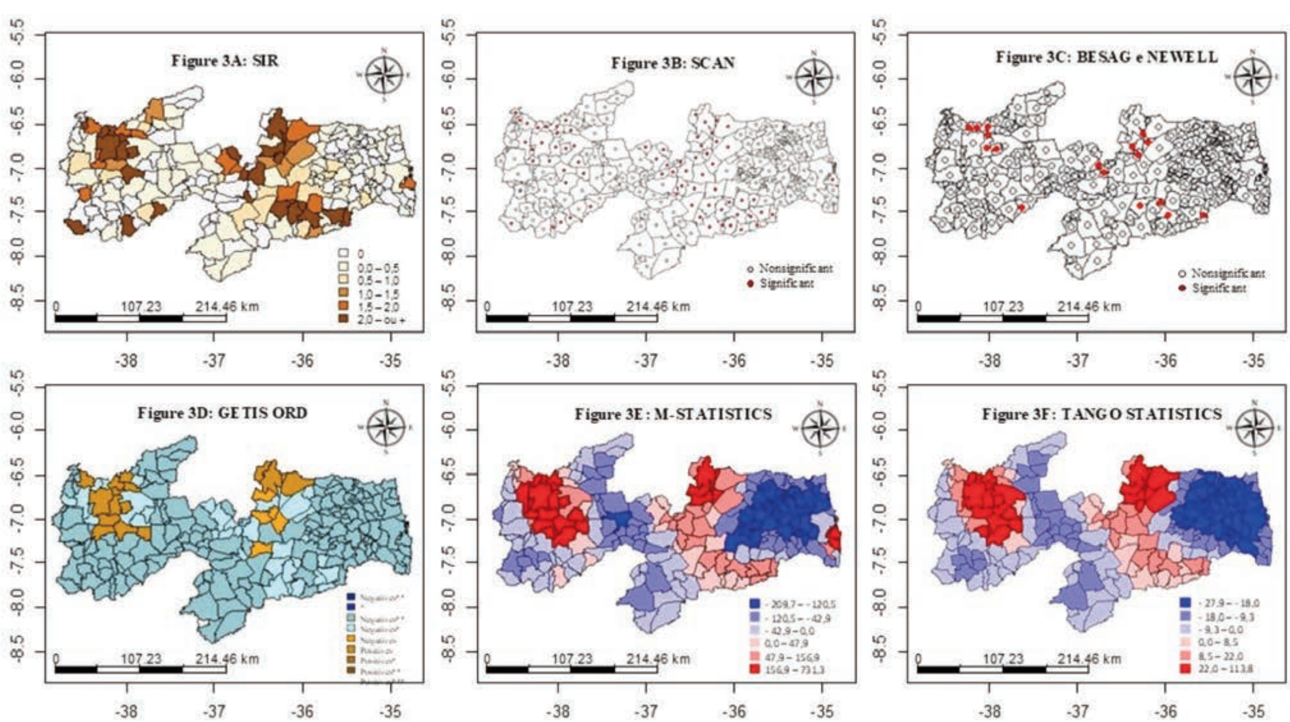

Figure 3. Comparison of the different statistical approaches spatial with the incidence ratio of dengue cases reported 2018.

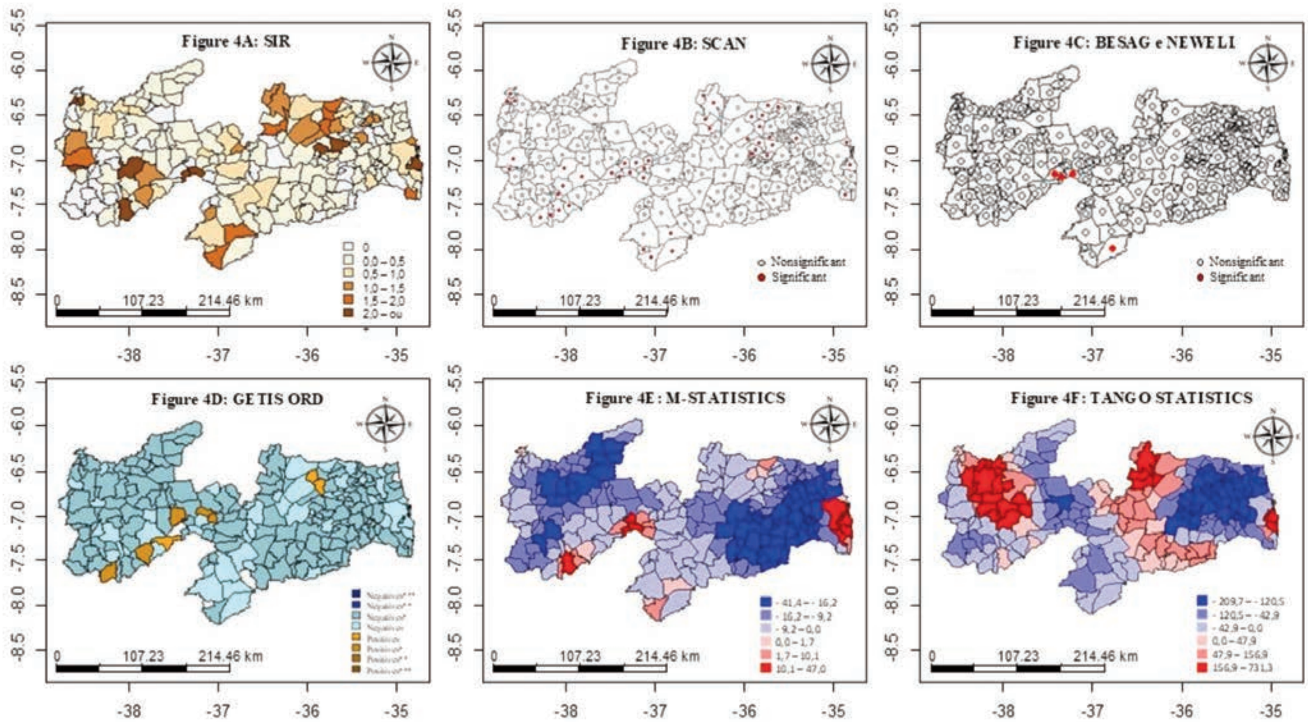

Figure 4. Comparison of the different statistical approaches spatial with the incidence ratio of dengue cases reported 2019.

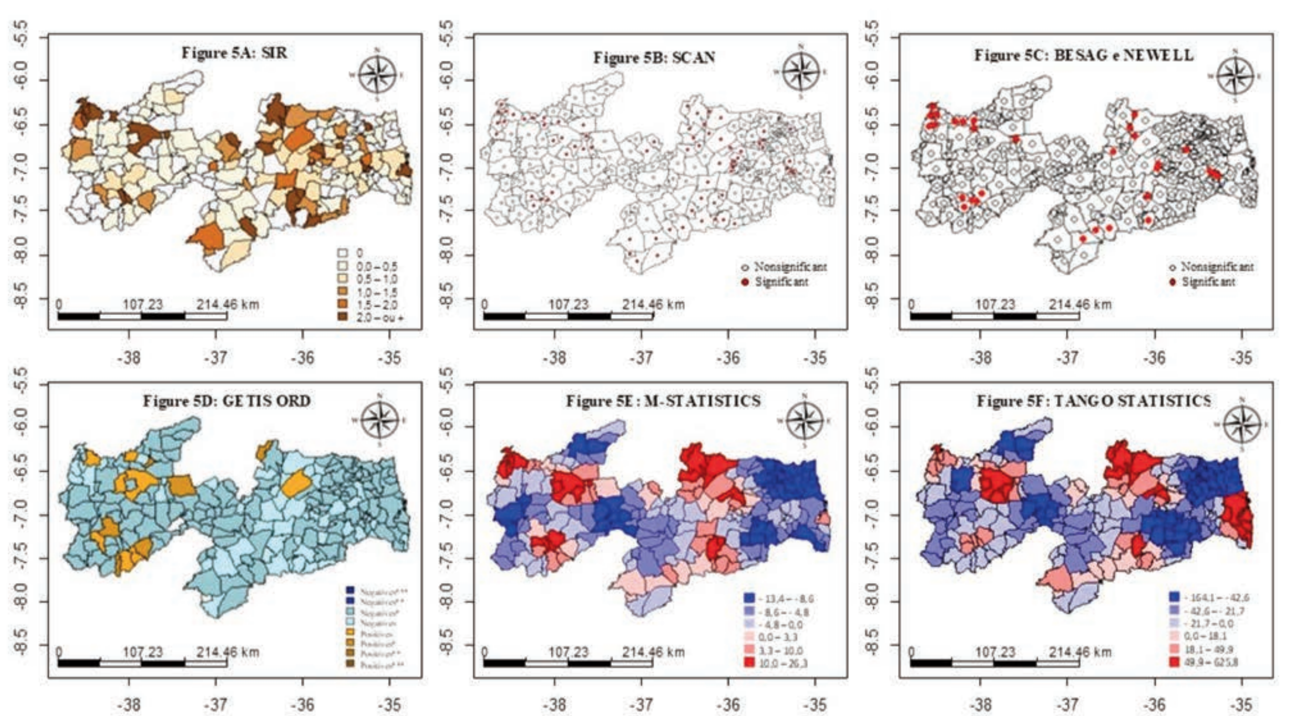

Figure 5. Comparison of the different statistical approaches spatial with the incidence ratio of dengue cases reported 2020.

All methods used also provided some false significant high values (Figures 3-7). It can be seen that Getis-Ord, M-statistic and Tango methods created large spatial clusters which included municipalities with high and low values, with Scan statistic and Besag-Newell also providing some of them. However, the Scan statistic provided better agreement with high SIR values than Besag-Newell: for this reason, the Scan statistic achieved the better compatibility index (Table 2). However, Table 2 shows that the other methods provided acceptable results in specific situations. For instance, Besag-Newell achieved the second-best compatibility in 2018, while the M-statistic achieved the same position in the years 2019 and 2022. This can also be observed with the Tango method in the 2020 and 2021.

Discussion

In Epidemiology, spatial clustering methods are used to detect regions with significant risk for a disease. It can support intervention effectiveness, resource allocation, and strategic planning in health. This paper presented a brief comparison among five popular spatial clustering methods applied to dengue fever recorded data for the period 2018-2022 in the state of Paraíba, Brazil. WE found that assumptions of each method must be taken into account in order to select the most appropriate method for each application. The results indicated that areas with a high incidence of dengue cases presented a heterogeneous spatial distribution throughout the study period. The year 2018 stood out for recording the highest number of municipalities with SIR values >1.5. These findings corroborate the results published by Rocha *et al.* (2024), who also demonstrated a heterogeneity in the distribution of the disease throughout the state together with high SIR values for 2018.

An interesting issue highlighted in this study is the presence of false significant high values in the maps resulting from some spatial clustering methods. In general, Getis-Ord, M-statistic and Tango had a tendency to create spatial clusters including geo-objects of high and low values inside them, while Scan statistic and Besag-Newell showed a lower tendency in these cases. It is worth mentioning that Besag-Newell provided lower numbers of significant geo-objects when compared with other methods. A possible reason

Table 2. Compatibility index based on the *Kappa* Coefficient computed for all methods in this comparison, using SIR as reference map.

Years and Methods	Scan	Besag-Newell	Getis-Ord	M-statistic	Tango
2018	0.78	0.57	0.37	0.56	0.51
2019	0.51	0.15	0.19	0.38	0.009
2020	0.59	0.34	0.12	0.32	0.47
2021	0.62	0.20	0.01	0.29	0.33
2022	0.51	0.40	0.22	0.41	0.36

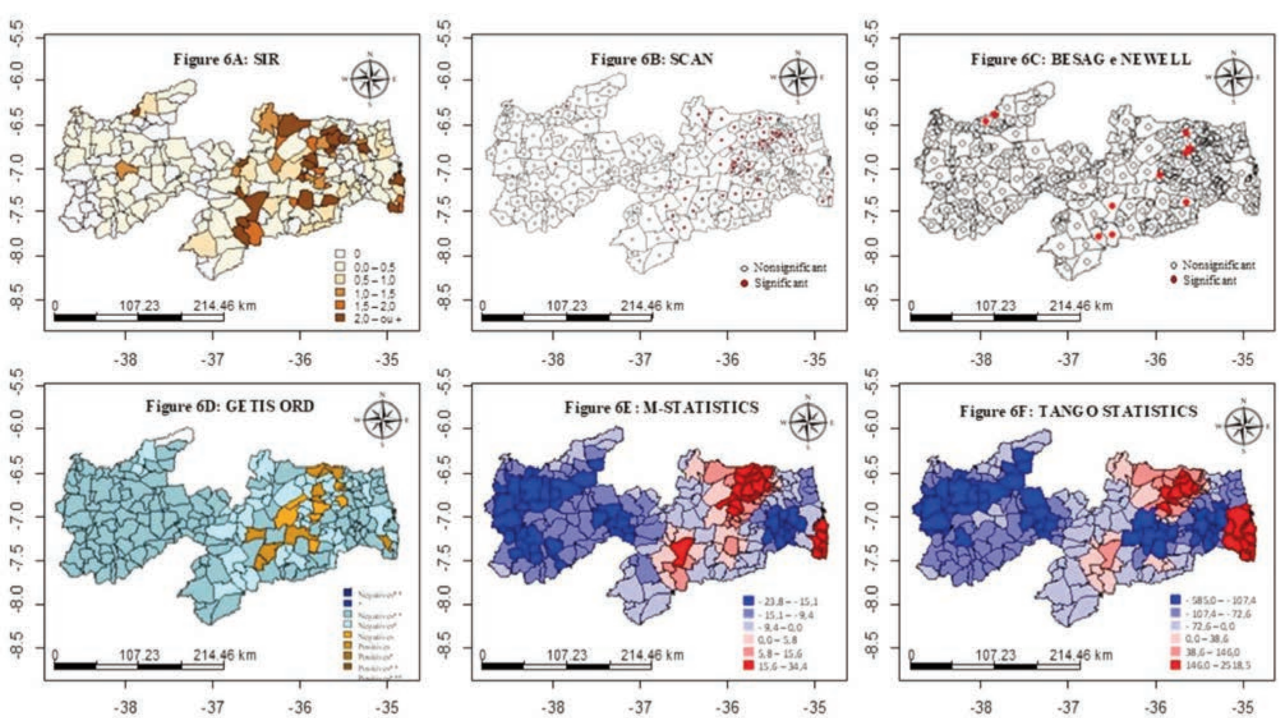

Figure 6. Comparison of the different statistical approaches spatial with the incidence ratio of dengue cases reported 2021.

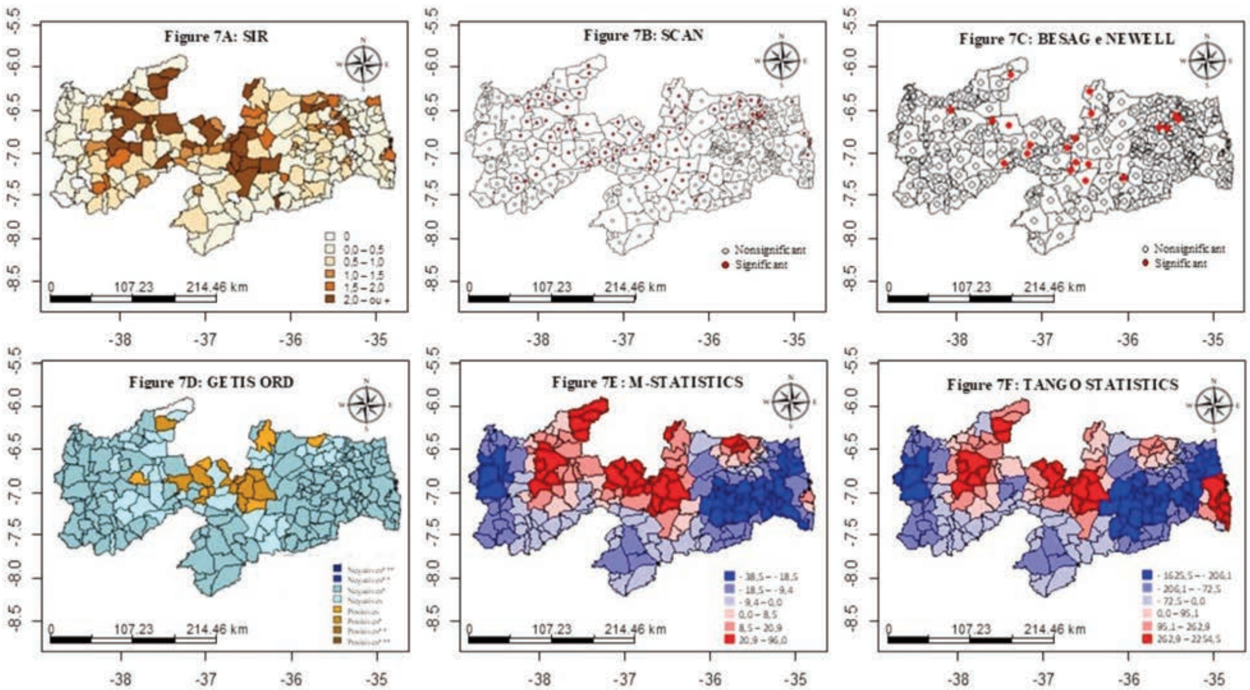

Figure 7. Comparison of the different statistical approaches spatial with the incidence ratio of dengue cases reported 2022.

could be that the fixed number of cases may not be suitable for all kind of studies. This is also corroborated by Rocha *et al.* (2024). The appropriate choice of method for detecting spatial clusters is essential for the guidance of effective public health intervention strategies. In this study, the results showed that the Scan statistic performed best in all comparisons performed. This method was also used by Chen *et al.* (2016), who used epidemiological data on dengue cases in Taiwan, referring to the years 2014 and 2015, with the aim of proactively identifying active foci of transmission, supporting health professionals in similar contexts by facilitating the early detection of vector-borne epidemics and enabling the adoption of more targeted control measures. Similarly, Santos *et al.* (2020) applied the Scan statistic to identify priority areas for dengue control, corroborating the effectiveness of this approach in guiding rapid and accurate public health interventions.

Comparing the circular Scan and Besag-Newell methods in the analysis of the spatial distribution of dengue in the city João Pessoa, Lucena and Moraes (2009) observed that both identified significant clusters, especially in the northern and south-eastern areas of the city. However, while the Scan method detected areas of high and low risk, the modified Besag and Newell method identified only high-risk areas with great precision. Costa and Assunção (2005) tested and compared the spatial Scan method and Besag-Newell and found that they had similar results, except for clusters in sparsely populated regions, where spatial scanning gave better results. From the results presented above, the Scan method outperformed the other methods by presenting greater compatibility with SIR highlighting that a given method may not always be suitable in all situations.

The results presented also that the Besag-Newell outperformed Getis-Ord by providing better compatibility indices with the SIR based on the *Kappa* coefficient in some periods. However, Rocha *et al.* (2024) performed a comparative analysis between Besag-Newell and Getis-Ord using annual data on confirmed dengue cases in the state of Paraíba, Brazil. Despite the variability observed in the results, the Getis-Ord method in their study showed greater compatibility with the SIR maps.

Conclusions

The five cluster detection methods compared in this study are illustrated by maps and compatibility matrices using SIR as reference and a compatibility index based on the *Kappa* Coefficient, which provided relevant elements that can assist decision-makers in the management of diseases, such as dengue fever and other vector-borne diseases, using spatial clustering methods. It was observed that all methods occasionally provided significant false high values. Maps presented Getis-Ord, M-Statistic and Tango methods created large spatial clusters. Besag-Newell's method provided lower numbers of significant municipalities when compared with the other methods. Scan Statistic provided a better compatibility with respect to the SIR map, according to the compatibility index for all years used in this comparison.

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