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Partitioned Variance Analysis of Dengue Incidence in Rio de Janeiro City: Exploring the Impact of Urban Thermal Structure and Neighborhood Clustering

Análise da Variância Particionada da Incidência da Dengue na Cidade do Rio de Janeiro: Explorando o Impacto da Estrutura Térmica Urbana e Agrupamento por Bairros

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Abstract

This study investigates the spatial distribution of dengue cases in the city of Rio de Janeiro by employing neighborhood-level partitioned variance analysis, k-means clustering, and multivariate linear regression modeling. By analyzing weekly dengue case reports from the Brazilian Ministry of Health alongside meteorological data from AlertaRio mesonet stations, we reveal a significant correlation between urban thermal structures—specifically the Urban Heat Island (UHI)—and dengue incidence. Notably, increases in daily maximum and minimum temperatures precede peaks in dengue cases by up to one week, indicating a potential influence of urban heat on dengue transmission and severity. The variance analysis identifies four distinct neighborhood clusters, each accounting for a substantial portion of the total variance in dengue incidence, with a confidence level exceeding 90%. These findings highlight the intricate interplay between urban environments, local climate patterns, and the proliferation of vector-borne diseases such as dengue. Furthermore, they underscore how critical socio-economic factors, such as inadequate infrastructure and limited access to healthcare, exacerbate community vulnerability. This study emphasizes the need for integrated urban planning and public health strategies to mitigate health risks associated with UHI, ultimately enhancing resilience against vector-borne diseases in densely populated urban areas.

Keywords: Socio-economic vulnerability; Urban heat island effect; Public health

Resumo

Este estudo investiga a distribuição espacial dos casos de dengue na cidade do Rio de Janeiro, utilizando análise de variância em nível de bairro, agrupamento k-médias e modelagem de regressão linear multivariada. Ao analisar relatórios semanais de casos de dengue do Ministério da Saúde brasileiro em conjunto com dados meteorológicos das estações mesonéticas AlertaRio, revelamos uma correlação significativa entre as estruturas térmicas urbanas — especificamente a Ilha de Calor Urbana (UHI) — e a incidência de dengue. Notavelmente, aumentos nas temperaturas máximas e mínimas diárias precederam máximos nos casos de dengue em até uma semana, indicando uma potencial influência do calor urbano na transmissão e gravidade da dengue. A análise de variância identificou quatro clusters de bairros distintos, cada um explicando uma parte substancial da variância total na incidência de dengue, com um nível de confiança superior a 90%. Os resultados ressaltam a complexa interação entre ambientes urbanos, padrões climáticos locais e a proliferação de doenças transmitidas por vetores, como a dengue. Além disso, enfatizam que fatores socioeconômicos críticos, como infraestrutura inadequada e acesso limitado a serviços de saúde, agravam a vulnerabilidade das comunidades. Este estudo destaca a necessidade de estratégias integradas de planejamento urbano e saúde pública para mitigar os riscos à saúde associados à UHI, aumentando, assim, a resiliência contra doenças transmitidas por vetores em áreas urbanas densamente povoadas.

Palavras-chave: Vulnerabilidade socioeconômica; Efeito de ilha de calor urbana; Saúde pública

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1 Introduction

Dengue fever was first identified in the State of Rio de Janeiro in 1986 and has since spread across Brazil (Braga & Valle 2007), with the majority of cases concentrated in the Metropolitan Region of Rio de Janeiro (Miagostovich et al. 1993; Rio de Janeiro 2011; Gomes et al. 2012). The city exhibits diverse urban environments characterized by variations in topography, land use, microclimates, Urban Heat Island (UHI) effects, sanitation, urbanization, and vulnerability — all of which significantly influence the incidence and spread of dengue within neighborhoods (WMO 2009; Xavier et al. 2017; Oliveira 2019; Brasil 2009).

Various analytical approaches, including statistical data analysis and epidemiological modeling, have been employed to investigate dengue transmission. One promising tool is wavelet transform, which offers advanced capabilities in signal analysis compared to traditional methods like Fourier transform. While wavelet analysis provides detailed insights into temporal variations in dengue cases, linear regression modeling is also commonly utilized for its simplicity in generating unbiased average results, assuming normal or generalized distribution errors while considering synchronous or lagged data.

Evidence suggests that rising temperatures may expand regions susceptible to dengue epidemics and enhance the ability of *Aedes* mosquitoes to transmit the virus. Climate change and variability are facilitating the spread of dengue globally (IPCC 2022). Temperature variability significantly impacts the life cycle of the *Aedes aegypti* mosquito vector, with optimal conditions for development and virus transmission occurring between 21°C and 29°C (Beserra et al. 2006). Studies in Brazil have demonstrated that higher temperatures shorten the mosquito's incubation period, thereby affecting both mosquito survival and virus transmission rates (Consoli & Lourenço-de-Oliveira 1994; Beserra et al. 2009; Farnesi et al. 2009).

Models and case data from the Americas consistently indicate that dengue transmission occurs most efficiently between 18°C and 34°C, with peak transmission observed between 26°C and 29°C (Mordecai et al. 2017). This temperature range aligns with optimal conditions for *Aedes aegypti* development, contributing to higher dengue incidence rates during warmer periods (Baracho 2013).

Spatial analyses in Rio de Janeiro have demonstrated that higher average surface temperatures correspond to increased *Aedes aegypti* larval distribution, highlighting the spatial correlation between temperature and dengue risk (Lemos, Oscar Júnior & Assis Mendonça 2021). Similar findings in São Paulo and Taubaté indicate a strong association between temperature levels and dengue incidence, underscoring the impact of environmental factors on disease transmission (Araujo et al. 2015; Alexandrino 2017; Cardoso et al. 2017; Cardoso & Amorim 2018).

The urban heat island (UHI) effects (Oke et al. 2017) significantly exacerbate conditions favorable for mosquito proliferation in urban environments. Elevated temperatures associated with UHI can accelerate mosquito development, resulting in higher reproductive rates and an increased risk of dengue transmission (Lima-Câmara 2016). In Rio de Janeiro, extensive research has explored the temporal and spatial dynamics of UHI using both observational and modeling approaches. These studies highlight the considerable impact of UHI on local climate and public health outcomes (e.g., Marques Filho et al. 2009; Karam et al. 2010; Lucena et al. 2013, 2015; Lucena & Peres 2017; Monteiro et al., 2021). Collectively, these analyses suggest that UHI conditions may influence the spatial distribution of heterogeneous fluxes throughout the city. The potential connections between rising temperatures, population distribution, and the intensity of disease transmission are further investigated.

In addition to temperature effects, socioeconomic factors and urbanization patterns also influence dengue transmission dynamics. Studies have emphasized the role of vector breeding sites and community vulnerability in explaining local variations in infection rates (Knoblauch et al. 2023).

Studies have shown that urbanization and increased temperatures can create environments that are conducive to the proliferation of disease vectors like mosquitoes, further exacerbating the public health risks associated with dengue (Gubler 2002; Johansson et al. 2009). Research indicates that areas with higher population density often experience greater transmission rates of vector-borne diseases due to factors such as increased human-mosquito contact and more favorable breeding conditions (Patz et al. 2005; Da Silva Queiroz & de Andrade Medronho 2021). This correlation highlights the interplay between demographic and environmental factors in shaping disease dynamics in urban settings.

This study aims to analyze the spatial distribution of severe dengue cases across Rio de Janeiro's neighborhoods using Partitioned Analysis of Variance (ANOVA), with a focus on the population distribution and thermal dynamics of urban heat islands as critical determinants.

2 Materials and Methods

Cluster analysis is a statistical method designed to categorize data based on the levels of similarity and dissimilarity among the n observations in a given dataset. Its applications are diverse, ranging from understanding wind speed patterns in the Northeast region (Santana & Da Silva 2019) to investigating similarities in rainfall patterns for Rio Grande do Norte in conjunction with sea surface temperature patterns (Amorim et al. 2020), analyzing occurrences of droughts in various river basins (Silva & Costa 2020; Melo & Sousa 2021), and verifying homogeneity in the distribution of outbreaks of fires (Silva et al. 2021), among others.

According to Wilks (2019), the groups' constituent points should have small distances among themselves in relation to distances between each group. The Euclidean distance, representing the shortest distance between two objects in a multidimensional space, is the most commonly used distance metric (Braz et al. 2020). Cluster analysis can be implemented through various separation methods, with or without hierarchical origins, with two commonly used methods being *k-means* and hierarchical.

The *k-means* method follows an iterative clustering profile, wherein objects are reassigned to the cluster with the closest clustering mean. Additionally, it is considered an unsupervised clustering algorithm, generating clusters based on a predetermined number of classes (Braz et al. 2020). The algorithm requires the user to predefine the number k of groups before implementation. One method for choosing the group number is through intragroup sum of squares, where the total number of k-means groups corresponds to the number of groups minimizing the difference between the sum of squares of the distance between the object and the central cluster. Following the determination of the group number k, the sequence involves calculating the centroids/averages of the vectors for each group, determining the distance between the current point and the centroid, and reallocating the point to the group with the closest mean if it does not belong to that group already. This sequence repeats for all points until they are allocated to a group with the closest average, reaching a point where no further reallocations occur.

Conversely, the hierarchical method does not permit the relocation of analysis objects once placed within a group. As the name suggests, this method involves a predetermined hierarchy of sets of groups, each formed by merging a pair of previously defined groups (Wilks 2019). Hierarchical analysis can be carried out in two ways: agglomerative and divisive. In the agglomerative format, each point begins as its own cluster, and new, similar pairs of clusters are added as one ascends the hierarchy. In the divisive format, all data starts in a single group and is divided into different groups. The divisive format is rarely used in hierarchical groupings due to its complexity, making its application challenging in larger databases (Metz 2006). The hierarchical method employs the concept of distance between groups as a method for aggregating data, with various ways to calculate this distance, including complete/maximum, minimum, mean, and centroid (Wilks 2019).

Analysis of Variance (ANOVA) is a statistical method utilized to test differences among three or more population means, based on variance analysis between population samples. To conduct ANOVA, certain conditions must be met: the samples must be mutually independent, the data distribution must approximate a normal distribution, and the populations must exhibit variance values close to each other (Vieira 2006, cited in Moraes Júnior 2015). This methodology finds application in diverse areas, such as testing probability distributions in rainfall series, studying the potential relationship between sea surface temperature and occurrences of squall lines in the Atlantic Ocean, and examining the possible trend of average temperature increase in western Pará (Pereira et al. 2014; Silva et al. 2017; Dos Santos Gomes et al. 2015).

The ANOVA method operates on two assumptions. Under the first hypothesis, H_0, it is assumed that all population means (μ_1, μ_2, μ_3,...μ_k) are approximately equal, indicating no differentiation between groups (Moraes Júnior 2015). The second hypothesis, H_1, known as the alternative hypothesis, posits a difference between the means of the populations or at least in some of them. To determine which hypothesis holds true for the data under study, the *F-test* is performed, considering a pre-established α level of statistical significance. If the *F-test* yields a value above the rejection threshold for H_0, with a p-value of statistical significance less than α, the null hypothesis is rejected.

In this study, ANOVA was applied to partition the variance across different components, capturing the influence of multiple factors on the response variable. ANOVA is a well-established technique for testing the significance of group differences and understanding the unique contribution of each factor and their interactions (Montgomery 2019). In more complex models, where factors are hierarchically structured or include mixed effects, variance partitioning is crucial for accurately capturing the contributions of both fixed and random variables (Searle, Casella & McCulloch 2009). Additionally, Gelman (2005) highlights the importance of ANOVA in modern contexts, particularly in multivariate and hierarchical data analyses, underscoring that variance decomposition across different classes enhances the understanding of data variability. This approach was especially useful for identifying the specific effects of environmental and spatial variables in this study, showcasing the significance of variance structure to address the complexities of factor interactions in environmental and epidemiological research (Rabe-Hesketh & Skrondal 2012).

2.1 Study Area

Rio de Janeiro is located at approximately 22°54'23"S latitude and 43°10'21"W longitude. It borders several municipalities of the Baixada Fluminense to the north, near the Serra do Mar escarpments. To the south, it is bounded by the Atlantic Ocean, while Guanabara Bay lies to the east and Sepetiba Bay to the west. Situated in Brazil's southeastern region, the city covers an area of 1,197 km², characterized by a unique blend of coastal and mountainous terrain. The population was recorded at 6,747,815 in the 2010 IBGE census (IBGE 2010), with a 2024 estimate of approximately 6.8 million residents according to recent IBGE data.

The municipality is geographically divided into four main zones: north, south, west, and center. As the second-largest population center in Brazil, Rio de Janeiro is characterized by pronounced socio-spatial segregation, diverse land use and occupation, and varied landscapes.

An influential factor for the local climate is the presence of secondary Atlantic forest, along with the influence of the Atlantic coast and rocky massifs that divide the conurbation (Santos et al. 2020). The climate is tropical, characterized by hot and humid conditions in summer, with typical temperatures ranging from 20°C to 27°C. The rainiest period spans from November to April, and extreme events can see maximum temperatures reaching 40°C (Câmara et al. 2009). The region serves as a transition zone between the tropical climate in the north and the subtropical climate in the south.

In 2020, the neighborhood of Irajá in Rio de Janeiro was identified as the hottest area in the city (Altino 2021). With a population of 96,382 recorded in 2010 (IBGE 2010), Irajá, situated in the North Zone, is predominantly composed of residential and commercial areas with limited tree cover (IPP 2018). This sparse vegetation classifies Irajá as a hotspot within the Urban Heat Island (UHI) framework, as defined by Lucena & Peres (2017). Further in this study, the temporal relationship between the Irajá hotspot and dengue incidence will be examined.

2.2 Dengue Worsening Data

Dengue infection notification data will be obtained online from the Municipal Health Department (SMS) website, where publicly available datasets are organized into annual tables covering all neighborhoods in the municipality. These records provide data from 2000 to 2019, segmented by year, with weekly reporting intervals available from 2000 to 2010 and from 2015 to 2019. For the period between 2011 and 2014, dengue cases are aggregated by month. This structured dataset offers detailed insights into dengue trends over time and is accessible through the following link of Rio Municipal Health Department - Dengue Data (http://www.rio.rj.gov.br/web/sms/exibeconteudo?id=2815389).

To perform the partitioned ANOVA of dengue transmission within the municipality, dengue data from SMS covering the period 2000 to 2019 were used. Weekly totals for the years reported with weekly intervals (2000-2010 and 2015-2019) were aggregated to create monthly totals, ensuring a consistent temporal resolution across the entire dataset. This alignment allowed for a more standardized analysis, enhancing comparability across years and supporting a robust assessment of trends and spatial patterns in dengue transmission.

2.3 Statistics and Metrics

This study presents a statistical analysis based on Multiple Linear Regression (MLR). Two regression analyses were conducted: the first considered the incidence of dengue in the entire municipality as the dependent variable, with the incidence per neighborhood as explanatory variables; the second regression utilized the mean of neighborhoods, incorporating the result of the k-means cluster analysis as explanatory variables. The *k-means* cluster analysis yielded four groups, which proved sufficient to explain the total variance.

Descriptive statistics, linear regressions, and partitioned ANOVA were performed, with the test result on the *null hypothesis* (H_0) considered. The *F-test* of the null hypothesis employed the following statistics: *p-value*, *F-value*, and R^2 (Wilks 2019).

- ***p-value*:** This indicates the probability of obtaining a test statistic (*F-value*) that exceeds a specific threshold, leading to the rejection of the *null hypothesis* (H_0), which *assumes equal variances and differing means among subsamples* in the case of partitioned ANOVA. The significance level is set at 0.05; a *p-value* below this threshold indicates statistical significance. Larger (smaller) sample sizes produce smaller (larger) *p-values*. In the context of the MLR model, it is used alongside the *F-test* to assess the significance level of the predictor variables.
- ***F-value*:** This is defined as the ratio of the variance of sample means to the within-group variance of the independent variable of each group. The *F-value* is typically presented in ANOVA tables, where a *larger*

F-value suggests the potential rejection of the null hypothesis H_0: $\sigma_1^2 = \sigma_2^2 = \ldots = \sigma_k^2$ (the variances of the groups are equal).

- R^2**:** The coefficient of determination, indicating the extent to which the observed variance is explained by model variance.

3 Discussion of Results

All variables underwent scaling (i.e., mean subtraction and division by the standard deviation) prior to statistical analysis, ensuring uniformity and facilitating the interpretation of results. Cluster analysis was employed for both the absolute values of worsening notifications by neighborhoods and the population-weighted values. The determination of the number of groups for the cluster analysis was based on analyzing the explanatory variance curve as a function of the number of groups. From this analysis, four groups were selected, collectively explaining more than 60% of the total variance.

The partitioned ANOVA, a subtype of piecewise ANOVA, was employed to evaluate the explanatory contributions of subgrouped data. This analysis considered both individual neighborhoods and clusters, providing insights into the variance contributions within these distinct subgroups. Customized *R-scripts* were utilized for cluster analysis and mapping, leveraging the geobr library for geographical data representation.

3.1 Clustering and Partitioned ANOVA

The covariance matrix for neighborhoods notifications is a square matrix that provides the covariances between different pairs of neighborhoods (Figure 1). It gives insights into how the notifications in one neighborhood are related to the notifications in another. The diagonal elements represent the variances of notifications in each neighborhood, while the off-diagonal elements represent the covariances between pairs of neighborhoods. The covariance matrix is a useful tool in understanding the relationships and patterns in the data related to dengue notifications across different neighborhoods. Observably, the dengue cases appear widely dispersed according to the covariance matrix (Figure 1). Neighborhoods with apparent subsampling (i.e., Grumari and Juá) stand out when subsets of minimum and maximum covariance are sampled (Figure 1A and 1B).

The k-means clustering analysis identified four distinct groups (Figure 2), which collectively accounted for a substantial portion of the variance in the data. This analysis illustrates the spatial distribution of these groups, revealing notable concentrations in the West Zone for both the 3rd and 4th groups.

In Figure 2A, the highest absolute numbers of dengue cases are observed. The groups are presented in descending order based on the number of neighborhoods they encompass. The 3rd group, indicated in yellow, comprises neighborhoods such as Bangu (145), Campo Grande (148), Santa Cruz (156), and Realengo (143), all located in the West Zone, which has high population totals. The 4th group, shown in purple, consists of neighborhoods like Senador Camará (146), Guaratiba (152), and Paciência (155), primarily situated in the West Zone, along with Complexo do Alemão in the North Zone, contributing significantly to the overall number of dengue cases. The 2nd group, represented in burgundy, includes a diverse array of neighborhoods across the West, North, and South Zones, making a substantial contribution to the total dengue cases. In contrast, the 1st group, depicted in blue, comprises neighborhoods with the lowest absolute contribution to the total cases, located near the coordinate pair (0,0).

Figure 2B illustrates the proportional distribution of dengue notifications across the city. Notably, the aggregation of groups becomes more pronounced when the data is standardized by the population of the neighborhoods, with values expressed as proportional figures. The 1st group, depicted in burgundy, encompasses a diverse range of neighborhoods, reflecting the enhanced aggregation achieved through scaling. The neighborhoods not included in the first group are represented in purple, forming the 4th group, which comprises Caju (4), Anil (120), Curicica (122), Bonsucesso (41), and Saúde (1). Additionally, the smaller 3rd group consists solely of the neighborhoods Joá (130) and Grumari (137).

ANOVA was conducted on dengue cases in Rio de Janeiro, utilizing data from all neighborhoods and normalized means of each group, considering both absolute and proportional totals. The *F-value* distribution indicates high statistical reliability, with *p-values* below 0.05, leading to the rejection of the null hypothesis H_0. Residuals have very small absolute values, suggesting a satisfactory fit (Figure 3A). For proportional predictors, scaled by neighborhood's population (Figure 3B), some bias may be associated with the lack of statistical significance, possibly due to underreporting.

The spatial distribution of the *F-test* across neighborhoods in Rio de Janeiro is depicted in Figure 4. In Figure 4A, significant variations in *F-test* values for absolute incidence are evident, with neighborhoods in the western part of the city exhibiting lower values, while those in the eastern part show higher values. This trend corresponds to the greater incidence of cases in the more populous western

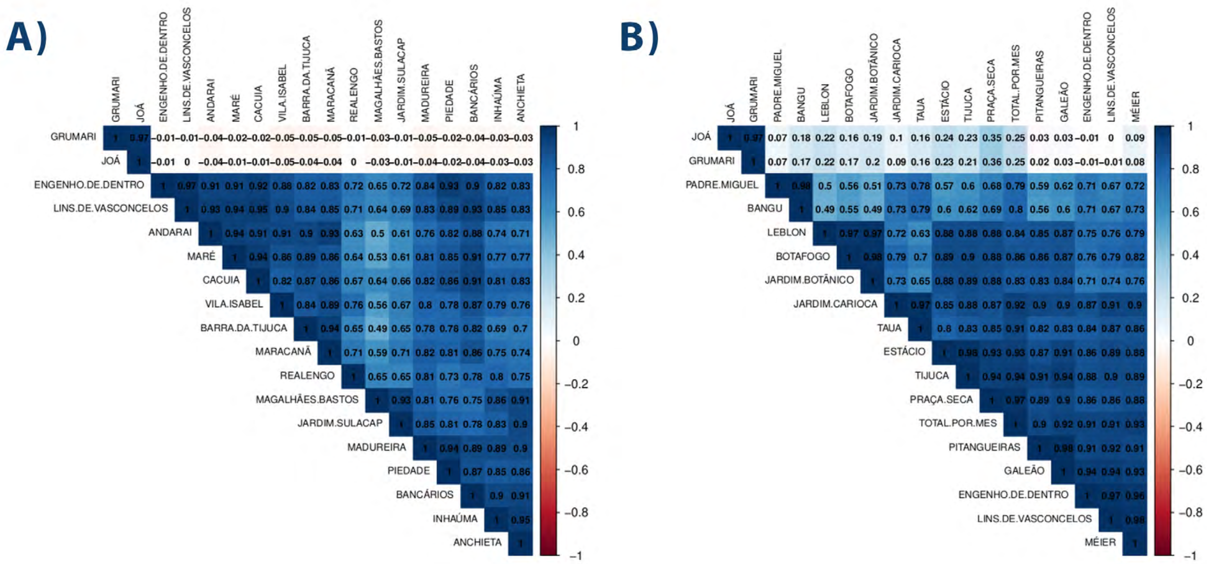

Figure 1 Subsampled values from the covariance matrix for neighborhood notifications: A. Minimum values; B. Maximum values (i.e., values immediately next to the unitary main diagonal).

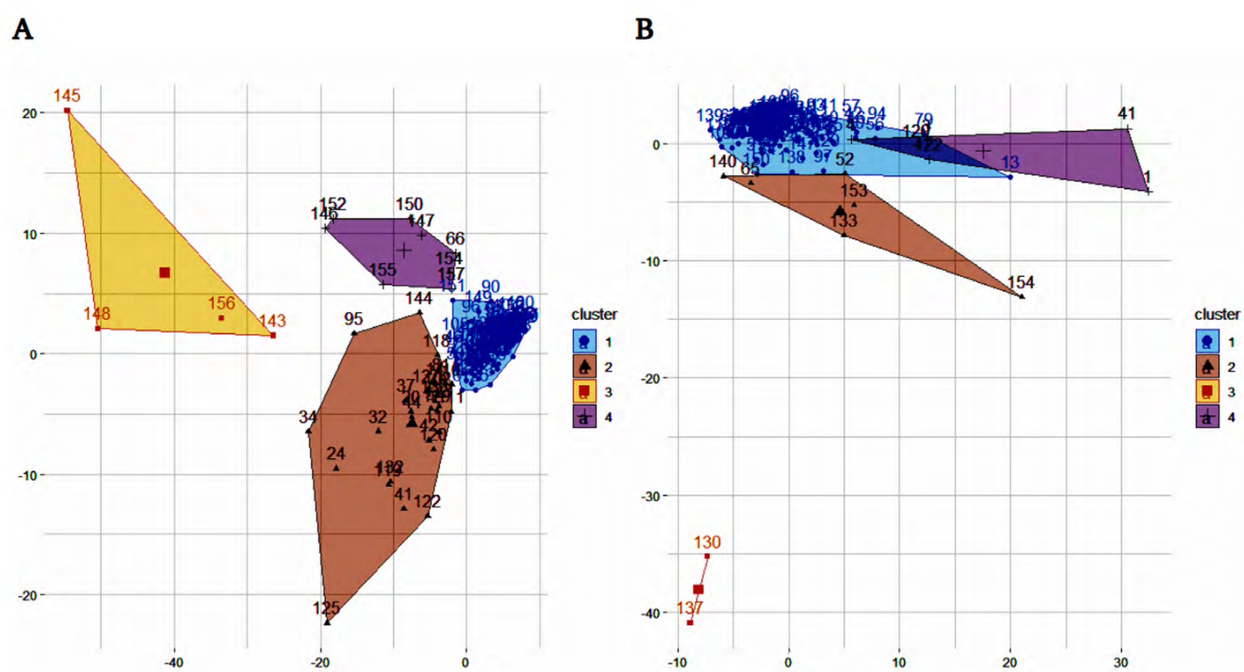

Figure 2 Clusters in Rio de Janeiro city were identified using the k-means method, with different neighborhoods indicated by numbers: A. Clusters using absolute numbers of dengue worsening notifications. B. Clusters using scaled data based on neighborhood population.

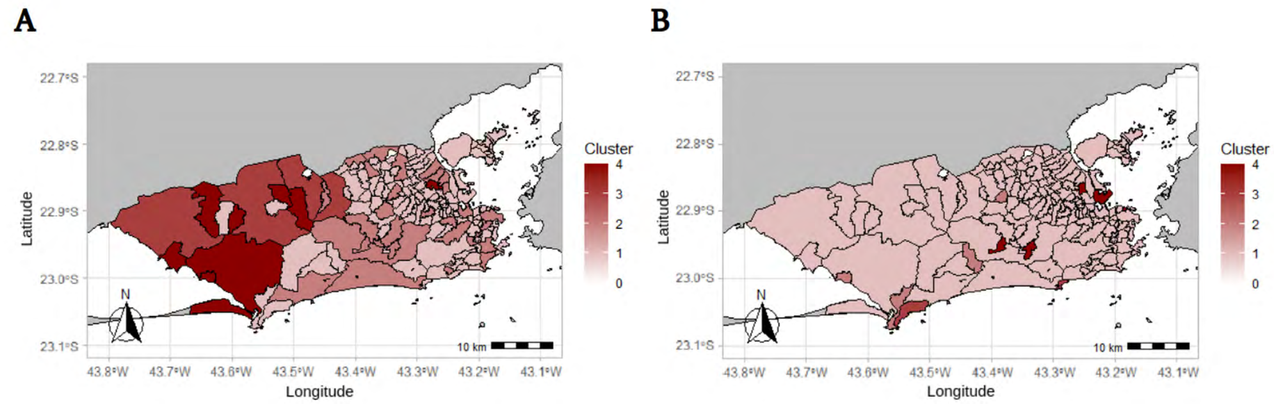

Figure 3 The statistical clusters obtained through the k-means method elucidate the spatial distribution of Dengue incidence throughout neighborhoods in Rio de Janeiro: A. Distribution based on the absolute totals of dengue cases by neighborhood; B. Distribution based on scaled values for each neighborhood's population, revealing biases associated with sub-sampling.

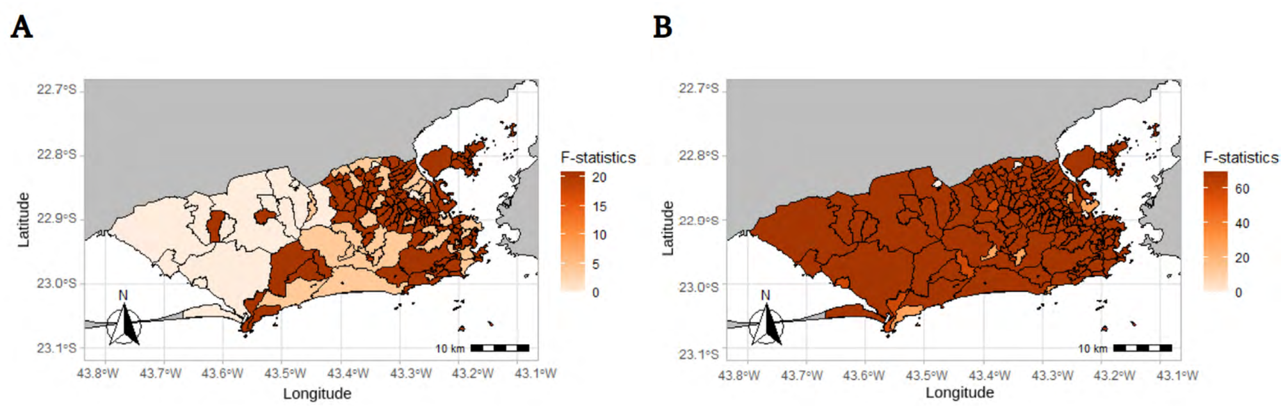

Figure 4 The spatial distribution of the *F-test* obtained in the cluster analysis is depicted as follows: A. Absolute totals of dengue cases by neighborhood in the city of Rio de Janeiro; B. Proportionalized totals of dengue cases by population in each neighborhood of the city of Rio de Janeiro.

neighborhoods, which enhances the statistical reliability in these areas, indicating the presence of different averages. Figure 4B illustrates the *F-test* distribution for locally scaled population values, revealing heterogeneous variances for neighborhoods with the same mean or consistent variances across different means. This suggests a rejection of the null hypothesis H_0. Furthermore, neighborhoods that are likely subject to underreporting exhibit significant deviations from the mean F-test distribution, highlighting disparities in data reporting and incidence rates.

The spatial distribution of the *logarithm of the F-test* enhances the visualization of statistical reliability of H_0 across neighborhoods (Figure 5), effectively filtering out areas with evident underreporting. In this analysis, the distributions of the *logarithms* of absolute values and those adjusted for neighborhood population size show remarkable similarity. A discernible west-to-east gradient emerges in the distribution of statistical reliability within the partitioned ANOVA framework in this case. As a result, the discrepancies in the representativeness of the linear fitting associated with population distribution tend to diminish.

This finding emphasizes the critical need to consider demographic factors when interpreting statistical results, as these elements can significantly influence conclusions regarding spatial patterns of disease transmission and the reliability of data analyses. Larger F-test values suggest a

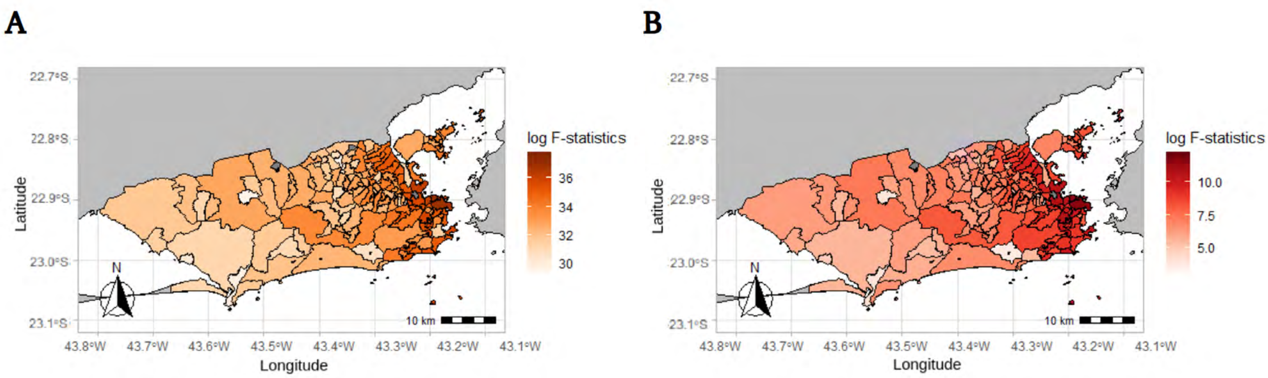

Figure 5 *ANOVA F-test distribution of logarithmic values* using: A. Absolute logarithmic values; B. Logarithmic scaled values by each neighborhood's population. Neighborhoods with probable subsampling were excluded from the mapping.

rejection of the null hypothesis (H_0) (i.e., that the means are equal and variances are different), thereby reinforcing the importance of the observed statistical variations among neighborhoods, particularly from a logarithmic perspective. In this case, the rejection of (H_0) indicates either different means or equal variances (according to De Morgan's laws). This underscores the necessity of incorporating demographic insights into statistical evaluations to improve the accuracy and relevance of analyses in public health contexts.

Integrating these demographic considerations into the analysis enhances the robustness of the findings and supports more accurate interpretations of the underlying data patterns.

Research has shown that accounting for demographic variables is essential in epidemiological studies to better understand disease dynamics and inform public health interventions. For instance, studies indicate that neighborhood characteristics, including population density and socio-economic factors, can affect disease transmission patterns (Diez Roux & Mair 2010; Galea & Vlahov 2011). Thus, integrating demographic considerations enhances the robustness of statistical analyses and supports more accurate interpretations of the data.

The distributions of reported dengue cases, partitioned by neighborhoods, during the epidemics of 2002, 2008, 2012, and 2016 are shown in Figure 6. The highest incidences occurred in neighborhoods in the North and West zones of the city of Rio de Janeiro. These neighborhoods are located within the Urban Heat Island, exhibiting relatively high air temperature values. While the contribution of the most populous neighborhoods is substantial in shaping the modeled results, leading to a reduction in bias and improved representativity, it is essential to approach the generalization of proportional predictors with caution. Additional investigation into local factors is warranted for a more comprehensive understanding.

3.2 Joint Incidence of Dengue and Urban Heat Island

The Urban Heat Island effect is a phenomenon where urban areas experience higher temperatures than their surrounding rural areas due to human activities, modifications to the land surface, and the heat-retaining properties of urban structures.

Understanding the joint incidence involves investigating whether there is a connection between the prevalence of dengue cases and the existence or intensity of the Urban Heat Island effect. This analysis aims to explore how environmental factors, such as increased temperatures associated with the UHI, may influence the spread, transmission, or severity of dengue fever.

Monitoring the joint incidence of dengue and the Urban Heat Island can provide valuable insights into the complex interactions between climate, urbanization, and the occurrence of vector-borne diseases like dengue. It helps researchers and public health officials better understand the environmental conditions that contribute to the spread of dengue in urban areas, allowing for more targeted and effective strategies for disease prevention and control.

The following analysis delves into the dynamics of dengue in the Irajá neighborhood, chosen as a representative hotspot within Rio de Janeiro's Urban Heat Island (UHI). The objective is to assess the connections between thermal patterns and documented cases of dengue fever. To streamline the analysis, essential statistics (average, maximum, and minimum weekly temperatures) of the Irajá neighborhood were extracted from the AlertaRio weather stations, covering the years 2015 to 2019, along with the corresponding dengue totals.

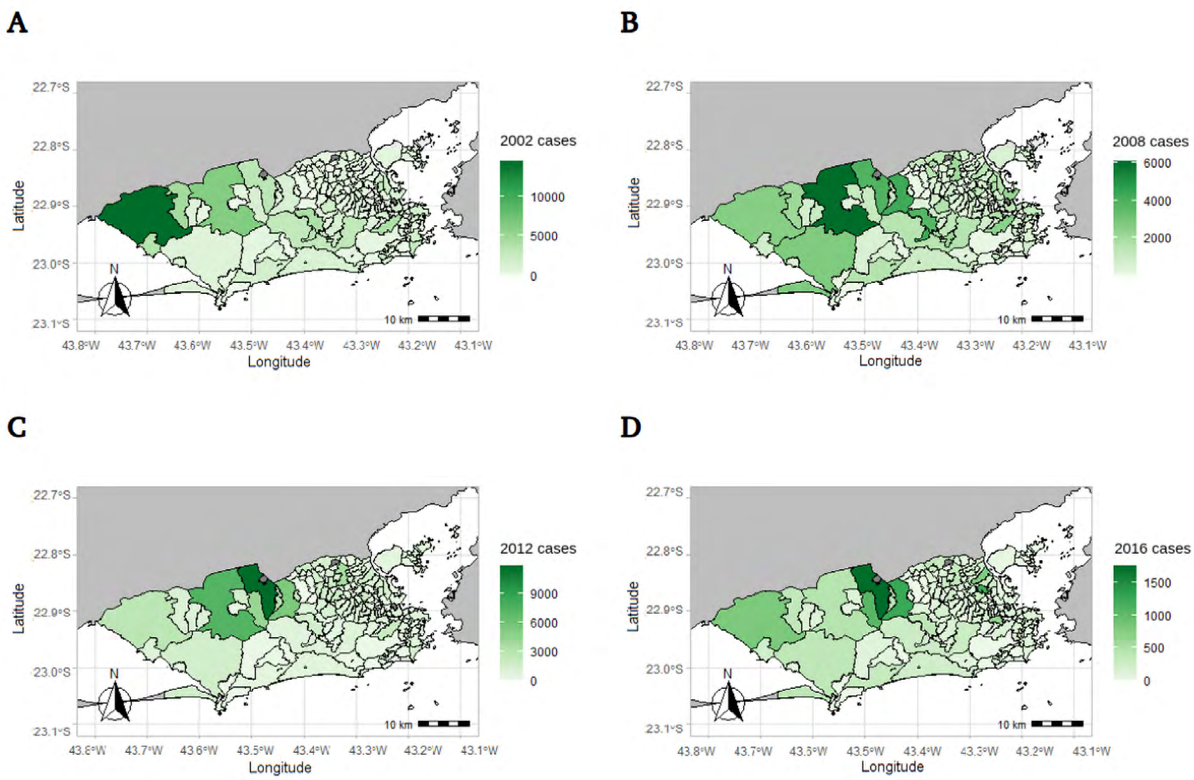

Figure 6 Total cases by neighborhoods during epidemic years: A. 2002; B. 2008; C. 2012; D. 2016.

All thermal variables were normalized for comparative purposes. During the period from 2015 to 2019, there was a significant rise in high-temperature records observed in Irajá, likely associated with changes in instrumental exposure. Two dengue epidemics occurred in 2015-2016 and 2019, with the latter showing a more subtle impact in the normalized series (figures not shown).

In early 2015, a slight rise in average and minimum temperatures was observed, preceding a sudden surge in dengue notifications for Irajá, peaking as temperatures decreased mid-year. After the decline in cases in 2015, an increase in maximum temperature occurred toward the year-end, followed by a subsequent temperature drop. At the onset of 2016, a new surge in average and minimum temperatures was witnessed, accompanied by another peak in dengue notifications. Throughout 2016, temperatures (maximum, mean, and minimum) declined, mirroring the decrease in dengue totals. This suggests a relative dependence on air temperature and its seasonal variation.

In 2017 and 2018, some dengue cases occurred, but were insufficient for an epidemic outbreak. In 2018, there was a reduction in the amplitude of maximum temperatures, and a slightly more substantial decrease was observed in mid-2018 compared to other years.

From late 2018 to 2019, there was a renewed increase in average and minimum temperatures. Shortly afterward, the maximum temperature rose and started to decline again, aligning with the average and minimum temperatures. A few weeks after these temperature peaks, a smaller-scale dengue peak occurred compared to 2015 and 2016, accompanied by a slight temperature increase.

However, it is noteworthy that the average weekly temperatures observed in the Irajá neighborhood, representing a hotspot in the Urban Heat Island of Rio de Janeiro, were correlated with reports of worsening dengue. An increase in daily maximum (minimum) temperatures tended to precede the surge in reports of worsening dengue by about a week, during both epidemics and endemics.

In the years 2015, 2016, and 2019, dengue epidemics occurred in the city of Rio de Janeiro, resulting in 17,451 cases, 23,946 cases, and 14,343 cases, respectively. These epidemics were of smaller magnitude compared to earlier occurrences in 2002 and 2008, where 139,400 and 120,440 cases were officially registered, respectively. In 2012, the total recorded cases of dengue worsening throughout the municipality were 50,184.

Following these major epidemics, several initiatives to combat dengue were implemented in Rio de Janeiro, contributing to the gradual reduction in dengue totals during epidemics from 2012 onwards. Notable among these actions is the release of the "National Guidelines for Prevention and Control of Dengue Epidemics" by the Ministry of Health (Brazil, 2009). These guidelines outlined surveillance and dengue control measures to be applied at the state and municipal levels. Additionally, the El Niño-La Niña Southern Oscillation (ENSO) was found to be out of phase with the dengue epidemic period, occurring every 3 to 4 years in the city of Rio de Janeiro (Santos et al., 2022).

Local government initiatives were also carried out and implemented in Rio de Janeiro based on Municipal Decree No. 34.377/2011 dated August 31, 2011. This decree declared a state of alert against dengue and outlined necessary actions for the prevention and control of the disease in the municipality (Rio de Janeiro 2011).

In addition, a collaborative effort between the Oswaldo Cruz Foundation and Getúlio Vargas Foundation resulted in the launch of a system for monitoring dengue occurrences in the municipality (FioCruz 2015). Touching briefly on the issue of climate variability, the epidemics in 2015 and 2016 coincided with El Niño episodes (Santos et al. 2022), as did the 2019 epidemic, as indicated by ENSO indexes published by NOAA (https://www.esrl.noaa.gov/psd/enso/dashboard.html). Instances of high temperatures were recorded, including the breaking of records in 2015 during the spring in the Metropolitan Area of Rio de Janeiro (PBMC 2022) and elevated temperatures during the summer, with the highest maximum values occurring at the end of autumn and winter in the neighborhood of Irajá (AlertaRio 2019).

The spatial distributions of total case numbers per neighborhood are illustrated in Figure 7, encompassing absolute values (Figure 7A) (excluding incomplete neighborhood data, shown in grey), values scaled by neighborhood population (Figure 7B), logarithmic transformation of absolute values (Figure 7C), and cases

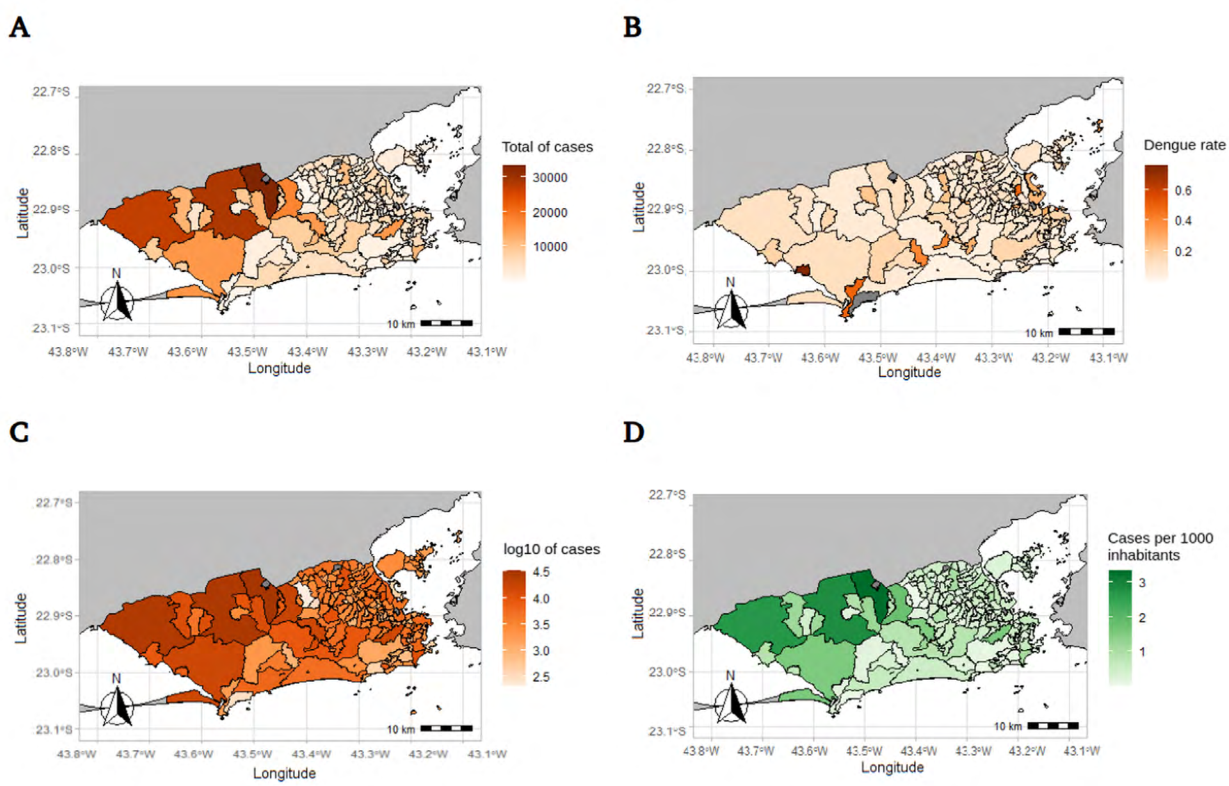

Figure 7 Spatial distribution of the total number of dengue notifications: A. Absolute values, excluding incomplete neighborhood data (shown in grey); B. Rescaled by neighborhood population; C. Logarithm of total absolute values; D. Cases per 10,000 inhabitants.

per 10,000 inhabitants (Figure 7D). This later highlights a concentration of cases in the north-west neighborhoods of Rio de Janeiro. These areas should be the primary targets for mitigation efforts, involving enhancements in public healthcare through the Unified Health System (SUS), case monitoring for expedited recovery, and proactive measures to reduce *Aedes aegypti* breeding sites.

The incidence of dengue epidemics in the most populous areas of Rio de Janeiro corresponds closely with the UHI hotspots. Thus, both factors—neighborhood population density and the presence of localized maxima in urban heat—likely can contribute to the intensification of epidemic outbreaks.

Indeed, further studies are needed to establish the relationship between Urban Heat Island (UHI) intensity and dengue incidence in the city of Rio de Janeiro. This study focused exclusively on very hot spots that significantly contribute to the intensity or core of the urban heat island and the incidence of dengue in these areas. It was assumed that over the years studied (from 2000 to 2018), the spatial structure of the UHI did not change significantly, indicating that urbanization in these regions has slowed down or progressed at a reduced pace. Therefore, the study primarily examined simultaneous or lagged temporal variations in dengue case notifications relative to periods of maximum temperature (periods of intense heat).

Based on the findings of the study, the conclusions regarding the relationship between Urban Heat Island (UHI) intensity and dengue incidence—particularly in UHI hotspots—are bolstered by the observed temporal patterns in dengue case notifications relative to peak temperature periods. Nonetheless, it is crucial to acknowledge certain limitations of the study, such as the assumption of stability in UHI spatial structure from 2000 to 2018 and the presumption of minimal urbanization changes in these areas. These assumptions may affect the generalizability of the findings to other urban environments or time periods. While the conclusions drawn from this study are supported by the data, acknowledging its limitations and proposing avenues for further research would enhance the robustness and applicability of the findings.

To assess the relationship between the distribution of dengue severity notifications during epidemic periods across neighborhoods (Figure 7) and the distribution of the urban heat island (UHI) in Rio de Janeiro, the RGB thermal map published by Lucena et al. (2015) was utilized for comparison. The map created by Lucena was based on land surface temperature retrieval using Landsat-5 TM

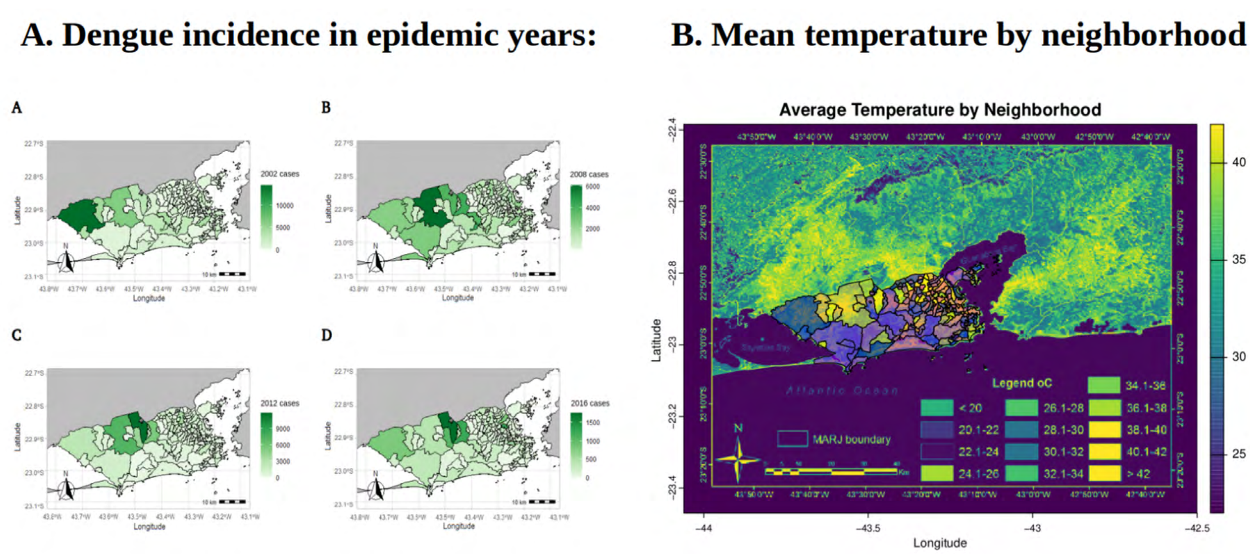

Figure 8 Seemingly similar patterns between the distribution of Dengue incidence: A: Figure 6 and the structured distribution of the Urban Heat Island (UHI); B. The background in B is derived from the luminance of the RGB thermal map of 1998, as published by Lucena et al. (2015), overlaid with neighborhood shapes filled with associated mean temperature.

data for the Metropolitan Area of Rio de Janeiro (MARJ) on August 25th, 1998.

Luminance was calculated from the sum of the blue (B) and red (R) channels, representing the extremes of the color scale while assuming a linear relationship between luminosity (resulting from satellite-received thermal infrared radiance) and surface skin temperature. This calculation yielded a luminance distribution ranging from 0 to 1. The distribution was then rescaled to derive a temperature distribution between values along the interval from 22°C to 42°C. These temperature values were utilized to compute average values within the polygon shapes of each neighborhood in the municipality of Rio de Janeiro (Official Rio datafile shapes) (Figure 8).

The distribution of average UHI temperatures obtained from the linear model described above, as a function of luminance, qualitatively resembles the distribution of Dengue incidence in the investigated epidemic years. It is assumed that the spatial structure of the UHI remains consistent throughout the months of the year, varying primarily in intensity. Future works may in deep investigate this. Further details are omitted here to maintain focus on the objective propose, preserve simplicity here. The figures below illustrate the initial similarity between Dengue incidence during epidemics and the UHI structure depicted by neighborhood thermal averages associated with UHI.

The socio-economic context of the northern and western regions of Rio de Janeiro is discussed, with a focus on profiles, income levels, and residential status in relation to dengue transmission, as outlined in Table 1. The key points from the table are as follows:

Socio-Economic Profile: The regions are characterized by lower-income populations, making them more vulnerable to public health issues such as dengue fever.

Income Level: Low to middle-income households have been identified, with poor living conditions that further exacerbate health risks.

Residential Status: High population densities and widespread informal settlements have been observed, which create conditions favorable for mosquito breeding and enhance the transmission of vector-borne diseases like dengue.

Although the available studies are limited, they provide crucial insights into the socio-economic and environmental factors influencing dengue transmission in the northern and western regions of Rio de Janeiro. For instance, Rodrigues et al. (2018) and de Almeida et al. (2022) investigate how spatial distribution, population density, and inadequate urban infrastructure in low-income neighborhoods elevate exposure to arboviruses such as dengue. Their findings emphasize that these factors, in conjunction with poor sanitation and limited access to healthcare, significantly enhance the vulnerability of these communities.

Moreover, global research, including that of Sutherst (2004), highlights how rapid urbanization, transportation networks, and the lack of essential services in impoverished areas amplify public health risks associated with vector-borne diseases. This broader perspective reinforces the local patterns observed in Rio de Janeiro, illustrating the compounded effects of socio-economic disparities on disease transmission.

Additionally, the studies by Freitas et al. (2010) and Santos et al. (2020) shed light on the socio-environmental factors affecting dengue transmission in Rio de Janeiro. Freitas et al. (2010) discuss the influence of land cover heterogeneity on Aedes aegypti populations, linking variations in vegetation and urban infrastructure to increased dengue incidence, thereby suggesting that effective land management strategies could help mitigate outbreaks. In contrast, Santos et al. (2020) underscore the consequences of rapid urbanization and the Urban Heat Island (UHI) effect, revealing how these dynamics, alongside precarious living conditions, heighten vulnerability to dengue in urban contexts. Collectively, these studies illustrate the

Table 1 Socio-Economic Context of the Northern and Western Regions of Rio de Janeiro. References: (1) Rodrigues et al. (2018), (2) de Almeida et al. (2022), (3) Freitas et al. (2010), and (4) Santos et al. (2020).

Region	Socio-Economic Profile	Income Level	Residential Status	References
Northern Region	Predominantly lower-income neighborhoods	Low to middle-income	High population density; significant presence of informal settlements	(1),(2)
Western Region	Primarily low-income households	Low-income	High-density residential areas; inadequate infrastructure	(1),(2)
Common Characteristics	Vulnerable populations with limited access to healthcare	Below average income	Proximity to UHI hotspots; conducive conditions for mosquito breeding	(1),(2),(3),(4)

complex interplay between urban planning, environmental factors, and public health, underscoring the necessity for integrated strategies to combat dengue transmission in densely populated areas.

These studies offer vital evidence regarding how socio-economic inequalities in Rio de Janeiro contribute to the spatial distribution and proliferation of dengue, particularly in lower-income, densely populated regions. Furthermore, the present study emphasizes the significance of the Urban Heat Island (UHI) effect as a critical factor in exacerbating dengue incidence by fostering conditions that facilitate greater vector-borne proliferation in these vulnerable areas. The interaction between socio-economic factors and environmental conditions underscores the compounded risks that heighten disease transmission, necessitating a holistic approach to address these public health challenges effectively.

In this discussion, we highlight the classification of Irajá as a hotspot within the Urban Heat Island (UHI) effect in the urban area of Rio de Janeiro. By drawing on the methodologies outlined by Lucena and Peres (2017), we provide a comprehensive analysis of the spatial and temporal temperature variations that characterize this region, particularly between different years. Their insights into the interplay between urbanization and climate dynamics are crucial for understanding the implications of UHI on local health outcomes.

Furthermore, our findings are contextualized by comparing them with existing literature that highlights the relationship between Urban Heat Island (UHI) hotspots and the increased incidence of heat-related health issues (Heaviside 2020; Wang & Chang 2020). By directly incorporating population density data and indirectly considering socio-economic factors, we demonstrate that vulnerable communities in Irajá face elevated risks due to higher temperatures.

This analysis emphasizes the urgent need for targeted urban planning and public health interventions, as highlighted by Mayrhuber et al. (2018). Ultimately, this enhanced discussion not only reinforces our findings but also underscores the critical requirement for integrated strategies to address the health risks associated with UHI in densely populated urban areas.

4 Conclusions

The cluster analysis of dengue cases in Rio de Janeiro has revealed significant spatial distribution patterns of the disease, with the highest incidence rates predominantly found in the West and North Zones, correlating closely with larger population sizes in these areas. Subsequent ANOVA tests identified four distinct neighborhood groups, accounting for a substantial proportion of the total variance in dengue cases, with a confidence level exceeding 90%.

Despite the heterogeneous thermal structure of the Urban Heat Island (UHI) across the city and its dynamic daily and seasonal cycles, dengue incidence appears remarkably uniform when standardized by neighborhood population. This consistency suggests that the population is concentrated in areas where UHI effects reach local maxima, indicating an endemic condition and underscoring the complex interplay between UHI and dengue transmission.

The neighborhoods exhibiting the highest dengue incidences are primarily low to middle-income areas, characterized by high population densities and conditions conducive to mosquito breeding. This correlation is particularly pronounced in the north and northwest regions of Baixada Fluminense. While the incidence rate per 100,000 inhabitants does not vary significantly across neighborhoods, the fluctuations in population density align closely with UHI hotspots, exacerbating the transmission of dengue.

Moving forward, recognizing the intricate relationship between UHI and the Urban Boundary Layer is essential, particularly as it responds to urbanization-driven surface changes. The complex interactions of local breezes—sea-land, urban, and plain-mountain—may significantly influence local advection, contributing to the observed consistency in dengue incidence throughout the city. This study posits that UHI hotspots may correlate with increased vector reproductive capacity, further enhancing vector dispersal and the risk of disease transmission.

These findings underscore the critical relationship between UHI hotspots and the socio-economic factors influencing dengue transmission, such as inadequate infrastructure and limited access to healthcare, which heighten the vulnerability of affected communities. Consequently, there is an urgent need for integrated urban planning and public health strategies to address these health risks and bolster community resilience against vector-borne diseases.

In summary, this study illuminates the multifaceted dynamics of dengue transmission within the urban environment, emphasizing the necessity for further research to elucidate the mechanisms linking urban heat islands, local climate patterns, and the prevalence of vector-borne diseases. By fostering a deeper understanding of these interactions, we can develop more effective interventions to combat the health risks associated with dengue in densely populated urban areas.

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Suellen Araujo Franco dos Santos: conceptualization; formal analysis; methodology; validation; writing-original draft; writing – review and editing; visualization. **Hugo Abi Karam**: conceptualization; formal analysis; methodology; validation; writing-original draft; writing – review and editing; visualization.

Conflict of interest

The authors declare no conflict of interest.

Data availability statement

Scripts and code are available on request.

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