Analysis of Environmental and Social Factors in the Dynamics of Arboviruses in Bahia: A Methodological Proposal

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Arboviruses represent a significant challenge to public health, requiring a careful analysis of the environmental factors that impact their propagation. This research project mapped the relationships between epidemiological, climatic, and environmental data for the development of more effective public policies. The methodology adopted was based on experimental research and followed an iterative and incremental path, divided into stages ranging from data collection to the analysis and interpretation of the results found. The results include the development of a model of the relationships between variables and the analysis of the patterns found.
Keywords: Arboviruses. Environmental Health. Data Analysis. Methodological Model. PDCA.

The spread of arboviruses like Dengue, Zika, and Chikungunya represents a persistent public health problem in Brazil. The complexity of their dynamics in urban and rural centers demands an investigative approach that transcends purely epidemiological analysis, integrating multiple factors influencing their dissemination, whose recent impact can be observed in the expressive increase of cases across the country.

The state of Bahia, due to its climatic and social characteristics, presents a complex epidemiological scenario, with recurrent outbreaks that impact the population and overload health services. Understanding the mechanisms of diffusion of these diseases in the Bahian territory is, therefore, a fundamental step, with previous studies already highlighting the non-local dispersion of dengue [1] and the relevance of transportation networks in the distribution of cases [2].

This work's general objective is to map and analyze the relationships between epidemiological data of arboviruses and environmental, climatic, and social factors in the state of Bahia. From this analysis, the aim is to generate subsidies that can assist public managers in formulating more targeted and efficient surveillance and control policies.

Received on 12 March 2026; revised 26 May 2026.
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J Bioeng. Tech. Health 2026;9(7):638-642

Literature Review

Scientific literature consistently indicates the multifactorial nature of arbovirus dynamics. Climatic factors like temperature and precipitation directly influence the life cycle of the *Aedes aegypti* mosquito, the main vector in Brazil. Studies, such as Oliveira and colleagues [3], examine the paradox between sanitation and rainfall in dengue cases, highlighting that infrastructure alone is insufficient without proper management during high rainfall periods.

Beyond climatic factors, human mobility has been identified as a key driver of the spatial spread of epidemics. Research focusing on Bahia, like that by Saba and colleagues [2], has shown the importance of transportation networks for the correlation and distribution of dengue cases, suggesting that municipalities with stronger road connections tend to experience synchronized outbreaks [4-7]. This view is supported by Araújo and colleagues [1], who investigated the nonlocal dispersion of dengue in the state, and by Santos and colleagues [8], who employed complex network analysis to compare the dynamics of various arboviruses within the same geographical area [8-10].

Time series analysis of cases also provides valuable insights, as demonstrated by Azevedo and colleagues [11], who identified self-affinity properties in dengue series, indicating memory and complexity in occurrence patterns [11-16]. Consequently, this study's approach aims to integrate these diverse dimensions—climatic, spatial, and social—to construct a more comprehensive model of territorial vulnerability to arboviruses.

Materials and Methods

The methodological strategy was designed for iterative and incremental execution, organized according to the four phases of the PDCA (Plan-Do-Check-Act) cycle, as proposed by Gil [17].

Plan

In this phase, the research foundations were defined:

1. **Problem Identification and Objectives:** The central problem was defined as the need to understand the relationships between environmental/social factors and the incidence of arboviruses in Bahia. The objectives were established as: (i) collecting and integrating data from different sources; (ii) analyzing the relationships between variables; and (iii) discussing the implications of the findings for public health.
2. **Database Survey:** Public and reliable data sources were selected. For epidemiological data, the Notifiable Diseases Information System (SINAN) [18], was used. For climatic data, the National Institute of Meteorology (INMET) [19], was consulted. Socioeconomic and mobility data were obtained from the Brazilian Institute of Geography and Statistics (IBGE) [20], and the State Agency for Regulation of Public Energy, Transport, and Communications Services of Bahia (AGERBA, [21]).
3. **Study of Applicable Models:** A review of analytical techniques was carried out, including, but not limited to, Correlation Analysis, Time Series Analysis, and Spatial Analysis.

Do

This phase corresponded to the technical execution of the plan:

1. **Data Pre-processing and Integration:** The raw data underwent a cleaning process, treatment of missing values, and aggregation into common temporal (monthly) and spatial (municipal) units.
2. **Elaboration of Relationship Mapping:** The analytical techniques were applied to generate correlation matrices, models, and thematic maps.

Check

In this phase, the results were critically evaluated:

1. **Analysis and Interpretation:** Quantitative results were interpreted in light of epidemiological knowledge and the reviewed literature.

Act

Based on the analysis, this phase focused on consolidation and dissemination:

1. **Consolidation of Findings and Scientific Writing:** The results and discussions were consolidated in this article.

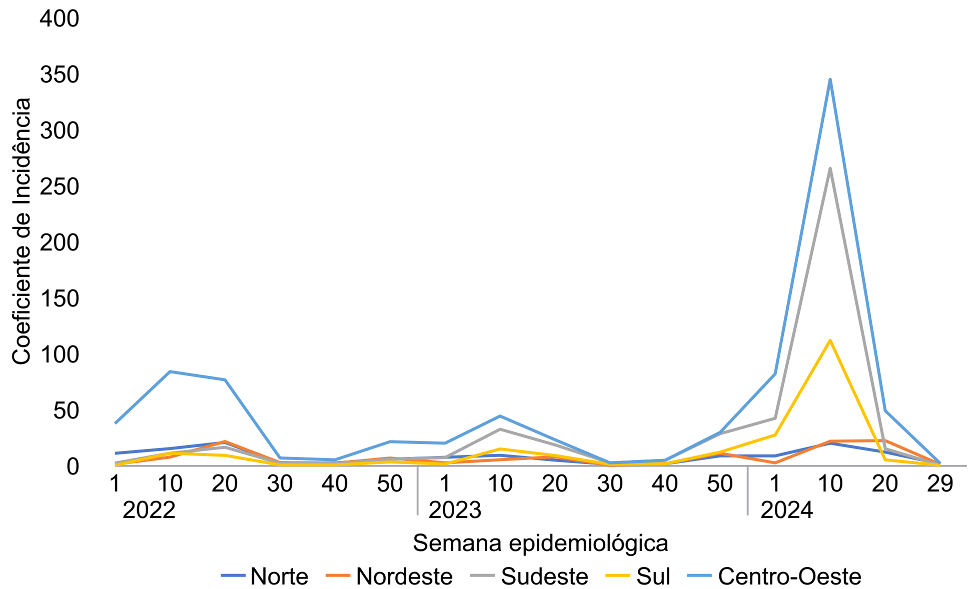
Results and Discussion

The exploration of the dataset revealed significant association patterns.

Relationship between Precipitation and Dengue Cases

The historical series of the dengue incidence coefficient in Brazil demonstrates clear and recurrent seasonality (Figure 1). It is observed that, for all geographical regions, including the Northeast, case peaks consistently concentrate in the first half of each year, a period that typically coincides with higher rainfall volumes and higher temperatures in much of the country. The year 2024, in particular, shows an outbreak of exceptional magnitude compared to previous years [4].

Figure 1. Incidence coefficient (cases per 100,000 inhabitants) of dengue by geographical region according to the epidemiological week of symptom onset – Brazil, 2022-2024.



Source: Brazil. Ministry of Health (2024) [4].

The seasonal pattern visualized in Figure 1 is the starting point for investigating the environmental factors that modulate it. The central hypothesis is that climatic variations, especially precipitation, are the main triggers for the increase in the vector mosquito population. The correlation analysis performed in this study sought to quantify this relationship for the state of Bahia, revealing a positive association with a temporal lag between peaks in rainfall and peaks in dengue cases. This finding, aligned with the literature [3], suggests that increased rainfall expands the availability of breeding sites for *Aedes aegypti*, and the time lag (approximately 1-2 months) corresponds to the mosquito's life cycle and the virus's incubation period.

<u>Analysis of the Spatial Distribution of Arboviruses in Bahia</u>

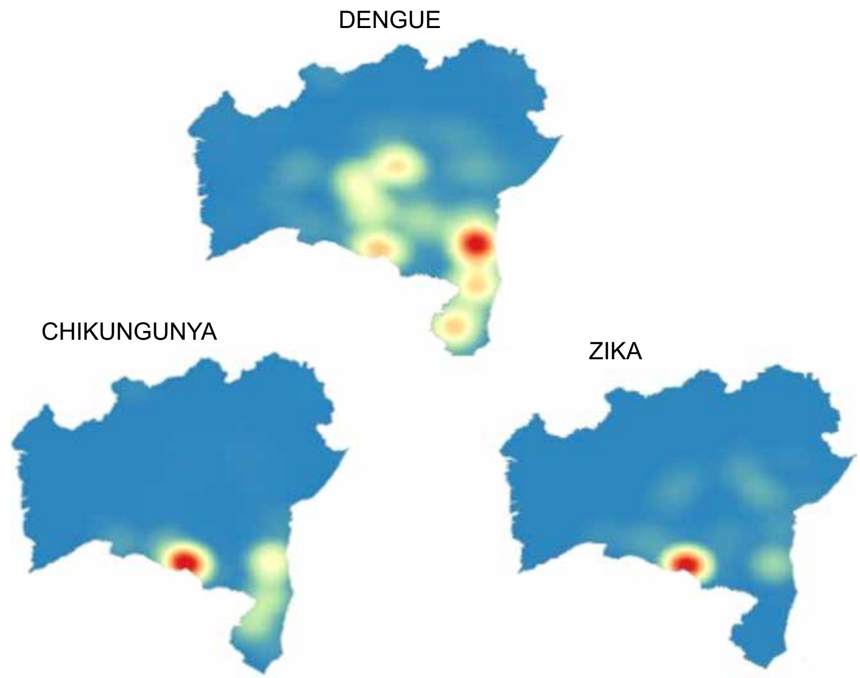
In addition to temporal patterns, the spatial distribution of arboviruses in the Bahian territory shows significant heterogeneity. According to data from the State Operative Plan for Arbovirus Control (SESAB) [5], up to Epidemiological Week 11 of 2023, the state recorded 11,001 probable cases of dengue, 4,348 of Chikungunya, and 391 of Zika. The density maps in Figure 2 illustrate the concentration of these cases, revealing the formation of "hotspots" with a higher risk of illness.

The overlapping risk areas for the three arboviruses, especially in the Southwest region, suggest the existence of common environmental and social factors that persistently favor vector proliferation and viral transmission. Identifying these critical areas is fundamental for directing resources and intensifying actions in surveillance, vector control, and healthcare, as recommended by the state plan (SESAB)[5]. Analyzing these hotspots allows for more strategic planning, focusing efforts where the public health impact is most pronounced.

Study Limitations

Firstly, underreporting of arbovirus cases is a chronic problem in Brazil, which can impact the accuracy of epidemiological data. Secondly, this study is based on data aggregated by municipality, which can lead to the "ecological fallacy"—the

Figure 2. Density maps (hotspots) of Dengue, Chikungunya, and Zika cases in the state of Bahia.



Source: Bahia State Health Secretariat (2023) [5].

assumption that relationships observed at the aggregated level are valid at the individual level. Finally, as emphasized, the statistical associations found here do not establish a causal relationship but rather generate hypotheses that require validation through other types of studies.

Conclusion

This work analyzed the relationship between environmental, climatic, and social factors and the incidence of arboviruses in the state of Bahia. The data investigation allowed for the identification of relevant association patterns, such as the temporal lag between rainfall and dengue outbreaks and the heterogeneous spatial distribution of cases. The main contribution of the study was the characterization of a vulnerability model that integrates these multiple factors. It is concluded that the research findings provide subsidies for the optimization of surveillance and control strategies, allowing for the development of more targeted and proactive actions by health managers.

References

1. Araujo MLV, et al. Nonlocal dispersal of dengue in the state of Bahia. Sci Total Environ. 2018;631-632:40-6.
2. Saba H, et al. Relevance of transportation to correlations among criticality, physical means of propagation, and distribution of dengue fever cases in the state of Bahia. Sci Total Environ. 2018.
3. Oliveira JB, et al. Paradox between adequate sanitation and rainfall in dengue fever cases. Sci Total Environ. 2023;860:160491.
4. Brasil. Ministério da Saúde. Secretaria de Vigilância em Saúde e Ambiente. Monitoramento das arboviroses urbanas transmitidas pelo *Aedes aegypti* (dengue, chikungunya e zika), Semanas Epidemiológicas 1 a 24, 2024. Boletim Epidemiológico [Internet]. 2024;55(11). Available from: https://www.gov.br/saude/pt-br/centrais-de-conteudo/publicacoes/boletins/epidemiologicos/edicoes/2024/boletim-epidemiologico-volume-55-no-11.pdf
5. Bahia. Secretaria da Saúde do Estado da Bahia (SESAB). Plano Operativo Estadual de Enfrentamento das Arboviroses Urbanas na Bahia – 2023 [Internet]. Salvador: SESAB; 2023. Available from: https://www.saude.ba.gov.br/wp-content/uploads/2023/03/Plano-Operativo-das-Arboviroses-2023.pdf
6. Miranda JGV, et al. Scaling effect in COVID-19 spreading: the role of heterogeneity in a hybrid ODE-

network model with restrictions on the inter-cities flow. Physica D. 2021;415:132792.
7. Saba H, et al. Synchronized spread of COVID-19 in the cities of Bahia, Brazil. Epidemics. 2022;39:100587.
8. Santos ES, et al. Complex network analysis of arboviruses in the same geographic domain: differences and similarities. Chaos Solitons Fractals. 2023;168:113134.
9. Macedo MCF, et al. Correlation between hospitalized patients' demographics, symptoms, comorbidities, and COVID-19 pandemic in Bahia, Brazil. PLoS One. 2020;15:e0243966.
10. Rosário RS. Sincronização por motifs: uma proposta para análise de redes cerebrais variantes no tempo [dissertação]. Salvador: Universidade Federal da Bahia; 2013.
11. Azevedo SM, et al. Self-affinity in the dengue fever time series. Int J Mod Phys C. 2016;27(1):1650143. Filho ASN, et al. A spatio-temporal analysis of dengue spread in a Brazilian dry climate region. Sci Rep. 2021;11:11892.
12. Naziazeno R, et al. Explorando dinâmicas epidêmicas: estudo de um modelo compartimental e suas aplicações. Rev Bras Ensino Fis. 2024;46:e20240128.
13. SimaClim. Casos de dengue aumentam 346% em relação a 2023 [Internet]. Available from: https://simaclim.com.br/casos-de-dengue-aumentam-346-em-relacao-a-2023/
14. Saba H, Miranda JGV, Moret MA. Self-organized critical phenomenon as a q-exponential decay—avalanche epidemiology of dengue. Physica A. 2014;413:205-11.
15. Saba H, Oliveira MA, Miranda JGV. Modelo computacional para auxílio no combate a epidemias com base em redes sociais. In: Anais do WIVA 2008; 2008.
16. Saba H, et al. Spatio-temporal correlation networks of dengue in the state of Bahia. BMC Public Health. 2014;14:1085.
17. Gil AC. Como elaborar projetos de pesquisa. 4th ed. São Paulo: Atlas; 2002.
18. Brasil. Ministério da Saúde. DATASUS. Sistema de Informação de Agravos de Notificação (SINAN) [Internet]. Brasília: Ministério da Saúde. Available from: http://portalsinan.saude.gov.br/
19. Instituto Nacional de Meteorologia (INMET). Banco de Dados Meteorológicos para Ensino e Pesquisa (BDMEP) [Internet]. Brasília: INMET. Available from: https://portal.inmet.gov.br/banco-de-dados-meteorologicos
20. Instituto Brasileiro de Geografia e Estatística (IBGE). Censo Demográfico 2022 [Internet]. Rio de Janeiro: IBGE; 2022. Available from: https://www.ibge.gov.br/estatisticas/sociais/populacao/22827-censo-demografico-2022.html
21. Agência Estadual de Regulação de Serviços Públicos de Energia, Transportes e Comunicações da Bahia (AGERBA). Anuário Estatístico de Transportes [Internet]. Salvador: AGERBA; 2023. Available from: http://www.agerba.ba.gov.br/