

Time Series Methods in Epidemiological Studies of Dengue in Brazil: A Scoping Review

Métodos de Séries Temporais em Estudos Epidemiológicos da Dengue no Brasil: Uma Revisão de Escopo
Métodos de Series Temporales en Estudios Epidemiológicos del Dengue en Brasil: Una Revisión de Alcance

RESUMO

Objetivo: No Brasil, a dengue deixou de ser um problema sazonal e passou a representar um desafio complexo de saúde pública, com surtos difíceis de prever pelos métodos tradicionais. Em 2024, o recorde de casos e os impactos da pandemia de COVID-19 evidenciaram limitações nos registros e na vigilância epidemiológica. **Método:** Este estudo mapeou a produção científica brasileira (2020–2025) sobre métodos de séries temporais, por meio de uma revisão de escopo baseada nas diretrizes JBI e PRISMA-ScR, analisando 32 artigos de bases como PubMed, Scopus, LILACS e SciELO. **Resultados:** Observou-se que, embora modelos modernos como LSTM estejam em crescimento, predominam métodos clássicos, como Prais-Winsten e ARIMA/SARIMA, devido à sua aplicabilidade prática. A principal limitação identificada foi a baixa qualidade dos dados do SINAN. **Conclusão:** Conclui-se que avanços dependem da integração de modelos robustos com dados mais confiáveis.

DESCRIPTORES: Brasil; Dengue; Revisão de Escopo; Séries Temporais; Vigilância Epidemiológica.

ABSTRACT

Objective: In Brazil, dengue has shifted from a seasonal issue to a complex public health challenge, with outbreaks that are difficult to predict using traditional methods. In 2024, record case numbers and the impacts of the COVID-19 pandemic highlighted limitations in epidemiological surveillance and data quality. **Methods:** This study mapped Brazilian scientific production (2020–2025) on time series methods through a scoping review based on JBI and PRISMA-ScR guidelines, analyzing 32 articles from databases such as PubMed, Scopus, LILACS, and SciELO. **Results:** Although modern models like LSTM are gaining ground, classical methods such as Prais-Winsten and ARIMA/SARIMA still predominate due to their practical applicability. The main limitation identified was the poor quality of SINAN data. **Conclusion:** Progress depends on integrating robust models with more reliable data.

DESCRIPTORS: Brazil; Dengue; Scoping Review; Time Series; Epidemiological Surveillance.

RESUMEN

Objetivo: En Brasil, el dengue ha dejado de ser un problema estacional y se ha convertido en un desafío complejo de salud pública, con brotes difíciles de predecir mediante métodos tradicionales. En 2024, el número récord de casos y los impactos de la pandemia de COVID-19 evidenciaron limitaciones en la vigilancia epidemiológica y en la calidad de los datos. **Método:** Este estudio analizó la producción científica brasileña (2020–2025) sobre métodos de series temporales mediante una revisión de alcance basada en las directrices JBI y PRISMA-ScR, evaluando 32 artículos de bases como PubMed, Scopus, LILACS y SciELO. **Resultados:** Aunque los modelos modernos como LSTM están en crecimiento, predominan los métodos clásicos como Prais-Winsten y ARIMA/SARIMA debido a su aplicabilidad práctica. La principal limitación identificada fue la baja calidad de los datos del SINAN. **Conclusión:** Se concluye que el avance depende de integrar modelos más robustos con datos más confiables.

DESCRIPTORES: Brasil; Dengue; Revisión de alcance; Series temporales; Vigilancia epidemiológica.

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**Elton Gustavo José de Souza**

Bachelor of Pharmacy from the Federal University of Pernambuco. Public Health Specialist and Pharmacist at the Pernambuco State Health Department.

ORCID: <https://orcid.org/0000-0002-9951-0283>

**Eloisa da Conceição Souza**

Bachelor of Nursing from Estácio College of Recife.

ORCID: <https://orcid.org/0009-0006-5638-1983>

**Junior Pereira de Melo**

Bachelor of Pharmacy from UNINASSAU. Specialist in Clinical and Hospital Pharmacy.

ORCID: <https://orcid.org/0009-0003-3818-110X>

**Rôgean Vinícius Santos Soares**

Public Health Biologist. PhD Candidate in Collective Health at the Federal University of Rio de Janeiro (UFRJ).

ORCID: <https://orcid.org/0009-0006-8010-6076>

INTRODUCTION

For several decades, dengue has been one of the main public health problems in Brazil. The disease is associated with a high burden of morbidity, significant socio-economic impact, and recurring major epidemics. It is a widely distributed arbovirus infection throughout the country, whose transmission is sustained by the widespread presence of the *Aedes aegypti* vector, favored by tropical climatic conditions, haphazard urbanization processes, and historical socio-environmental inequalities^(1,2). In recent decades, the country has experienced successive epidemic cycles, with a marked increase in the number of reported cases, hospitalizations, and deaths, underscoring the centrality of dengue on the epidemiological surveillance agenda⁽³⁾.

From an epidemiological perspective, the occurrence of dengue epidemic peaks in Brazil is strongly associated with periods of higher temperatures and precipitation. The simultaneous circulation of different viral serotypes, partial immunity in the population, and climatic variability also contribute to the complexity of transmission dynamics. According to Teixeira et al.⁽²⁾, these factors produce nonlinear temporal patterns, in which successive observations exhibit serial dependence—a key characteristic of epidemiological time series.

Dengue surveillance in Brazil relies primarily on data from health information systems, particularly the No-

tifiable Diseases Information System (SINAN), which organizes records into weekly, monthly, or annual time series. These records constitute the primary empirical basis for epidemiological analyses, supporting disease monitoring, the identification of trends, and the evaluation of control strategies⁽¹⁾.

However, the analytical exploration of these data requires statistical methods capable of adequately handling autocorrelation, seasonality, and noise—elements inherent to time series. Although essential for epidemiological surveillance, SINAN is a passive reporting system, subject to underreporting and delays in data entry—limitations that were particularly pronounced during the COVID-19 pandemic⁽⁴⁾.

Historically, a significant portion of studies on dengue in Brazil have used simple descriptive approaches or classical linear regression models to analyze temporal trends. As discussed by Antunes and Cardoso⁽⁵⁾, this type of approach, while useful in exploratory analyses, has significant limitations when applied to time-dependent data, primarily due to a violation of the assumption of independence between observations. Consequently, interpretations based exclusively on these methods may produce inaccurate estimates and biased conclusions regarding the evolution of the disease.

In recent decades, the epidemiology of dengue in Brazil has progressively incorporated specific time-series analysis methods in response to the

limitations observed in traditional descriptive approaches. Models such as *Prais-Winsten* regression, *Joinpoint* regression, and autoregressive integrated moving average (ARIMA) models have come to be employed more systematically to estimate trends, identify structural changes, and make short-term forecasts. These approaches allow for the explicit incorporation of the temporal dependence of the data, providing greater analytical consistency to epidemiological inferences^(5,6).

More recently, the literature has incorporated spatiotemporal models and techniques based on *machine learning* and *deep learning*, expanding the capacity for dengue analysis and prediction. According to McGough et al.⁽⁷⁾, *Long Short-Term Memory (LSTM)* recurrent neural networks and *ensemble* models exhibit greater sensitivity to nonlinear patterns and the potential to integrate multiple sources of information, such as climatic and environmental variables. Nevertheless, these authors highlight challenges related to the interpretability of the models and the feasibility of incorporating these approaches into the routine operations of health surveillance services.

Despite the observed methodological advances, recent scientific literature on the use of time series in dengue epidemiology in Brazil remains fragmented. Studies differ in terms of the models adopted, the epidemiological indicators analyzed, the temporal and spatial scales used, and the recognized

methodological limitations. This heterogeneity hinders a comprehensive understanding of the state of the art and makes it less clear to systematically identify gaps and trends in the field, as evidenced by recent studies included in this review.

This diversity of methodological approaches, combined with the heterogeneity of the contexts analyzed, highlights the need to map the scope of recent scientific research. Unlike traditional systematic reviews, this type of approach allows for the exploration of research fields characterized by conceptual and methodological diversity⁽⁸⁾.

Nevertheless, the Brazilian literature still lacks a critical synthesis that would allow us to understand not only which methods have been used, but also in which contexts these models prove to be most appropriate or limited. It is also observed that most temporal analyses remain focused on case incidence, with less attention paid to outcomes related to disease severity.

The lack of recent methodological syntheses hinders the development of analytical guidelines for dengue surveillance in Brazil. Thus, the present study aimed to map and synthesize the time-series analysis methods employed in epidemiological studies on dengue conducted in Brazil and published between 2020 and 2025, identifying the models used, the indicators analyzed, and their main findings and limitations.

MATERIALS AND METHODS

This scoping review was conducted in accordance with the methodological guidelines proposed by the *JBI Manual for Evidence Synthesis*, and the study report followed the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews* (PRISMA-ScR). The choice of this methodological design is based on the conceptual and

methodological diversity observed in the literature regarding the use of time series in dengue epidemiology, which makes it pertinent to adopt an approach capable of comprehensively mapping the methods employed and the existing gaps⁽⁹⁾.

The research question was formulated according to the PCC (Population, Concept, and Context) acronym, as recommended by the JBI. The population was defined as epidemiological data related to dengue; the concept, as time-series analysis methods; and the context, as studies conducted in Brazil. The guiding question of the review was defined as: "What are the time-series methods used, the epidemiological indicators analyzed, and the methodological limitations in the scientific literature on dengue in Brazil over the past five years?"

The search strategy was designed to include the main keywords related to dengue and time series analysis, combined using the Boolean operators AND and OR. Searches were conducted in the PubMed/MEDLINE,

Scopus, SciELO, and LILACS/BVS databases, considering studies published between 2020 and 2025 in Portuguese, English, and Spanish, with open access to the full text. This period was chosen because it represents the most recent phase of incorporation of predictive techniques and *machine learning*-based models into the national literature. The decision to include open-access studies aimed to ensure the reproducibility of the analysis and methodological transparency. The searches were conducted in December 2025, and a complete breakdown of the search strategies used in each database is presented in Table 1.

Original studies that applied time-series analysis methods to epidemiological data on dengue in Brazil were considered eligible. Review articles, methodological studies without empirical application, editorials, car s to the editor, dissertations, theses, and studies that did not present a temporal analysis of the data or that did not refer to the Brazilian context were excluded.

Table 1 – Search strategies used in the databases

Database	Search strategy
PubMed (MEDLINE)	(("Dengue"[Mesh] OR "Dengue"[Title/Abstract] OR "Severe Dengue"[Mesh]) AND ("Time Series"[Title/Abstract] OR "Interrupted Time Series Analysis"[Mesh] OR "Spatio-Temporal Analysis"[Mesh] OR "Forecasting"[Mesh] OR "Trend Analysis"[Title/Abstract] OR "Prais-Winsten"[Title/Abstract] OR "ARIMA"[Title/Abstract] OR "SARIMA"[Title/Abstract] OR "Joinpoint"[Title/Abstract] OR "Temporal Trends"[Title/Abstract])) AND ("Brazil"[Mesh] OR "Brazil"[Title/Abstract] OR "Brasil"[Title/Abstract])
LILACS / BVS	(tw:(dengue)) AND (tw:(("series temporais" OR "time series" OR "prais-winsten" OR "joinpoint" OR "arima" OR "sarima" OR "tendencia temporal" OR "analise de tendencia")) AND (tw:(brasil OR brasil)))
SciELO	(Dengue) AND ("Series Temporais" OR "Time Series" OR "Prais-Winsten" OR "ARIMA" OR "Joinpoint" OR "Tendencia Temporal" OR "Trend Analysis") AND (Brasil OR Brazil)
Scopus	TITLE-ABS-KEY ("Dengue") AND TITLE-ABS-KEY ("Time Series" OR "Prais-Winsten" OR "ARIMA" OR "SARIMA" OR "Joinpoint" OR "Trend Analysis" OR "Forecasting") AND TITLE-ABS-KEY ("Brazil" OR "Brasil")

Source: Prepared by the author (2025).

The study selection process was conducted in stages. First, duplicates were removed. Next, titles and abstracts were evaluated against the eligibility criteria. Potentially relevant studies were reviewed in full text to confirm inclusion. All screening and selection stages were conducted independently by two reviewers, and any disagreements were resolved by consensus.

Data extraction was performed using a pre-designed instrument, which included information on year of publication, study location, source of epidemiological data, indicators analyzed, time-series methods employed, inclusion of covariates, and the studies' main findings. The extracted data were organized systematically, enabling a descriptive and analytical synthesis of the findings.

The synthesis of the results was conducted in a descriptive and narrative manner, with the studies presented according to previously defined analytical categories. The absence of a quality assessment of the selected studies does not compromise the objectives of this study, since this scoping review aims to map methods and address gaps, rather than to estimate effects. The protocol for this review was previously registered on the *Open Science Framework* (OSF) under DOI 10.17605/OSF.IO/7E36X, ensuring the transparency and reproducibility of the methodological process.

RESULTS

The database search resulted in the initial identification of a set of potentially relevant studies. After removing duplicates and applying the eligibility criteria, 32 studies were included in the final synthesis. The selection process followed the steps recommended by PRISMA-ScR and is illustrated in the flowchart shown in Figure 1.

Regarding the publication period, there was a progressive increase in the

number of publications over the analyzed period, with a higher concentration beginning in 2023, indicating a recent growth in scientific interest in the use of time-series methods applied to the epidemiology of dengue in Brazil during the period under consideration.

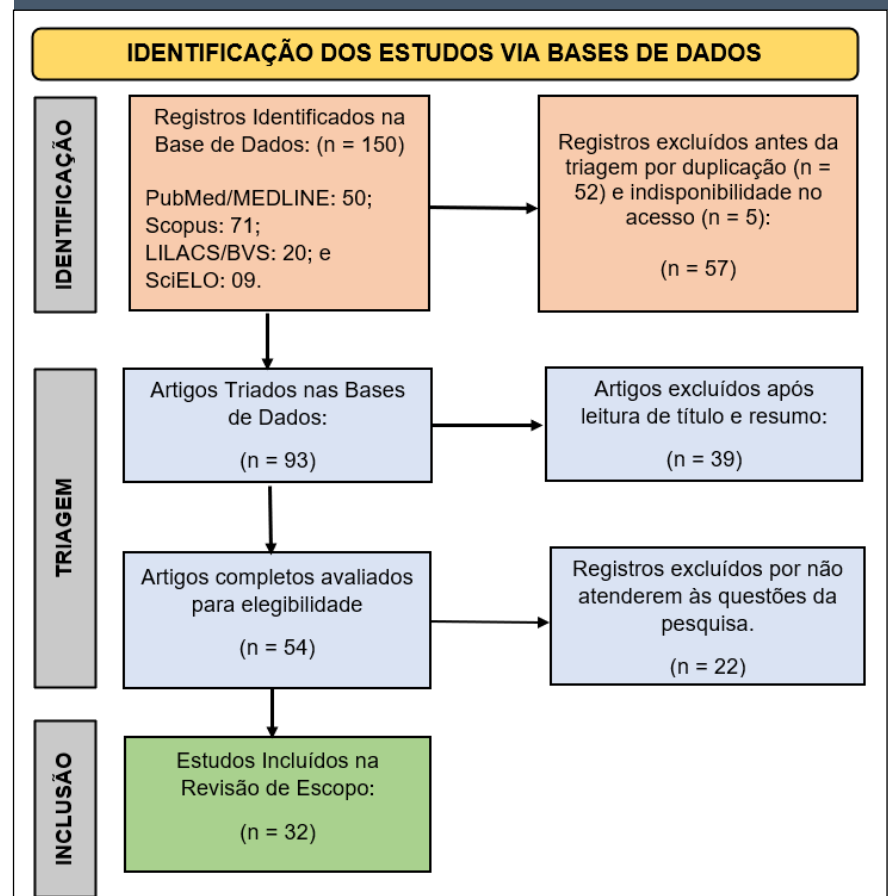
Regarding geographic scope, most studies had a national scope or focused on specific regions of the country, particularly the Southeast and Northeast regions. A smaller number of studies were conducted at the municipal level or in states in the North and Central-West regions, highlighting inequality in scientific output depending on the territory analyzed.

The most frequently analyzed epidemiological indicator was the

number of reported cases, generally expressed as an incidence rate. Other indicators, such as hospitalizations, deaths, and case-fatality rates, were used on an ad hoc basis, usually in complementary analyses or in studies with specific designs. The predominance of incidence reflects the greater availability and standardization of this indicator in surveillance systems.

Regarding sources of epidemiological data, the use of information from SINAN predominated, either alone or in combination with other official databases. Some studies also used secondary data on hospitalizations and mortality, although these outcomes were explored less frequently compared to the incidence of reported cases.

Figure 1 – PRISMA-ScR Flowchart of the Study Selection Process



Source: Prepared by the author (2025).

Integrative Review

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With regard to time series analysis methods, the included studies revealed significant heterogeneity in methodological approaches, ranging from descriptive trend models to predictive techniques based on *machine learning*. Descriptive trend models, such as *Prais-Winsten* regression and analyses of interrupted time series, were widely used, especially in studies aimed at assessing long-term trends. Autoregressive models, such as ARIMA and SARIMA, were also frequently employed, particularly in short-term predictive analyses. This pattern suggests a recent shift in the national literature—still marked by descriptive approaches—toward models with a greater predictive focus.

Some of the studies incorporated spatiotemporal models, seeking to simultaneously capture the temporal

dependence and spatial heterogeneity of dengue transmission. These approaches were more common in investigations at the regional or state level. A current increase was also observed in the use of techniques based on *machine learning* and *deep learning*, including *LSTM*-ural networks and *ensemble* models, especially in studies that integrated climatic and environmental variables.

The incorporation of covariates into temporal models was reported in a significant proportion of the studies. The most frequently used variables included temperature, precipitation, and environmental indicators, as well as socioeconomic variables to a lesser extent. In general, studies that included covariates reported improved model performance, although they acknowledged methodological challenges associated with the selec-

tion and handling of these variables.

The methodological limitations most frequently reported by the authors involved problems related to the quality of epidemiological data, such as underreporting of cases, delays in reporting, and inconsistencies in records over time. Limitations related to the complexity of the models used were also mentioned, especially in the case of *machine learning*-based approaches, including difficulties in interpreting the results and increased computational demands.

A detailed summary of the characteristics of the included studies, the time-series methods used, and the main findings of the studies is presented in Table 1.

Table 1 – Characterization of the studies included in the scoping review (n = 32)

AUTHOR(S) / YEAR	TIME SERIES METHOD	TIME SCALE / SERIES PERIOD	EPIDEMIOLOGICAL INDICATOR	MAIN CONTRIBUTIONS	REPORTED LIMITATIONS
Achcar et al., 2020 ⁽¹⁰⁾	Bayesian polynomial regression + stochastic volatility model (MCMC)	Monthly series (2007–2016)	Dengue cases	Joint modeling of the mean and variability of the epidemiological time series	High computational complexity
Alves et al., 2025 ⁽¹¹⁾	Spatio-temporal Bayesian model (CAR/INLA)	Weekly series (2015–2018)	Dengue cases by neighborhood	Integration of entomological, climatic, and socio-environmental variables for forecasting	Not reported by the authors
Araújo et al., 2024 ⁽¹²⁾	Neural network + Interrupted Time Series	Historical time series (2011–2020)	Dengue cases	Assessment of the impact of urban mobility on transmission during the pandemic	Not reported by the authors
Bomfim et al., 2020 ⁽¹³⁾	Recurrent neural networks + ARIMA + mechanistic model	Weekly time series (2007–2015)	Dengue cases by neighborhood	Use of human mobility data to improve outbreak forecasting	Not reported by the authors
Castro et al., 2021 ⁽¹⁴⁾	Spatio-temporal modeling with environmental covariates	Weekly series (2010–2016)	Dengue cases	Identification of spatiotemporal patterns of outbreaks	Dependence on the quality of historical data
Chen & Moraga, 2025 ⁽¹⁵⁾	AR, MA, ARIMA, SARIMAX, RF, SVM, XGBoost, LSTM + ensemble	Weekly time series (Jan 2016–Jan 2024)	Dengue cases	Systematic comparison between statistical and ML models	Not reported by the authors
Chen & Moraga, 2025 ⁽¹⁶⁾	LSTM with climate variables and spatial effects	Weekly series (2016–2022)	Dengue cases by state	National forecast integrating climate and spatial dependence	Sensitive to regions with low connectivity
Conceição et al., 2021 ⁽¹⁷⁾	Negative binomial regression with seasonality and lags	Daily time series (Jan–Aug 2020)	Confirmed cases of dengue	Assessment of the impact of social isolation on transmission	Underreporting and delays in reporting
Daudt-Lemos et al., 2025 ⁽¹⁸⁾	Joinpoint regression + spatiotemporal analysis	Weekly series (2023–2024)	Incidence of arboviral diseases	Identification of recent trends in epidemiological spread	Not reported by the authors

De Lima & Laporta, 2020 ⁽¹⁹⁾	ARIMA, ETS, TBATS, STLM, StructTS, NNETAR, MLP	Monthly series (2000–2017)	Confirmed cases	Extensive comparison of predictive models for dengue	Influence of arbovirus co-circulation
Drumond et al., 2020 ⁽²⁰⁾	Fourier series (seasonal decomposition)	Monthly series (2007–2017)	Probable cases	Characterization of seasonality and epidemic persistence	Not reported by the authors
Figueredo et al., 2023 ⁽²¹⁾	Trend-free cross-correlation (ρ DCCA)	Weekly series (2017–2021)	Confirmed cases	Association between climate variables and incidence	Discontinuity in climate data during the pandemic
Freitas et al., 2025 ⁽²²⁾	Negative binomial Bayesian model with time effects	Weekly series (2022–2025)	Probable cases	Construction of epidemic probability bands	Not reported by the authors
Geral dini et al., 2024 ⁽²³⁾	Linear regression with ARIMA errors and climate variables	Monthly series (2013–2022)	Incidence	Effect of temperature and precipitation on the disease	Not reported by the authors
Gomes et al., 2024 ⁽²⁴⁾	GAM + DLNM + meta-analysis	Daily series (2010–2019)	Reported cases	Modeling of lagged and nonlinear climate effects	Regional heterogeneity
Leandro et al., 2022 ⁽²⁵⁾	Prais–Winsten + spatial analysis	Annual series (2012–2021)	Municipal cases	Temporal trends associated with social and environmental factors	Use of secondary data
Li et al., 2022 ⁽²⁶⁾	LSTM with geospatial big data	Weekly series (2007–2019)	Weekly cases	Forecast integrated with environmental and historical data	Not reported by the authors
Li, 2022 ⁽²⁷⁾	LSTM with climate variables (Google Earth Engine)	Weekly series (2013–2020)	Dengue cases	Forecasting system using deep learning and environmental data	Reliance on large volumes of data
Lopes et al., 2024 ⁽²⁸⁾	Case time series + DLNM	Daily time series (2010–2019)	Dengue hospitalizations	Association between temperature and clinical severity	Not reported by the authors
Martins et al., 2020 ⁽²⁹⁾	Joinpoint + spatiotemporal analysis	Annual series (2001–2019)	Incidence	Identification of trend shifts and clusters	Not reported by the authors
McGough et al., 2021 ⁽⁷⁾	Ensemble learning + SVM + HMM	Annual series (2001–2017)	Epidemic years	Early prediction of outbreak years	Variable performance across regions
Monnaka & Oliveira, 2021 ⁽³⁰⁾	Temporal correlation (Google Trends)	Weekly series (2017–2019)	Dengue cases	Use of digital data as an early indicator	Dependence on search behavior
Oliveira et al., 2020 ⁽³¹⁾	Multivariate VAR model	Weekly series (2013, 2015, and 2016)	Confirmed/ruled-out cases of arboviral diseases	Interdependence between dengue, Zika, and chikungunya	Quality of reporting
Pereira et al., 2025 ⁽³²⁾	Spatio-temporal analysis	Longitudinal series (2007–2023)	Incidence	Geographic spread of dengue in southern Brazil	Not reported by the authors
Roster et al., 2024 ⁽⁴⁾	Interrupted Time Series + ML	Weekly series (Mar–Apr 2020)	Dengue cases	Estimates of Underreporting During the Pandemic	Sensitive to data quality
Santana et al., 2022 ⁽³³⁾	Spatio-temporal Bayesian model (Poisson)	Annual series (2007–2017)	Deaths from dengue	Spatial dynamics of mortality	Not reported by the authors
Sebastianelli et al., 2024 ⁽³⁴⁾	Spatio-temporal ensemble machine learning	Monthly series (2001–2019)	Incidence	National multimodal predictive system	Reduced performance in areas of low incidence
Silva AAP et al., 2022 ⁽³⁵⁾	ARIMA + GLM + cluster analysis	Annual series (2001–2019)	Dengue cases and vegetation	Relationship between deforestation and incidence	Not reported by the authors
Silva TFG et al., 2025 ⁽³⁶⁾	Temporal trend analysis	Annual series (2001–2022)	Incidence and case fatality rate	National temporal trends of the disease	Reliance on secondary data
Silva TR et al., 2022 ⁽³⁷⁾	Spearman's correlation + spatial analysis	Annual series (2009–2019)	Confirmed cases	National trend and spatial distribution	Potential underreporting
Souza et al., 2024 ⁽³⁸⁾	Temporal trend + spatiotemporal analysis	Weekly series (2024)	Probable cases	Identification of clusters during a recent large outbreak	Short time frame
Xavier et al., 2021 ⁽³⁹⁾	ARMAX with climate variables	Monthly series (2007–2016)	Incidence	Integration of climate data via remote sensing	Monthly frequency limited to monitoring

Source: Prepared by the author based on the studies included in the review (2026).

DISCUSSION

Analysis of the studies included in this review demonstrates that different time-series methods have been employed to address distinct demands in dengue epidemiological surveillance, with no evidence of a single approach capable of addressing all analytical contexts. As summarized in Table 1, there is a coexistence of descriptive trend models, spatio-temporal approaches, and predictive techniques based on *machine learning*, reflecting both the diversity of analytical objectives and the operational and institutional limitations of the Brazilian context.

Although the studies reveal important methodological advances, this progress is uneven. Classical methods, such as Prais-Winsten regression and Joinpoint regression, remain widely used in long-term trend analyses, while more complex models—such as recurrent neural networks (*LSTM*) and *ensemble* approaches—are concentrated in isolated, often exploratory studies, with low methodological standardization and limited comparability among them.

The persistent prevalence of the *Prais-Winsten* method in studies of temporal trends suggests that operational factors exert a significant influence on methodological choice. As noted in Table 1, this model is particularly common in analyses based on annual or long-term time series, in which the estimation of overall trends is the primary objective. Its widespread availability in traditional statistical *software* and the interpretive clarity of its results contribute to its recurrent adoption, particularly in the context of routine epidemiological surveillance. According to Antunes and Cardoso⁽⁵⁾, these approaches offer important advantages for the analysis of temporal trends in epidemiological data, primarily due to their simplicity of application and

interpretive clarity.

In the set of studies analyzed, these characteristics proved particularly relevant in investigations focused on long-term surveillance and the assessment of external events, such as changes in reporting patterns during the COVID-19 pandemic, as discussed by Conceição et al.⁽¹⁷⁾. Nevertheless, the studies themselves indicate that the exclusive application of these models may be insufficient to capture the spatial complexity of dengue transmission.

In light of the findings reported by Drumond et al.⁽²⁰⁾ and by Martins et al.⁽²⁹⁾, the incorporation of the spatial dimension represents a significant methodological advance. Spatio-temporal models allow for the identification of persistent regional patterns and areas of higher risk over time, avoiding overly aggregated interpretations that tend to mask territorial inequalities. This approach has proven particularly relevant in the Brazilian context, which is marked by significant socio-environmental heterogeneity and distinct regional dynamics of dengue transmission.

Another aspect that stands out in the results is the recent growth in the use of predictive models. According to De Lima and Laporta⁽¹⁹⁾, autoregressive models, such as ARIMA and SARIMA, continue to be widely used for short-term forecasts, especially in scenarios where the interpretability of parameters is a key requirement. In contrast, more recent studies indicate that *machine learning*-based techniques are better able to capture non-linear patterns and integrate multiple data sources⁽¹⁵⁾.

As discussed by Li et al.⁽²⁶⁾ and McGough et al.⁽⁷⁾, *LSTM-type* neural networks and *ensemble* models have demonstrated superior predictive performance, particularly when climatic and environmental variables are incorporated into the modeling. While classical models, such as ARIMA and

SARIMA, offer greater transparency and ease of implementation, the predictive gains observed in *LSTM* models are often accompanied by operational challenges that have yet to be thoroughly discussed in national studies. The 2024 epidemic particularly starkly exposed as-yet-under-explored limitations in the models reviewed, raising the hypothesis that approaches calibrated during stable periods may not adequately capture extreme epidemiological events.

Although *machine learning*-based predictive models have shown superior performance in several studies, as summarized in Table 1, their operational applicability in epidemiological surveillance remains limited. High computational complexity, reduced interpretability of results, and dependence on large volumes of data constitute significant barriers to the routine incorporation of these approaches, especially in municipal contexts within the Unified Health System, where analytical infrastructure is heterogeneous. Few studies discuss in depth how these gains translate into operational decisions in the context of health surveillance.

According to McGough et al.⁽⁷⁾, the reduced interpretability of the results and the increased computational demands pose significant challenges to the incorporation of these approaches into routine health surveillance. This issue becomes even more evident when considering the context of the Unified Health System, especially at the municipal level, where analytical infrastructure and the availability of specialized technical teams vary widely. Thus, the choice of models should consider not only statistical performance but also their operational feasibility and practical utility for decision-making.

With regard to the incorporation of environmental covariates, the included studies indicate that integrating variables such as temperature and

precipitation tends to enhance the explanatory power of temporal models. According to Teixeira et al.⁽²⁾, dengue should be understood as an ecoepidemiological phenomenon in which climatic, environmental, and social factors interact in complex ways.

Studies that incorporated climatic variables into temporal modeling, such as those by Xavier et al.⁽³⁹⁾, Gerardini et al.⁽²³⁾ and Gomes et al.⁽²⁴⁾, demonstrated that the inclusion of these factors contributes to a more realistic representation of dengue dynamics. However, these studies also highlighted significant methodological challenges, including multicollinearity among environmental variables and the appropriate definition of time lags—aspects that require careful attention in the specification and interpretation of the models.

Time-series analysis in Brazil remains heavily constrained by the operational characteristics of SINAN, whose delays in municipal data entry and fluctuations in coverage limit the performance of sensitive predictive models. Notably, in this context, the continued use of methods such as the *Prais-Winsten* model suggests that operational ease and widespread availability in traditional statistical *software* still largely dictate the pace of national scientific output.

According to Santana et al.⁽³³⁾, underreporting of cases and delays in updating information systems remain structural challenges for dengue surveillance in Brazil. This observation aligns directly with the findings of this review, since such limitations affect both descriptive analyses and predictive models, compromising the reliability of estimates and forecasts. As pointed out by the Ministry of Health⁽¹⁾, strengthening health information systems is an indispensable condition for improving epidemiological analyses. Mathematical precision, however, is hampered by the poor quality of primary data.

Finally, there is a significant gap in the analysis of outcomes related to the severity of dengue. According to Lopes et al.⁽²⁸⁾, indicators such as hospitalizations and case fatality rates are still underutilized in temporal models, despite their importance for health services planning. This observation aligns with the pattern identified in the studies included in this review, in which incidence was the predominant indicator. Expanding the use of these outcomes in future analyses may contribute to a more comprehensive understanding of the impacts of dengue on the health system.

The findings of this review indicate that the choice of time-series methods should consider not only the statistical performance of the models but also their suitability for the temporal scale under analysis, the quality of available data, and the operational capacity of surveillance services. The complementarity among descriptive, spatiotemporal, and predictive approaches emerges as a central strategy for balancing methodological rigor and practical utility in the context of dengue epidemiological surveillance in Brazil. Methodological choices should consider the objective of the analysis, the quality of available data, the spatial and temporal scales, and the operational capacity of health services, in order to balance analytical rigor and practical applicability in the Brazilian context.

FINAL CONSIDERATIONS

This scoping review demonstrated that time-series analysis is a key tool for understanding the epidemiological dynamics of dengue in Brazil. Recent scientific literature reveals significant methodological progress, marked by the expanded use of spatiotemporal models and predictive approaches, while continuing to apply traditional descriptive methods

that are well-established in the field of epidemiological surveillance.

The findings of this review indicate that no single analytical approach, on its own, is capable of addressing the multiple demands of dengue epidemiological surveillance, especially in a context marked by territorial heterogeneity and structural limitations of information systems. Descriptive trend models remain relevant for long-term monitoring and for the assessment of external events, while spatiotemporal approaches contribute to the identification of territorial inequalities and priority areas for intervention. In turn, predictive models, including *machine learning*-based techniques, expand the capacity to anticipate scenarios, although they pose challenges related to interpretability and operational feasibility.

The discussion of the results also highlights that methodological advances cannot be separated from the quality of available epidemiological data. Underreporting of cases, delays in reporting, and inconsistencies in information systems remain structural limitations that affect both descriptive and predictive analyses. In this regard, improving health surveillance systems is an indispensable prerequisite for the effective use of more robust analytical models within the context of the Unified Health System.

Another relevant aspect concerns the predominance of studies focused on dengue incidence, with limited exploration of outcomes related to disease severity, such as hospitalizations and case fatality rates. The systematic incorporation of these indicators into temporal models represents an important opportunity for future research, especially with regard to resource planning and the assessment of dengue's impact on health services.

In light of the above, the results of this review reinforce the need for methodological choices that consider not only the statistical performance

of the models but also their interpretability, practical applicability, and suitability for different scales of epidemiological surveillance. The complementarity between descriptive, spatiotemporal, and predictive approaches emerges as a fundamental strategy for aligning analytical rigor with operational utility.

By systematically mapping the time-series methods employed in

epidemiological studies on dengue in Brazil, this study contributes to the consolidation of methodological knowledge in the field of public health and to the development of an integrated methodological understanding of national research on dengue. It is hoped that the findings presented here will inform future research and guide the critical and context-specific use of analytical

methods in dengue surveillance and control, thereby strengthening the response capacity of health services to the challenges posed by this arbovirus. The future challenge extends beyond refining models to the ability to translate methodological innovation into timely responses within the context of epidemiological surveillance.

REFERENCES

1. Brasil. Ministério da Saúde. Boletim epidemiológico: dengue. Brasília (DF): Ministério da Saúde; 2023. Disponível em: <https://www.gov.br/saude/pt-br/assuntos/saude-de-a-z/d/dengue>
2. Teixeira MG, et al. Epidemiological trends of dengue disease in Brazil (2000–2010). *PLoS Negl Trop Dis*. 2013;7(12):e2520. doi:10.1371/journal.pntd.0002520.
3. Brasil. Ministério da Saúde. Monitoramento das arboviroses. Brasília (DF): Ministério da Saúde; 2025. Disponível em: <https://www.gov.br/saude/pt-br/assuntos/saude-de-a-a-z/a/aedes-aegypti/monitoramento-das-arboviroses>
4. Roster KO, et al. Impact of the COVID-19 pandemic on dengue in Brazil: interrupted time series analysis of changes in surveillance and transmission. *PLoS Negl Trop Dis*. 2024;18(12):e0012726. doi:10.1371/journal.pntd.0012726.
5. Antunes JLF, Cardoso MRA. Using time series analysis in epidemiological studies. *Epidemiol Serv Saude*. 2015;24(3):565–576. doi:10.5123/S1679-49742015000300024.
6. Box GEP, Jenkins GM, Reinsel GC. Time series analysis: forecasting and control. 5th ed. Hoboken: Wiley; 2015.
7. McGough SF, et al. A dynamic, ensemble learning approach to forecast dengue fever epidemic years in Brazil using weather and population susceptibility cycles. *J R Soc Interface*. 2021;18(179):20201006. doi:10.1098/rsif.2020.1006.
8. Peters DH, et al. Implementation research: what it is and how to do it. *Br J Sports Med*. 2014;48(8):731–736. doi:10.1136/bmj.f6753.
9. Tricco AC, et al. PRISMA extension for scoping reviews (PRISMA-ScR). *Ann Intern Med*. 2018;169(7):467–473. doi:10.7326/M18-0850.
10. Achcar JA, et al. Use of stochastic volatility models in epidemiological data: application to a dengue time series in São Paulo city, Brazil. *J Biostat Epidemiol*. 2020;6(1):19–29. doi:10.18502/jbe.v6i1.4755.
11. Alves MB, et al. ARBOALVO: a Bayesian spatiotemporal learning and predictive model for dengue cases in the endemic Northeast city of Natal, Rio Grande do Norte, Brazil. *PLoS Negl Trop Dis*. 2025;19(4):e0012984. doi:10.1371/journal.pntd.0012984.
12. Araújo JLB, et al. The impact of COVID-19 mobility restrictions on dengue transmission in urban areas. *PLoS Negl Trop Dis*. 2024;18(11):e0012644. doi:10.1371/journal.pntd.0012644.
13. Bomfim R, et al. Predicting dengue outbreaks at neighbourhood level using human mobility in urban areas. *J R Soc Interface*. 2020;17(171):20200691. doi:10.1098/rsif.2020.0691.
14. Castro LA, et al. Using heterogeneous data to identify signatures of dengue outbreaks at fine spatio-temporal scales across Brazil. *PLoS Negl Trop Dis*. 2021;15(5):e0009392. doi:10.1371/journal.pntd.0009392.
15. Chen X, Moraga P. Assessing dengue forecasting methods: a comparative study of statistical models and machine learning techniques in Rio de Janeiro, Brazil. *Trop Med Health*. 2025;53(1):52. doi:10.1186/s41182-025-00723-7.
16. Chen X, Moraga P. Forecasting dengue across Brazil with LSTM neural networks and SHAP-driven lagged climate and spatial effects. *BMC Public Health*. 2025;25(1):973. doi:10.1186/s12889-025-22106-7.
17. Conceição GM, et al. Effect of social isolation on dengue cases during the COVID-19 pandemic in São Paulo State, Brazil. *Travel Med Infect Dis*. 2021;43:102149.

doi:10.1016/j.tmaid.2021.102149.

18. Daudt-Lemos M, et al. Rising incidence and spatio-temporal dynamics of emerging and reemerging arboviruses in Brazil. *Viruses*. 2025;17(2):158. doi:10.3390/v17020158.

19. De Lima MVM, Laporta GZ. Evaluation of the models for forecasting dengue in Brazil from 2000 to 2017: an ecological time-series study. *Insects*. 2020;11(11):794. doi:10.3390/insects11110794.

20. Drumond B, et al. Dinâmica espaço-temporal da dengue no Distrito Federal, Brasil: ocorrência e permanência de epidemias. *Cien Saude Colet*. 2020;25(5):1641–1652. doi:10.1590/1413-81232020255.32952019.

21. Figueredo MB, et al. Analysis of the correlation between climatic variables and dengue cases in the city of Alagoinhas/BA. *Sci Rep*. 2023;13:7512. doi:10.1038/s41598-023-34349-8.

22. Freitas LP, et al. A statistical model for forecasting probabilistic epidemic bands for dengue cases in Brazil. *Infect Dis Model*. 2025;10(4):1479–1487. doi:10.1016/j.idm.2025.07.014.

23. Geraldini B, Johansen IC, Justus M. Influence of temperature and precipitation on dengue incidence in Campinas, São Paulo State, Brazil (2013–2022). *Rev Soc Bras Med Trop*. 2024;57:e00710–2024. doi:10.1590/0037-8682-0080-2024.

24. Gomes JPM, et al. Relação entre temperatura do ar e incidência de dengue: estudo de séries temporais em Minas Gerais, Brasil (2010–2019). *Cad Saude Publica*. 2024;40(3):e00076723. doi:10.1590/0102-311XPT076723.

25. Leandro GCW, et al. Análise temporal e espacial dos casos municipais de dengue no Paraná e indicadores sociais e ambientais, 2012 a 2021: estudo ecológico. *Rev Bras Epidemiol*. 2022;25:e220039. doi:10.1590/1980-549720220039.2.

26. Li Z, et al. Improving dengue forecasts by using geospatial big data analysis in Google Earth Engine and the historical dengue information-aided long short-term memory modeling. *Biology (Basel)*. 2022;11(2):169. doi:10.3390/biology11020169.

27. Li Z. Forecasting weekly dengue cases by integrating Google Earth Engine-based risk predictor generation and Google Colab-based deep learning modeling in Fortaleza and the Federal District, Brazil. *Int J Environ Res Public Health*. 2022;19(20):13555. doi:10.3390/ijerph192013555.

28. Lopes R, et al. Ambient temperature and dengue hospitalization in Brazil: a 10-year period case time series analysis. *Environ Epidemiol*. 2024;9(1):e360. doi:10.1097/EE9.0000000000000360.

29. Martins ABS, et al. Dengue in Northeastern Brazil: spatial and temporal analysis. *Rev Soc Bras Med Trop*. 2020;53:e20200012. doi:10.1590/0037-8682-0435-2020.

30. Monnaka VU, Oliveira CAC. Correlação e sensibilidade do Google Trends para surtos de dengue e febre amarela no estado de São Paulo. *Einstein (Sao Paulo)*. 2021;19:eAO5969. doi:10.31744/einstein_journal/2021AO5969.

31. Oliveira JF, et al. Interdependence between confirmed and discarded cases of dengue, chikungunya and Zika viruses in Brazil: a multivariate time-series analysis. *PLoS One*. 2020;15(2):e0228347. doi:10.1371/journal.pone.0228347.

32. Pereira SB, et al. Emergence and spatiotemporal incidence of dengue in Rio Grande do Sul, Brazil. *Sci Rep*. 2025;15(1):18933. doi:10.1038/s41598-025-02548-0.

33. Santana LMR, et al. Spatio-temporal dynamics of dengue-related deaths and associated factors. *Rev Inst Med Trop Sao Paulo*. 2022;64:e30. doi:10.1590/S1678-9946202264030.

34. Sebastianelli A, et al. A reproducible ensemble machine learning approach to forecast dengue outbreaks. *Sci Rep*. 2024;14:2575. doi:10.1038/s41598-024-52796-9.

35. Silva AAP, et al. Can the loss of vegetation drive the increase in dengue fever cases? *PLoS One*. 2022;17(1):e0262473. doi:10.1371/journal.pone.0262473.

36. Silva TFG, et al. Tendências na incidência e letalidade da dengue no Brasil, 2001–2022. *Epidemiol Serv Saude*. 2025;34:e20240424. doi:10.1590/s2237-96222025v34e20240424.pt.

37. Silva TR, et al. Tendência temporal e distribuição espacial da dengue no Brasil. *Cogitare Enferm*. 2022;27:e84000. doi:10.5380/ce.v27i0.84000.

38. Souza CDF, et al. Space-time dynamics of the dengue epidemic in Brazil, 2024. *BMC Infect Dis*. 2024;24(1):1056. doi:10.1186/s12879-024-09813-z.

39. Xavier LL, et al. Analysis of climate factors and dengue incidence in the metropolitan region of Rio de Janeiro. *PLoS One*. 2021;16(5):e0251403. doi:10.1371/journal.pone.0251403.