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REVIEW ARTICLE

Spatial Patterns of Dengue in Sri Lanka: A Systematic Review

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ABSTRACT

Dengue is a viral disease that causes a significant impact on Sri Lanka throughout the year. To study the spread of this disease, examining its spatial distribution is very important. The aim of this paper is to systematically review studies that have been conducted on the spatial distribution of dengue disease in Sri Lanka. Using the PRISMA method, thirty-three articles were selected by systematically filtering from the Scopus and Google Scholar databases. These articles were critically analyzed based on publication trends, their impact on society, the number of times spatial distribution analysis was conducted for each district, the time periods during which these studies were carried out, the variables studied, their impact, and the methodological choices used. The main finding identified is that various factors affect the spread of dengue disease in Sri Lanka. Additionally, there is a need to conduct a study covering all districts in Sri Lanka using approximately two decades of data, in a manner that addresses both spatial and temporal aspects.

1 Introduction

Dengue is a major public health concern that is transmitted to humans through the bites of infected mosquitoes. *Aedes* mosquitoes, primarily *Aedes aegypti* and *Aedes albopictus*, have been identified as the main vectors of the disease. Dengue spreads rapidly across the globe which has affected over one hundred countries, causing a significant economic burden, particularly in tropical and subtropical regions Dengue fever has been identified as one of the fastest-growing vector-borne diseases globally, affecting over three hundred and ninety million people annually, with Southeast Asia, South America, and Africa being severely affected from the disease (WHO, 2024). Due to climate change, globalization and urbanization number of dengue cases have been increased rapidly (IFRC, 2016). All over the world, regional hotspots were identified, and they are India, Thailand, Philippines, Brazil and Indonesia.

According to the WHO (2017), Sri Lanka which has been located in the dengue endemic South Asian region, is among the top thirty countries in the world in terms of the number of dengue cases reported annually. Tropical climate, frequent rain around the year and urbanization have made the country to be vulnerable to outbreaks (Lu et al., 2022). Distinct climatic regions, namely the wet and dry zones, further influence the spatial distribution of dengue, with transmission patterns varying across these zones. Overall, more than fifty thousand dengue cases are reported annually.

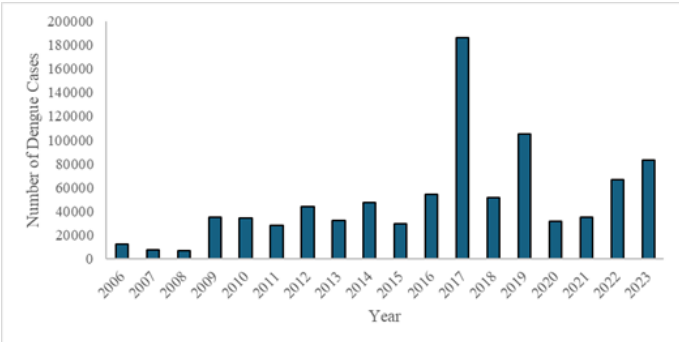

Fig. 1: Total number of reported dengue cases in Sri Lanka.

The country has witnessed several major dengue outbreaks in recent years, particularly in urban areas. In 2017, dengue outbreak recorded over one hundred and eighty-six thousand cases which is the highest in history (Tissera et al., 2020). Fig. 1 illustrates the total number of dengue cases in Sri Lanka reported since 2006, revealing a concerning upward trend over the past decade. To develop effective control strategies, it is crucial to identify the spatial distribution of dengue cases (Downs et al., 2020).

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This approach aligns with the World Health Organization's recommendations for dengue control (WHO, 2017). While previous studies have examined factors contributing to dengue spread, there remains a gap in analyzing these factors in relation to spatial distribution. Understanding these factors within their geographic context is essential, as they vary from one area to another. The objective of this paper is to systematically review and critically evaluate existing research on the spatial distribution of dengue in Sri Lanka.

The remaining parts of the paper are structured as follows: Section two presents the methodology, describing the PRISMA flow diagram and the article selection criteria. Section three presents the results, which include a detailed analysis of the selected studies. Section four discusses the findings, highlighting the research gaps, strengths, and weaknesses of the identified studies. The final section provides the conclusion, offering future directions and policy implications based on the study's findings.

2 Methodology

To achieve the study's objectives, a systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (PRISMA-Statement, 2020). Fig. 2 depicts the PRISMA flow diagram for the study, which presents the review process.

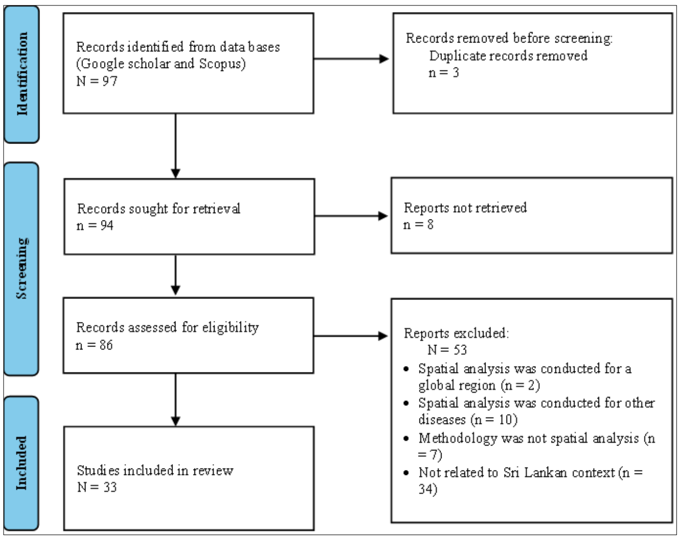

Fig. 2: PRISMA flow diagram.

The methodology included three main stages: identification, eligibility, and inclusion. Only peer-reviewed articles with full texts available were considered, and only those written in English were included. During the screening process, titles and abstracts were reviewed, identifying studies that focused on the spatial distribution analysis of dengue cases in Sri Lanka.

The systematic review aimed to evaluate studies on the spatial distribution of dengue cases in Sri Lanka using geospatial analysis methods, covering the period from 2007 to 2024. The initial search identified ninety-seven records from databases such as Google Scholar and Scopus, using the following keyword combination: ("dengue" OR "dengue fever") AND ("Sri Lanka") AND ("spatial distribution" OR "geographic spread" OR "hotspots" OR "spatial analysis") AND ("disease mapping" OR "GIS" OR "geospatial analysis").

The Scopus database was selected because it contains peer-reviewed, high-quality journal articles. Furthermore, the interdisciplinary combination of dengue and spatial analysis is limited in databases that focus mainly on medical and science aspects. This study does not focus on medical or epidemiological aspects. In addition, since Sri Lanka is a small geographic niche area, the Google Scholar database was selected to identify gray literature.

In this review, only highly cited articles written in English, articles with full-text availability, and studies specifically conducted in Sri Lanka were selected. Articles that focused on subject areas other than spatial distribution were not considered, and the review specifically included only studies related to dengue disease.

After removing duplicate records, three records were excluded, leaving ninety-four records considered for retrieval. However, eight records were excluded as the full texts were not available, bringing the number of records assessed for eligibility to eighty-six. Out of these, fifty-three records were excluded for various reasons: two studies conducted spatial analysis on a global region, ten focused on other diseases, seven did not employ spatial analysis methodology, and thirty-four were not related to the Sri Lankan context. Thus, thirty-three studies were included in the final review, contributing valuable insights into the spatial distribution of dengue fever in Sri Lanka.

3 Results

	Sum of cites per article	Count of articles
2007	3	1
2009	28	2
2012	1	1
2013	5	1
2014	1	2
2015	10	3
2016	15	1
2017	33	5
2018	1	2
2019	18	1
2020	21	5
2021	18	1
2022	33	1
2023	3	3
2024	0	4

Fig. 3: Publication trend.

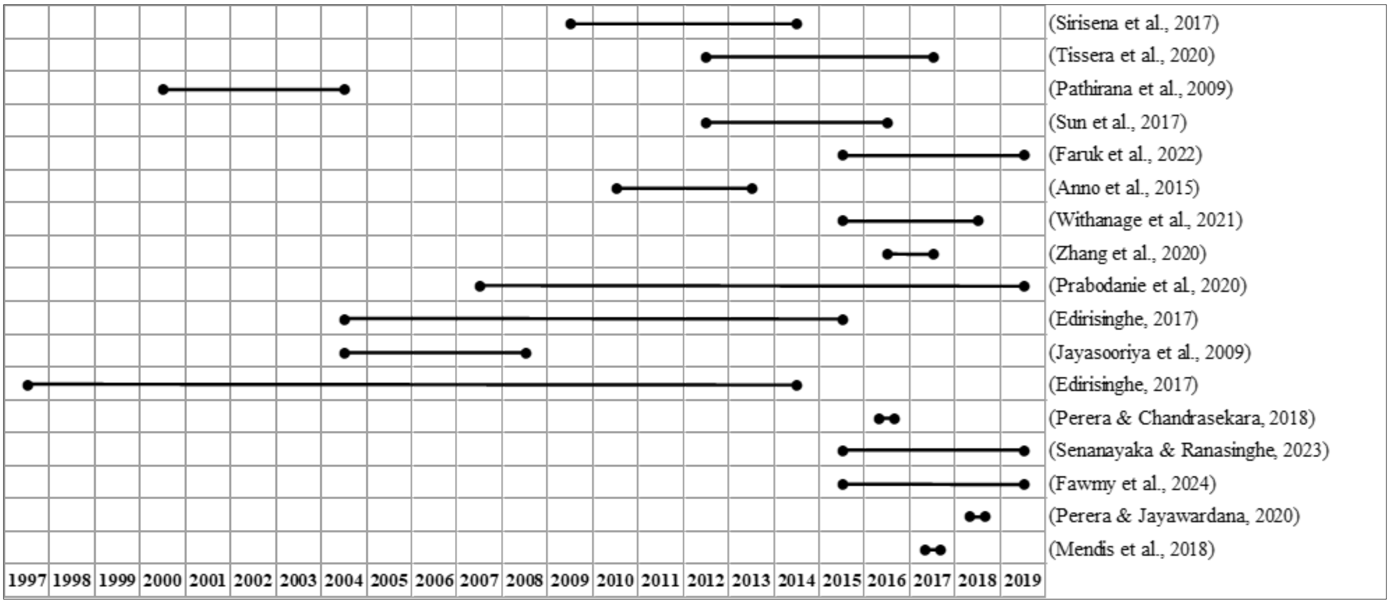

Fig. 4: Distribution of time spans of data used for spatial analysis of dengue transmission in Sri Lanka across selected research studies.

To identify the publication trend of selected research articles and the extent to which these articles have made an impact on society, the number of articles published per year within the period from 2007 to 2024, as well as the number of citations received by each individual article, is presented in Fig. 3. Per the figure, it is evident that there is a declining trend for the spatial analysis-based studies related to dengue in Sri Lanka, although a substantial number of articles were published in 2017. However, research conducted in 2017 and 2020 has made a considerable impact on society. It is essential to continue the upward trend of publications to fill existing knowledge gaps.

Fig. 4 indicates the time periods from which data have been obtained to conduct the spatial analysis of the selected research articles. Most researchers have considered data covering only a period of three to five years. In a study conducted by Edirisinghe (2017a), data covering a time span of eighteen years were used for the research, while Prabodanie et al. (2020) used data from thirteen years. In order to study the spread of dengue disease in relation to climatic variability, it is essential to capture the temporal aspect of disease transmission. Within the past five years, particularly due to the COVID-19 pandemic as well as the economic crisis faced by Sri Lanka, a temporal study should be conducted to examine how the spread of dengue disease has occurred. For this purpose, the spatial distribution of dengue cases in Sri Lanka should be studied over a period of approximately two decades.

Spatial distribution focuses on geographic location. A heat map was created showing the districts in Sri Lanka studied for dengue (Fig. 5). Districts that appear in more studies are shown in darker colors which indicates the frequency. When considering these thirty-three studies, an observable fact is that in some instances, these studies are limited to only a single district. The highest number of studies have been conducted focusing on the Colombo District. A notable number of studies have also been conducted in the Gampaha District. The Trincomalee District, Badulla District, and Galle District have also been studied to a considerable extent. However, only about five studies have conducted spatial distribution analysis by considering the entirety of Sri Lanka.

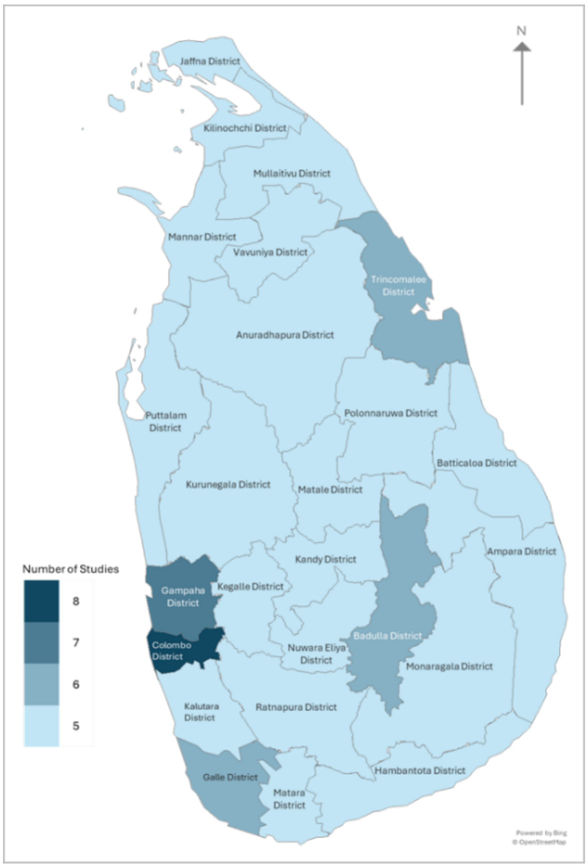

Fig. 5: District-wise focus of dengue spatial distribution studies in Sri Lanka.

Table 1: Factors affecting dengue transmission in Sri Lanka and their reported impacts.

	Research Paper	Factor Studied	Impact
Climatic and Meteorological Factors	(Sirisena et al., 2017)	Rainfall (lagged 2 months)	↗
	(Sirisena et al., 2017)	Rainfall (lagged 5 months)	↑
	(Chathurangika et al., 2024; Prabodanie et al., 2020; Tissera et al., 2020; Wickramathilaka et al., 2024)	Monsoon Rainfall	↑
	(Tissera et al., 2020)	Rainfall (cumulative weekly)	-
	(Pathirana et al., 2009)	Rainfall (post-rainfall period)	↑
	(Anno et al., 2014; Edirisinghe, 2017a; Edirisinghe, 2017b; Fawmy et al., 2024; Sirisena et al., 2017; Sun et al., 2017)	Rainfall	↑
	(Edirisinghe, 2017a; Faruk et al., 2022)	Climate Season (Northeast Monsoon)	↑
	(Edirisinghe, 2017a)	Southwest Monsoon Season (Higher Rainfall)	-
	(Withanage et al., 2021)	Southwest Monsoon Season (Higher Rainfall)	↑
	(Faruk et al., 2022)	Air Pressure	↑
	(Anno et al., 2015; Faruk et al., 2022; Fawmy et al., 2024; Sun et al., 2017)	Humidity	↑
	(Sirisena et al., 2017)	Humidity (average)	-
	(Sirisena et al., 2017)	Humidity (lagged 1 month)	↗
	(Sirisena et al., 2017)	Humidity (lagged 9 months)	↓
	(Sun et al., 2017)	High Temperature	↑
	(Zhang et al., 2020)	Minimum Daily Temperature (Tmin, 10-day lag)	↑
	(Sirisena et al., 2017)	Temperature (lagged 9 months)	↑
	(Anno et al., 2015; Edirisinghe, 2017a; Fawmy et al., 2024; Senanayake et al., 2012; Sirisena et al., 2017; Tissera et al., 2020)	Temperature	-
	(Sun et al., 2017)	High Wind Speed	-
	(Sun et al., 2017)	Low Wind Speed	↑
	(Sun et al., 2017)	Low Humidity	-
	(Tissera et al., 2020)	El Niño Southern Oscillation (Oceanic Niño Index)	-
	(Faruk et al., 2022)	Precipitation	↓
Topography and Geographic Factors	(Sirisena et al., 2017; Tissera et al., 2020; Wickramathilaka et al., 2024)	Elevation / High Altitude	↓
	(Withanage et al., 2021)	Elevation	-
	(Edirisinghe, 2017a; Edirisinghe, 2017b)	Gentle Slope / Low-Lying Terrain	↑
	(Prabodanie et al., 2020)	Geographical Proximity	-

Environmental and Ecological Factors	(Faruk et al., 2022)	Bioclimatic Zone (Wet Zone)	↑
	(Chathurangika et al., 2024; Prabodanie et al., 2020; Sun et al., 2017; Wickramathilaka et al., 2024)	Climatic Factors (Local Climate)	-
	(Chathurangika et al., 2024)	Environmental Pollution	↑
	(Perera and Jayawardana, 2020)	Forest Areas	↓
	(Kannathasan et al., 2013; Withanage et al., 2021)	Marshy Areas / Wetlands	↗
	(Perera and Jayawardana, 2020)	Marshy Areas / Wetlands	↓
	(Withanage et al., 2021)	Vegetation Coverage / Home Gardens	↑
	(Senanayake et al., 2012)	Normalized Difference Vegetation Index (NDVI)	-
Land Use and Built Environment	(Anno et al., 2015; Edirisinghe, 2017b; Fawmy et al., 2024; Jayadas et al., 2023; Kannathasan et al., 2013; Perera and Jayawardana, 2020; Perera and Chandrasekara, 2018; Senanayaka and Ranasinghe, 2023; Withanage et al., 2021; Zhang et al., 2020)	Land Use (Urban Areas)	↑
	(Zhang et al., 2020)	Land-use: Areas with Standing Water (StWtr)	↑
	(Zhang et al., 2020)	Land-use: Coastal Areas (Sea)	↑
	(Edirisinghe, 2017a; Edirisinghe, 2017b; Kannathasan et al., 2013; Perera and Jayawardana, 2020)	Land Use: Water Bodies	↑
	(Kannathasan et al., 2013)	Land Use: Agricultural Land	↗
	(Perera and Jayawardana, 2020)	Construction Sites	↑
Demographic and Population Factors	(Tissera et al., 2020)	Age (older schoolchildren and young adults)	↑
	(Pathirana et al., 2009)	Age (population under 18 years)	↑
	(Anno et al., 2015; Edirisinghe, 2017b; Fawmy et al., 2024; Jayadas et al., 2023; Kannathasan et al., 2013; Pathirana et al., 2009; Perera and Chandrasekara, 2018; Senanayaka and Ranasinghe, 2023; Sirisena et al., 2017; Sumanasinghe et al., 2016; Sun et al., 2017; Tissera et al., 2020; Wickramathilaka et al., 2024; Zhang et al., 2020)	Population Density	↑
Vector and Entomological Factors	(Tissera et al., 2020; Withanage et al., 2021)	Entomologic Indices (e.g., Breteau Index)	-
	(Chathurangika et al., 2024)	High Vector Population Density	↑
	(Tissera et al., 2020)	Type of Vector Breeding Habitat	-
Socioeconomic, Infrastructure and Governance Factors	(Edirisinghe, 2017a; Edirisinghe, 2017b; Fawmy et al., 2024; Senanayaka and Ranasinghe, 2023; Wickramathilaka et al., 2024)	Inadequate Waste and Water Management Practices	↑
	(Fawmy et al., 2024; Wickramathilaka et al., 2024)	Inadequate Monitoring and Surveillance Systems	↓
	(Edirisinghe, 2017a; Edirisinghe, 2017b; Wickramathilaka et al., 2024)	Lack of Public Awareness / Knowledge	↑
	(Wickramathilaka et al., 2024)	Public Awareness and Participation Gaps	↓
	(Edirisinghe, 2017a; Edirisinghe, 2017b; Jayadas et al., 2023)	Poverty / Low Income	↑
	(Wickramathilaka et al., 2024)	Resource Limitations (Financial, Manpower, Technical)	↓

Mobility, Proximity and Spatial Factors	(Zhang et al., 2020)	Prior cases within one and two weeks	↑
	(Withanage et al., 2021)	Clustering Radius (~150 m)	↑
	(Chathurangika et al., 2024; Prabodanie et al., 2020; Zhang et al., 2020)	Human Mobility	↑
	(Anno et al., 2015)	Transportation Networks	↑
	(Withanage et al., 2021)	Proximity to Roads	↑
	(Withanage et al., 2021)	Proximity to Public Places	↑
	(Perera and Chandrasekara, 2018)	Proximity to Drainage System / Water Sources	↑

Note: Arrows indicate the impact of the factor on dengue cases as follows.

↑	Strong Positive	–	No clear correlation	↓	Strong Negative
↗	Moderate Positive	↘	Moderate Negative		

By considering both Fig. 4 and Fig. 5, the gap identified is the need to conduct research that covers all districts of Sri Lanka, uses a recent dataset, and addresses both the spatial and temporal aspects.

The selected articles have examined not only the spread of dengue but also many factors influencing dengue transmission. For this critical analysis, individual articles were analyzed, and the factors studied in those articles were separately extracted. An observation that emerged is that a single research paper has analyzed multiple factors, and the same factor has been studied by several researchers. In instances where the same factor has been studied multiple times, there were cases where completely different findings were reported. These aspects are presented in detail in Table 1.

Table 1 presents the factors affecting dengue transmission in Sri Lanka that were studied by the researchers of these thirty-three articles. For each factor, its impact on dengue disease was considered, including whether it increases dengue transmission, increases transmission to some extent, has no impact, decreases transmission to some extent, or decreases dengue transmission. In addition, these factors were categorized into eight main categories named Climatic and Meteorological Factors, Topography and Geographic Factors, Environmental and Ecological Factors, Land Use and Built Environment, Demographic and Population Factors, Vector and Entomological Factors, Socioeconomic, Infrastructure and Governance Factors, and Mobility, Proximity and Spatial Factors.

By considering the distribution of factors across these selected categories, it can be observed that climatic and meteorological factors, particularly rainfall- and temperature-related variables, have been studied most frequently and were commonly reported to have a positive relationship with dengue incidence. A notable number of studies have also examined land-use and built-environment factors, including urban areas, construction sites, standing water locations, and waterbodies, which were largely associated with increased dengue transmission. Demographic and population-related factors, especially population density and age-related variables, have also been studied to a considerable extent and predominantly showed positive associations with dengue occurrence.

Topography and geographic factors revealed clear spatial patterns, where low-lying terrain was generally associated with increased dengue transmission, while higher elevation areas showed negative relationships. Environmental and ecological factors demonstrated mixed findings, with wet-zone conditions, marshy areas, and home garden vegetation often associated with higher dengue risk, whereas forest cover and vegetation indices showed weak or negative relationships in several studies. Vector-related factors and socioeconomic, infrastructure, and governance-related factors were also examined across multiple studies, with inadequate waste management, poverty, limited resources, and breeding site availability commonly reported as contributing to dengue transmission.

Overall, by considering Table 1, it is evident that dengue transmission in Sri Lanka has been studied in relation to a diverse set of interrelated factors, with climatic, urban, demographic, and mobility-related variables emerging as the most frequently analyzed across the reviewed literature.

The tree map (Fig. 6) visualizes the distribution of research methodologies used in the thirty-three selected studies for the review paper. The chart categorizes the methodologies into six main groups, highlighting the diversity and frequency of approaches employed in spatial and statistical dengue analysis. Each main category is subdivided into specific methods, providing a detailed view of the methodologies' contributions.

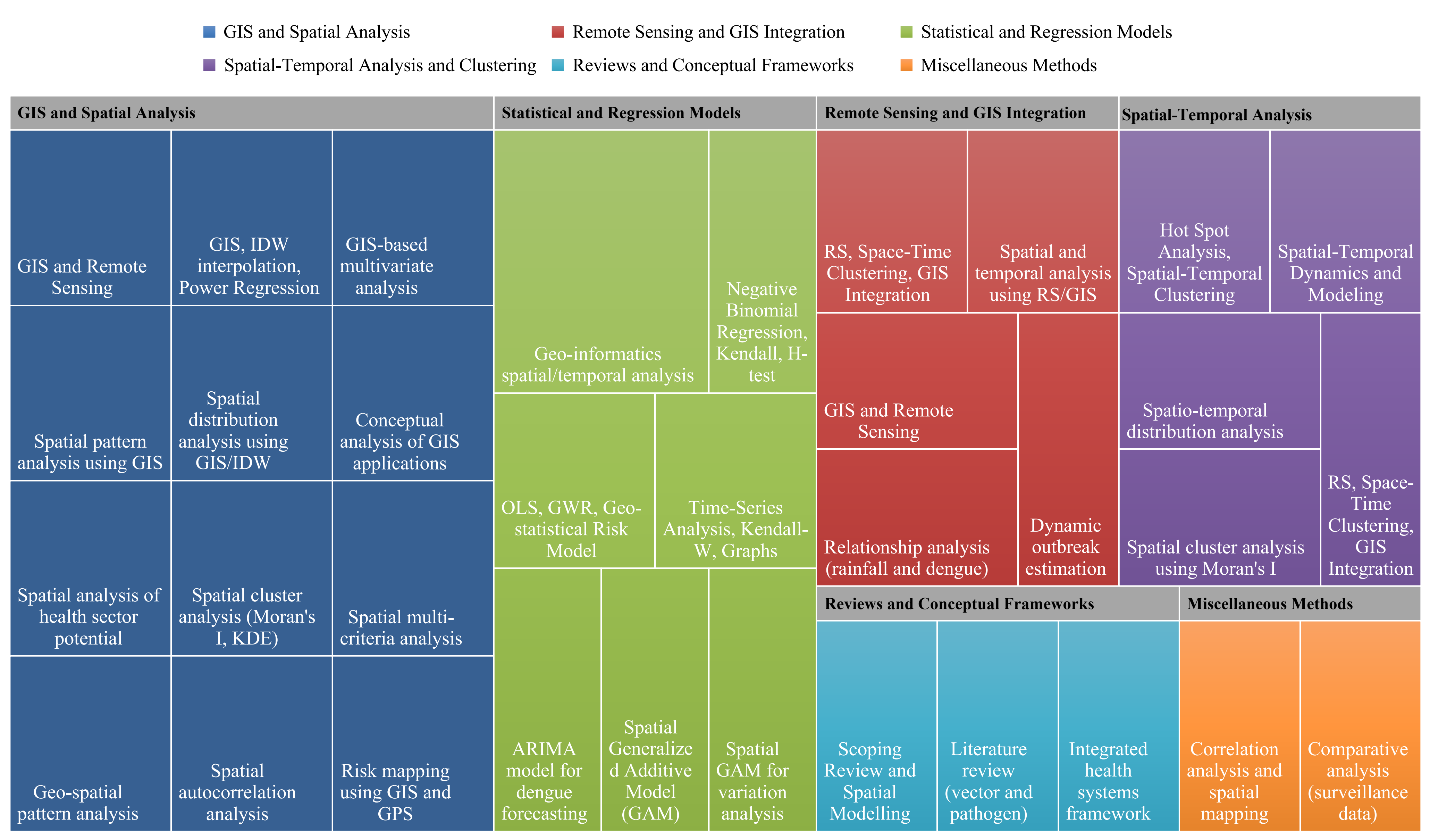

Fig. 6: Distribution of research methodologies.

Geographical Information Systems (GIS) and Spatial Analysis category with twelve studies represents the largest share of the studies, focusing on GIS and related spatial techniques. Subcategories include spatial distribution analysis, spatial cluster analysis (e.g., Moran's I, KDE), and GIS-based multivariate approaches. Methods like Inverse Distance Weighting (IDW) interpolation, spatial pattern analysis, and risk mapping are also prominent.

Remote Sensing (RS) and GIS Integration category with five studies in this group combine RS techniques with GIS for spatial and temporal analysis. Methods include space-time clustering, dynamic outbreak estimation, and exploring relationships between environmental factors, such as rainfall, and dengue.

Statistical and Regression Models category contains studies highlighting the statistical approaches used for spatial and temporal dengue analysis. Methods such as Negative Binomial Regression, Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), Autoregressive Integrated Moving Average (ARIMA), and spatial Generalized Additive Model (GAM) are frequently employed to model disease dynamics and variations.

Spatial-Temporal Analysis and Clustering category with five studies emphasize the integration of spatial and temporal clustering techniques, including hot spot analysis, spatial-temporal dynamics, and spatio-temporal distribution analysis. Moran's I and space-time clustering approaches are key techniques in this category.

Reviews and Conceptual Frameworks group with three studies includes literature reviews, scoping reviews, and conceptual frameworks. These studies explore vector and pathogen distributions, decision-making models, and the development of integrated health systems frameworks. Miscellaneous Methods category with only two studies focus on correlation analysis, spatial mapping, and comparative analysis using national surveillance data.

GIS and spatial analysis methods form the largest cluster, reflecting their central role in dengue spatial distribution studies. The use of RS and GIS integration highlights advancements in analyzing environmental influences on dengue spread. Regression and temporal modeling methods demonstrate the importance of statistical approaches in understanding disease dynamics. The chart reveals a balanced mix of spatial, temporal, statistical, and review-based studies, showcasing the multidisciplinary nature of dengue research.

4 Discussion

4.1 Key Spatial Trends in Dengue Distribution

Studies conducted by Sun et al. (2017) and Withanage et al. (2021) identified spatial clusters and hotspots. They utilized GIS, spatio-temporal clustering, and hotspot analysis to detect these clusters. Several key studies have identified urbanized areas as high-risk zones for dengue outbreaks (Pathirana et al., 2007; Zhang et al., 2020). Rainfall, as a climatic factor, was identified as a significant reason for dengue outbreaks in urban areas of Sri Lanka (Pathirana et al., 2007; Sumanasinghe et al., 2016).

Prabodanie et al. (2020) identified two main epidemic patterns: one occurring annually in the southwest wet zone, while the other wave occurred in northern and eastern regions. Epidemic patterns correlated with monsoons, inter-monsoons, human mobility, and geographical proximity. Mutucumarana et al. (2020) highlighted a high possibility of acute dengue cases in the rural northeast of the Southern Province.

Edirisinghe (2017a) conducted a spatial distribution analysis for the Matara district and identified hotspots clustered in urbanized areas with poor drainage systems (e.g., Hittatiya West, Fort). Similarly, Perera and Jayawardana (2020) found clustered dengue cases near drainage systems in the Kolonnawa Medical Officer of Health (MOH) area, with twenty hotspots identified. identified hotspots in the Kandy district using GIS.

Senanayaka and Ranasinghe (2023) conducted a spatial distribution analysis for the Badulla district and observed clustered spatial patterns with hotspots concentrated in urban areas. Another significant finding of their research is that seventy percent of dengue cases are reported annually in urban areas, with peaks observed in 2017 and 2019. High population density and improper waste disposal were identified as major contributors to dengue spread.

Fawmy et al. (2024) analyzed the spatial distribution of dengue incidence in the Trincomalee district, where climate and land-use factors were found to have a significant influence. Furthermore, buffer analysis and NDVI mapping identified risk zones, with human activities being the key contributors. A similar finding was observed in Jaffna, where land-use patterns and socio-economic factors were linked to high dengue incidence (Jayadas et al., 2023). The Nallur MOH division was identified as a hotspot through spatial multi-criteria GIS analysis.

When considering the studies conducted on the spatial distribution of dengue in Sri Lanka, several gaps were identified. A limited number of comparative analyses were conducted among the reviewed literature. Previous studies primarily focused on specific districts (e.g., Matara, Kolonnawa, Kandy, Badulla, Trincomalee) with limited cross-district comparisons. Although there are studies that integrate climatic factors and land-use patterns, there is a gap in research that simultaneously examines the combined influence of socio-economic, environmental, and human mobility factors on dengue transmission in the Sri Lankan context. Many studies concentrated on selected specific areas, and there are underrepresented regions, such as the rural northeast and less urbanized districts. There is a need for comprehensive spatial analysis that includes both urban and rural settings to better understand dengue transmission across the entire country. Most studies are conducted at the district level, with few offering a national-level perspective to identify broader patterns and trends in dengue outbreaks.

4.2 Strengths of Existing Studies

Many studies have utilized advanced spatial tools such as GIS, ArcGIS software, and spatial mapping techniques like IDW mapping. Furthermore, researchers have used Kernel Density, Moran's I index, and remote sensing data for hotspot identification and spatial analysis (Anno et al., 2014; Edirisinghe, 2017a; Jayasooriyaa et al., 2009).

These studies were not limited to spatial analysis; many combined spatial techniques with various statistical analyses. Most studies not only focused on dengue cases but also incorporated climatic (rainfall, humidity), geographic, demographic, and epidemiological data to identify spatial and temporal patterns (Anno et al., 2014; Pakaya et al., 2023). For instance, Senanayake et al. (2012) highlighted the benefits of GIS for disease tracking, health mapping, and facility accessibility, using it as a tool for integrating demographic, environmental, and service network data for health planning.

Wickramathilaka et al. (2024) utilized ARIMA models for dengue incidence forecasting, validating the forecasts against independent datasets and demonstrating the model's reliability. Similarly, Jayadas et al. (2023) combined spatial multi-criteria analysis with land-use, socio-economic, and demographic data for dengue case mapping. Perera and Jayawardana (2020) used advanced spatial autocorrelation techniques (Moran's I, Kernel Density) and greenness indices (NDVI) to assess dengue outbreaks.

By using advanced tools such as GIS, RS, and spatial modeling, studies have successfully identified clusters, hotspots, and high-risk zones (Sirisena et al., 2017; Tissera et al., 2020). Other statistical techniques, such as negative binomial regression, GWR, and spatial Poisson models, have also been applied for risk assessment (Faruk et al., 2022; Sumanasinghe et al., 2016).

Advanced methodologies include the application of ARIMA models for dynamic forecasting to enhance surveillance accuracy (Wickramathilaka et al., 2024), spatial multi-criteria analysis to incorporate socio-economic, demographic, and land-use factors (Jayadas et al., 2023), GWR for spatial non-stationarity analysis (Sumanasinghe et al., 2016), GAM and ARIMA for trend forecasting (Sirisena et al., 2017; Sun et al., 2017), and multivariate spatial Poisson models for analyzing risk hotspots (Withanage et al., 2021).

Even though the authors have created models to forecast dengue incidents, they are mainly based on historical data and not on real-time dynamic forecasting systems in the Sri Lankan context. Although GWR has been utilized in studies, its application has been limited. A research gap remains in addressing spatial non-stationarity to understand region-specific variations in dengue risk factors.

Among the thirty-three studies considered, only five studies focused on all the districts in Sri Lanka. Other studies have been limited to specific districts in the country (Senanayaka and Ranasinghe, 2023). Many studies have been conducted on the spatial distribution of dengue in the Northern and Southern provinces of Sri Lanka. However, a limited number of longitudinal studies were identified that focus on seasonal and long-term trends in the spatial distribution of dengue cases (Edirisinghe, 2017a; Fawmy et al., 2024; Jayadas et al., 2023; Mutucumarana et al., 2020).

4.3 Policy Implications

Findings from the studies emphasize the need for region-specific dengue prevention strategies, focusing on high-risk zones such as urbanized areas, hotspots, and rural emerging regions (Edirisinghe, 2017b; Jayasooriyaa et al., 2009; Sun et al., 2017; Zhang et al., 2020). Targeted vector control measures (e.g., source reduction, adulticides, and larvicides) should prioritize high-risk MOH divisions and GN areas (Edirisinghe, 2017b; Jayadas et al., 2023).

To enhance surveillance and early warning systems, the development of real-time geospatial tools, predictive risk models, and GIS-integrated early warning systems is essential (Mutucumarana et al., 2020; Pakaya et al., 2023; Withanage et al., 2021). GIS tools can assist policymakers in identifying priority areas for resource allocation, vector control, and health planning to effectively manage outbreaks (Senanayake et al., 2012; Wickramathilaka et al., 2024). Additionally, accurate incidence forecasts can improve public health preparedness and decision-making in resource allocation (Wickramathilaka et al., 2024). Spatial distribution analyses can also support the implementation of long-term intervention strategies (Anno et al., 2015).

In terms of urban management and infrastructure development, land-use impacts can inform policies related to urban planning, drainage systems, waste management, and habitat control to mitigate the spread of dengue (Chathurangika et al., 2024; Edirisinghe, 2017b; Perera and Jayawardana, 2020). Longitudinal studies are critical for understanding seasonal and long-term trends, enabling robust predictions for dengue control and prevention strategies (Fawmy et al., 2024; Sumanasinghe et al., 2016).

5 Conclusion

This paper systematically reviewed and critically evaluated studies conducted on the spatial distribution of dengue disease in Sri Lanka using the PRISMA method. A total of thirty-three articles were selected from the Scopus and Google Scholar databases and were analyzed based on publication trends, spatial and temporal coverage, factors studied, their impacts, and methodological choices. Through this review, existing research trends, gaps, and strengths related to dengue spatial distribution in Sri Lanka were identified.

The main findings indicate that dengue transmission in Sri Lanka is influenced by a diverse set of interrelated factors. Climatic and meteorological factors, particularly rainfall and temperature, were the most frequently studied and were commonly reported to have positive relationships with dengue incidence. Land-use and built-environment factors such as urban areas, construction sites, standing water locations, and waterbodies were also strongly associated with increased dengue transmission. Demographic factors, especially population density, along with mobility and proximity-related variables, emerged as key contributors to spatial clustering and hotspot formation, while low-lying terrain showed higher risk compared to high-altitude areas.

Despite these contributions, several limitations were identified. Most studies were limited to specific districts, with a strong focus on urbanized areas such as Colombo and Gampaha, while many rural and less urbanized districts remain underrepresented. The majority of studies used short temporal datasets, often covering only three to five years, limiting the ability to capture long-term and seasonal trends. In addition, findings for the same factors were sometimes inconsistent across studies, and there is a lack of comprehensive analyses that simultaneously integrate climatic, environmental, socio-economic, and human mobility factors at a national scale.

Future research should focus on conducting comprehensive spatial and temporal studies covering all districts in Sri Lanka using approximately two decades of data. There is a need for national-level analyses that integrate multiple factors and address spatial non-stationarity to better understand regional variations in dengue risk. The development of real-time geospatial surveillance systems and advanced spatial-temporal modeling approaches would further strengthen dengue prevention, control strategies, and policy decision-making in Sri Lanka.

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Author Contributions

Conceptualization, methodology, data collection, analysis, and writing – original draft preparation, Y. W.; review and editing, S. P. and P. K. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

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