

## SYSTEMATIC REVIEW

# Navigating Dengue Insight and Implication from Spatial and Temporal Risk Mapping Studies: A Systematic Review

Zulkifli Abdul Hadi<sup>1,4</sup>, Nazri Che Dom<sup>1,2,3</sup>, Rahmat Dapari<sup>5</sup>

<sup>1</sup> Centre of Environmental Health & Safety, Faculty of Health Sciences, Universiti Teknologi MARA (UiTM), UiTM Cawangan Selangor, 42300 Puncak Alam, Selangor, Malaysia

<sup>2</sup> Integrated Mosquito Research Group (I-MeRGe), Universiti Teknologi MARA (UiTM), 42300 Puncak Alam, Selangor, Malaysia

<sup>3</sup> Institute for Biodiversity and Sustainable Development (IBSD), Universiti Teknologi MARA, 40450 Shah Alam, Malaysia

<sup>4</sup> Kuantan District Health Office, 25200 Kuantan, Pahang, Malaysia

<sup>5</sup> Department of Community Health, Universiti Putra Malaysia, Serdang 43400, Malaysia

## ABSTRACT

**Introduction:** Arbovirus infections, particularly those caused by the dengue virus (DENV), pose a significant global public health challenge. Despite control efforts, dengue fever prevalence continues to escalate, with projections indicating further expansion into new regions. Spatial and temporal risk mapping has become pivotal in dengue prevention, yet current methodologies face accuracy and reliability limitations, especially in sparsely populated areas. **Aim:** This systematic review consolidates knowledge on dengue risk mapping, focusing on recent advancements, persistent challenges, and unexplored research avenues. **Design:** A systematic literature search was conducted using PRISMA guidelines, identifying relevant publications from Scopus and Web of Science between January 2011 to December 2022. Ten studies were selected based on rigorous inclusion criteria, revealing a recent surge in research activity, particularly in the last five years. **Results:** Environmental and meteorological factors emerged as key predictors in dengue risk models, alongside demographic and entomological variables. The integration of remote sensing techniques and interdisciplinary collaborations has shown promise in enhancing prediction precision. Despite diverse predictors and modelling methodologies, gaps persist, including data quality and availability limitations, and challenges in model validation and generalizability. **Conclusion:** This review highlights dengue risk mapping advancements, with environmental (37%) and meteorological (32%) factors as key predictors. INLA and Random Forest (13% each) improved accuracy, yet entomological data were underutilized (11%). Despite recent research growth, urban bias and data limitations persist, underscoring the need for comprehensive, interdisciplinary approaches in dengue prediction.

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## Corresponding Author:

Nazri Che Dom, PhD

Email: nazricd@uitm.edu.my

Tel : +603-32584447

## INTRODUCTION

Arbovirus infections, particularly those caused by the dengue virus (DENV), represent a significant and escalating global public health challenge. With its widespread prevalence across over 128 countries, nearly 4 billion people are at risk of contracting dengue, marking a dramatic increase in incidence, mortality, and disability-adjusted life years (DALYs) between 1990 and 2017 (1-2). Alarming projections indicate the expansion of dengue epidemics into previously unaffected regions, including Europe and South America

(3).

Dengue fever, the most prevalent mosquito-borne viral disease, manifests as a spectrum of clinical presentations, ranging from mild dengue fever (DF) to severe dengue shock syndrome (DSS), which poses a significant fatality risk if left untreated (4). Traditional vector control strategies face mounting challenges, such as rising costs and pesticide resistance, underscoring the urgent need for innovative prevention and control measures (5).

Spatial and temporal risk mapping, utilizing surveillance data, has emerged as a pivotal approach in arbovirus disease prevention. This proactive method complements existing reactive strategies by enabling targeted interventions and resource optimization. However, current methodologies often rely on single-component

models derived predominantly from clinical case reports, which limits their accuracy, particularly in sparsely populated or resource-limited areas (6). To address these shortcomings, frameworks such as the MOVE project's climate change framework and the Health Vulnerability Index (HVI) have been adapted to account for vulnerability factors in dengue research (7,8,9). Despite these advancements, significant gaps remain in integrating diverse predictors such as environmental, meteorological, demographic, and entomological variables into robust and generalizable models.

This review addresses these critical gaps by consolidating recent advancements in spatial and temporal dengue risk mapping and identifying persistent challenges in model development, data quality, and validation. Our findings highlight the importance of interdisciplinary approaches and emerging technologies, such as remote sensing and advanced predictive models, in improving risk mapping precision. By synthesizing these insights, this review provides a roadmap for enhancing the accuracy and applicability of dengue risk maps, ultimately supporting more effective public health interventions, resource allocation, and early warning systems to mitigate the global burden of dengue fever.

## MATERIALS AND METHODS

### Literature search and study selection

This section outlines the methodology employed to identify relevant publications on dengue virus and risk mapping in Southeast Asia. A systematic review was conducted using two major databases: Scopus and Web of Science. The process involved distinct phases: identification, screening, eligibility assessment, and data abstraction and analysis (Fig.1).

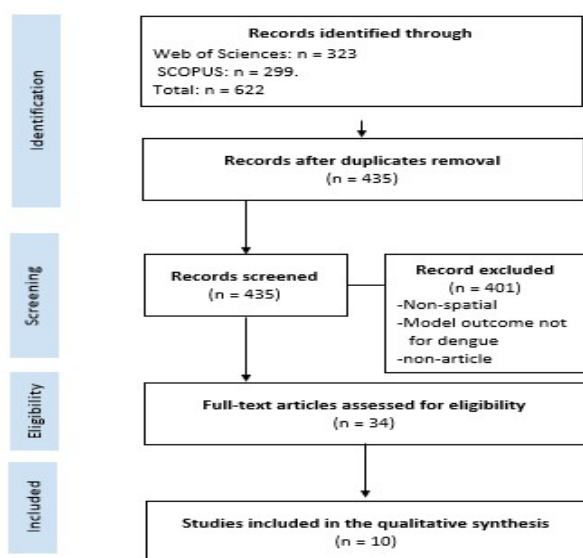


Fig. 1: The methodology framework of the present study on dengue related disease which illustrates the systematic review process, including the identification, screening, eligibility, and inclusion stages based on PRISMA guidelines, along with the criteria for study selection and analysis.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines served as the framework for this review (10, 11). PRISMA is acknowledged as a standard protocol for systematic literature reviews and meta-analyses, ensuring quality and transparency in review processes. Its utility extends to environmental management research due to its emphasis on defining precise research questions and systematic approaches. PRISMA's structured approach aids in the systematic exploration of knowledge repositories, particularly when direct access to comprehensive literature is limited.

The systematic review process was conducted by three researchers (ZAH, NCD and RD). Two independent reviewers (ZAH and NCD) performed the initial screening of titles and abstracts according to the predefined inclusion and exclusion criteria. The screened articles were categorized as 'include,' 'exclude,' or 'uncertain.' Full texts of articles marked as 'include' or 'uncertain' were subsequently retrieved and independently assessed by the same two reviewers. Any disagreements during the screening and full-text review processes were resolved through discussion, with the third reviewer (RD) serving as arbitrator when consensus could not be reached. The same two reviewers independently extracted data using a standardized form developed prior to the review. The extracted data were cross-checked for accuracy, with the third reviewer validating a random sample of 25% of the included studies to ensure consistency. Quality assessment using the CASP checklist was also conducted independently by two reviewers, with disagreements resolved through consensus discussions. Throughout the process, regular team meetings were held to discuss and resolve any challenges in article selection, data extraction, or quality assessment.

Adhering to PRISMA guidelines, this review methodically identified terms related to dengue disease and risk mapping. This structured approach enhances the integrity of the data collection process, thereby enriching environmental management research. The outcomes of this review are presented following the PRISMA flowchart (11). It's essential to note that while the protocol for this systematic review was not formally registered, it strictly adhered to PRISMA guidelines to uphold research thoroughness. The selection of Scopus and Web of Science databases was based on their comprehensive coverage of relevant literature in the field, ensuring a thorough exploration of available resources.

### Data sources

In this review, we utilized two primary databases renowned for their extensive coverage across various disciplines: Scopus and Web of Science (WoS). These databases were specifically chosen for their comprehensive inclusion of environmental science-related publications, a key focus of this review.

Web of Science, a product of Clarivate Analytics, offers an expansive collection of over 33,000 journals across 256 subject categories. It is particularly noted for its extensive historical archive, which includes over a century of scholarly publications and citation data, making it invaluable for longitudinal studies. Scopus, another pivotal source in this review, is acclaimed for its vast repository of peer-reviewed article abstracts and citations. Hosting content from over 5,000 publishers, it features more than 22,800 journals. Its broad scope encompasses critical areas relevant to our review, including environmental science, social science, and biological science, offering a diverse and global perspective on the subject matter.

Both databases provide a rich foundation for a comprehensive review, ensuring a diverse and inclusive range of scholarly works pertinent to dengue risk mapping. Specifically, Scopus and Web of Science support our research objectives through advanced search functionalities, citation tracking capabilities, and indexing of key journals in environmental science. For example, previous studies on dengue risk mapping, can be readily found and accessed within these databases. It's important to acknowledge potential limitations associated with using Scopus and Web of Science. These may include language bias, indexing limitations, and the exclusion of grey literature. However, despite these potential limitations, the comprehensive coverage and robust features of both databases make them valuable resources for our review.

### Formulation of research questions

This review utilized the PICO framework to formulate a relevant research question. PICO, encompassing Population/Problem, Intervention, and Context, guided the development of the study's focus. The three primary dimensions considered were:

- Population: The population at risk of dengue infection, including specific demographic characteristics, geographical locations, and other relevant factors.
- Intervention: The application of dengue risk mapping and early warning systems, encompassing methodologies, technologies, and strategies used to identify and mitigate dengue risk.
- Context: The context of existing reactive control strategies and risk mapping efforts, providing background information on current approaches to dengue prevention and control.

These elements were instrumental in defining the central research question:

- What are the key advancements, challenges, and gaps in dengue risk mapping and early warning systems?
- How do these developments influence the effectiveness of prevention and mitigation strategies against the global spread of dengue fever?

This question aims to explore the current state and impact of risk mapping and early warning systems in addressing the dengue threat, considering the population at risk,

intervention strategies, and contextual factors shaping prevention and mitigation efforts.

### Systematic search strategies

This systematic review on dengue risk mapping, adhering to PRISMA guidelines (10), focused on literature from the Web of Science (WoS) and Scopus databases, covering the period from January 1970 to December 2022. Search terms, aligned with the PICO question format, included 'risk,' 'vulnerability,' 'hotspot,' 'map,' 'model,' 'dengue,' 'dengue fever,' alongside names of specific Southeast Asian countries and regional entities such as 'ASEAN' and 'Southeast Asia.' These terms were combined using Boolean operators 'OR' and 'AND' to refine search outcomes (see Table I). The initial selection, based on titles and abstracts, was guided by inclusion and exclusion criteria focusing on the relevance of terms like 'dengue,' 'risk,' and 'map.' This was followed by a thorough evaluation to ascertain the suitability of articles for the review. Inclusion criteria encompassed studies that examined dengue risk mapping, early warning systems, or related interventions in Southeast Asia. Exclusion criteria included studies not written in English, studies focusing on other geographical regions, and studies lacking relevance to dengue risk mapping or early warning systems.

**Table I: Summary of constructed search strings for literature search in the database which detailed search strings and keywords used for querying Scopus and Web of Science databases**

Database	Search string
Web of Sciences (WoS)	((TS=(dengue) AND TS=((risk) OR (vulnerab*) OR ("hot spot")))) AND TS=((map) OR (model))) AND TS=((Cambodia) OR (Myanmar) OR ("Vietnam") OR ("Thailand") OR ("Laos") OR ("Indonesia") OR ("Malaysia") OR ("Philippines") OR ("Brunei") OR ("East Timor") OR ("Singapore") OR (ASEAN) OR ("Southeast Asia") OR ("South east Asia"))).
SCOPUS	( TITLE-ABS-KEY-AUTH ( dengue ) ) AND ( TITLE-ABS-KEY-AUTH ( ( risk ) OR ( vulnerab* ) OR ( "hot spot" ) ) ) AND ( TITLE-ABS-KEY-AUTH ( ( map ) OR ( model ) ) ) AND ( TITLE-ABS-KEY-AUTH ( ( cambodia ) OR ( myanmar ) OR ( "Vietnam" ) OR ( "Thailand" ) OR ( "Laos" ) OR ( "Indonesia" ) OR ( "Malaysia" ) OR ( "Philippines" ) OR ( "Brunei" ) OR ( "East Timor" ) OR ( "Singapore" ) OR ( asean ) OR ( "Southeast Asia" ) OR ( "South east Asia" ) ) ) )

Inclusion criteria for study selection encompassed comprehensive texts producing dengue risk maps or reviews that utilized dengue morbidity or mortality data, along with at least one additional predictor variable for model generation. These criteria ensured the inclusion of studies that provided in-depth analyses of dengue risk mapping, incorporating multiple variables to enhance the predictive accuracy of the models. Exclusion criteria were applied to temporal-only dengue risk models, studies focusing solely on international travellers,

and publications such as abstracts, letters, newspaper articles, or expert opinions, unless they constituted comprehensive reviews. Additionally, redundant publications or studies with overlapping data were excluded to ensure the inclusion of unique and relevant studies. Linguistically inaccessible or unavailable full-texts and studies conducted outside Southeast Asia were also excluded to maintain the focus on the region of interest. These criteria were systematically applied during the study selection process to ensure the inclusion of studies meeting the predefined criteria for relevance and quality

**Quality appraisal**

The quality appraisal process employed in this review utilized the Critical Appraisal Skills Program (CASP), renowned for its structured approach in evaluating diverse study designs and enhancing the validity of included studies. Each article underwent a thorough assessment using the CASP framework, which focused on critical aspects such as study design, methodology, data collection, analysis, and reporting. Tailoring the CASP checklists to the specific designs of the included studies allowed for a nuanced appraisal, ensuring that

the evaluation criteria were relevant and appropriate. This systematic application of CASP facilitated the identification of biases, strengths, and limitations, thereby enabling a balanced assessment of each article's contribution to the review. Quality assessment was conducted using a 10-item CASP checklist, where items were scored as '0' (indicating 'NO' or 'CAN'T TELL') or '1' (indicating 'YES'). The overall quality score ranged from '0–3' (indicating low quality), '4–6' (indicating moderate quality), to '7–10' (indicating high quality), providing a comprehensive evaluation of the included studies' quality and reliability.

**RESULTS**

**General characteristic of the selected studies**

In this systematic review, ten citations were selected based on eligibility criteria outlined in Table II. Despite no initial time constraints, the reviewed records (totaling 430) dated from 1997 onwards, with the selected articles published between 2011 and 2021. Notably, half of these publications were from the last five years, indicating a recent surge in research activity in the field area.

**Table II: Characteristic of the selected studies for systematic review which summarizes key details of the selected studies, including authors, publication year, geographical focus, study design, and main objectives.**

ID	Authors	Title	Country	Year	Model	Predictor	Type of risk level & map	Finding
1	Cheong et al.	Assessment of land use factors associated with dengue cases in Malaysia using boosted regression trees	Malaysia	2014	Boosted Regression Tree (BRT)	<u>Environmental</u> 1. Land use	<u>Risk Level</u> 1. Continuous <u>Risk Map</u> 1. Predictive 2. Early warning system	The most important land use factors are human settlements (model importance of 39.2%), followed by water bodies (16.1%), mixed horticulture (8.7%), open land (7.5%) and neglected grassland (6.7%).
2	Jaya et al.	Bayesian Spatial Modeling and Mapping of Dengue Fever: A Case Study of Dengue Fever in the City of Bandung, Indonesia	Indonesia	2016	1. Spatially Varying Coefficient (SVC) 2. Integrated Nested Laplace approximation methods (INLA)	<u>Environmental</u> 1. Healthy housing index <u>Meteorological</u> 1. Rainfall <u>Population</u> 1. Population density <u>Entomology</u> 1. Larval-free home index	<u>Risk Level</u> 1. Categorical risk <u>Risk Map</u> 1. Predictive	The research shows that the percentage of larva-free home index became the dominant effect on the relative risk and it is almost constant over region
3	Hnusuwan et al.	Dengue Risk Mapping from Geospatial Data Using GIS and Data Mining Techniques	Thailand	2020	1. Random Forest (RF) 2. J48 3. Random Tree (RT)	<u>Environmental</u> 1. Land use 2. Land cover 3. Elevation <u>Meteorological</u> 1. Rainfall 2. Temperature 3. Humidity	<u>Risk Level</u> 1. Categorical risk <u>Risk Map</u> 1. Predictive	The Random Forest model is the appropriate since the accuracy of the data is 96.7 percent followed by J48 with accuracy of 95.9 percent. The final sequence is Random Tree with accuracy of 93.5 percent.

CONTINUE

**Table II: Characteristic of the selected studies for systematic review which summarizes key details of the selected studies, including authors, publication year, geographical focus, study design, and main objectives. (CONT.)**

ID	Authors	Title	Country	Year	Model	Predictor	Type of risk level & map	Finding
4	Jeefoo et al.	Dengue risk zone index (DRZI) for mapping dengue risk areas	Thailand	2011	Analytical Hierarchy Process (AHP)	<p><b>Environmental</b></p> <ol style="list-style-type: none"> <li>Land use</li> <li>Elevation</li> </ol> <p><b>Meteorological</b></p> <ol style="list-style-type: none"> <li>Rainfall</li> </ol> <p><b>Population</b></p> <ol style="list-style-type: none"> <li>Population</li> </ol>	<p><b>Risk Level</b></p> <ol style="list-style-type: none"> <li>Categorical</li> </ol> <p><b>Risk Map</b></p> <ol style="list-style-type: none"> <li>Descriptive</li> </ol>	People who live in very high, high and moderately high possess the highest risk of getting dengue infection.
5	Sriklin et al.	Dengue transmission mapping with weather-based predictive model in three southernmost provinces of Thailand	Thailand	2021	<ol style="list-style-type: none"> <li>Poisson Regression (PR)</li> <li>Inversed Distance Weighted (IDW)</li> </ol>	<p><b>Meteorological</b></p> <ol style="list-style-type: none"> <li>Rainfall</li> <li>Rainy days</li> <li>Mean, min and max temperature</li> <li>Relative humidity</li> <li>Air pressure</li> </ol>	<p><b>Risk Level</b></p> <ol style="list-style-type: none"> <li>Categorical risk</li> </ol> <p><b>Risk Map</b></p> <ol style="list-style-type: none"> <li>Predictive</li> </ol>	<p>The air pressure, relative humidity, rainfall, rainy day, and min temperature are the main predictors in Pattani province, while air pressure, rainy day, and max/mean temperature seem to play important roles in the number of dengue cases in Yala and Narathiwat provinces. The goodness-of-fit analyses reveal that the model fits the data reasonably well.”</p> <p>At the significant level of 0.05, the results of logistic regression showed that only 10 out of 16 significant variables in the modeling process. The accuracy of the resulting model is 70.3%. A crucial feature of this study is a risk area map for incidence of DF and DHF in the study area</p>
6	Shafie, A.	Evaluation of the spatial risk factors for high incidence of Dengue Fever and Dengue Hemorrhagic Fever using GIS application	Malaysia	2011	Logistic Regression (LogR)	<p><b>Environmental</b></p> <ol style="list-style-type: none"> <li>Land use</li> </ol> <p><b>Meteorological</b></p> <ol style="list-style-type: none"> <li>Rainfall</li> <li>Temperature</li> </ol> <p><b>Population</b></p> <ol style="list-style-type: none"> <li>Demography</li> </ol>	<p><b>Risk Level</b></p> <ol style="list-style-type: none"> <li>Categorical risk</li> </ol> <p><b>Risk Map</b></p> <ol style="list-style-type: none"> <li>Predictive</li> </ol>	<p>The study suggested that any future population increase will associate with increased dengue fever risk in area which already accommodate this disease environmentally, climate, and socioeconomically.</p>
7	Dom et al.	Integration of GIS-based model with epidemiological data as a tool for dengue surveillance	Malaysia	2017	Kernel Density Estimation (KDE)	<p><b>Meteorological</b></p> <ol style="list-style-type: none"> <li>Min &amp; max temperature</li> <li>Rainfall</li> <li>Relative humidity</li> </ol> <p><b>Entomology</b></p> <ol style="list-style-type: none"> <li>Mosquito density</li> </ol> <p><b>Population</b></p> <ol style="list-style-type: none"> <li>Socio-economic</li> </ol>	<p><b>Risk Level</b></p> <ol style="list-style-type: none"> <li>Categorical risk</li> </ol> <p><b>Risk Map</b></p> <ol style="list-style-type: none"> <li>Predictive</li> </ol>	<p>Risk maps produced by Random Forest have high accuracy. More than 80% of the observed risk ranks fell within the 80% prediction interval. The observed and predicted risk ranks were highly correlated (r 0.86, P &lt;0.01).</p>
8	Ong et al.	Mapping dengue risk in Singapore using Random Forest	Singapore	2018	Random Forest (RF)	<p><b>Environmental</b></p> <ol style="list-style-type: none"> <li>NDVI</li> </ol> <p><b>Population</b></p> <ol style="list-style-type: none"> <li>Population density</li> </ol> <p><b>Entomology</b></p> <ol style="list-style-type: none"> <li>Breeding percentage</li> </ol>	<p><b>Risk Level</b></p> <ol style="list-style-type: none"> <li>Categorical risk</li> </ol> <p><b>Risk Map</b></p> <ol style="list-style-type: none"> <li>Predictive</li> <li>Early Warning System</li> </ol>	<p>Risk maps produced by Random Forest have high accuracy. More than 80% of the observed risk ranks fell within the 80% prediction interval. The observed and predicted risk ranks were highly correlated (r 0.86, P &lt;0.01).</p>

CONTINUE

**Table II: Characteristic of the selected studies for systematic review which summarizes key details of the selected studies, including authors, publication year, geographical focus, study design, and main objectives. (CONT.)**

ID	Authors	Title	Country	Year	Model	Predictor	Type of risk level & map	Finding
9	Chen et al.	Neighborhood level real-time forecasting of dengue cases in tropical urban Singapore	Singapore	2018	LASSO Regression (LR)	<p><b>Environmental</b></p> <ol style="list-style-type: none"> <li>Building age</li> <li>NDVI</li> </ol> <p><b>Meteorological</b></p> <ol style="list-style-type: none"> <li>Temperature</li> <li>Relative humidity</li> </ol> <p><b>Population</b></p> <ol style="list-style-type: none"> <li>Movement pattern</li> </ol>	<p><b>Risk Level</b></p> <ol style="list-style-type: none"> <li>Continuous</li> </ol> <p><b>Risk Map</b></p> <ol style="list-style-type: none"> <li>Predictive</li> </ol>	<p>The average Matthew's correlation coefficient for a classification of the upper risk decile (operational capacity) is similar to the predictive performance at the optimal 30% cut-off. The quality of the spatial predictive algorithm as a classifier shows areas under the curve at all forecast windows being above 0.75 and above 0.80</p>
10	Bett et al.	Spatiotemporal analysis of historical records (2001–2012) on dengue fever in Vietnam and development of a statistical model for forecasting risk	Vietnam	2019	Integrated Nested Laplace approximation methods (INLA)	<p><b>Environmental</b></p> <ol style="list-style-type: none"> <li>Land use</li> <li>Land cover</li> </ol> <p><b>Meteorological</b></p> <ol style="list-style-type: none"> <li>Rainfall</li> <li>Evaporation</li> <li>Temperature</li> <li>Relative humidity</li> <li>Sunshine (hrs)</li> <li>Wind velocity</li> <li>Atmospheric pressure</li> </ol>	<p><b>Level</b></p> <ol style="list-style-type: none"> <li>Continuous</li> </ol> <p><b>Risk Map</b></p> <ol style="list-style-type: none"> <li>Predictive</li> </ol>	<p>The study identified temperature, rainfall, altitude and area under urban settlement as being significant predictors of dengue incidence</p>

The final review focused on studies published between 2011 and 2022. This decision was based on several factors. First, research conducted after 2010 reflects significant advancements in spatial analysis, remote sensing, and machine learning techniques such as Random Forest and INLA, which have greatly enhanced dengue risk prediction. Second, dengue transmission patterns and control strategies have evolved over the past decade, making older studies less applicable to current public health efforts. Additionally, a noticeable surge in research activity between 2017 and 2021 highlights growing efforts to improve data quality, model validation, and climate-related risk assessments. By prioritizing more recent studies, this review ensures its findings remain relevant to modern interventions, such as early warning systems and targeted vector control strategies. The exclusion of pre-2011 studies was necessary to focus on methodologically robust insights that contribute to the advancement of dengue risk mapping and public health decision-making. The analysis categorized the articles into predictors, model types, risk levels, and risk map types, as detailed in Table 2. This categorization facilitated the examination of key characteristics and trends across the selected studies, providing insights into the methodologies and approaches utilized in dengue risk mapping research.

Meteorological factors emerged as the most common predictors, accounting for 37% of the selected studies,

followed by population (32%), environmental (21%), and entomological factors (11%). Among model types, Integrated Nested Laplace Approximation (INLA) and Random Forest models were prominent, each representing 13% of the choices. Categorical risk assessment was the most frequent risk level type, covering 60% of the studies, while continuous risk levels were observed in the remaining 40%. Predictive maps were the most prevalent type of risk map, constituting 75% of the studies, with early warning system maps at 17% and descriptive maps at 8%. These findings highlight the diversity of predictors and methodologies employed in dengue risk mapping research, underscoring the importance of considering various factors in assessing and predicting dengue risk, as in Table III.

**Table III: The list of distinct characteristics from the selected studies which highlights the unique aspects of each study, such as the types of predictors analyzed, data sources, geographical coverage, and outcomes, providing a comparative overview of their contributions to dengue risk mapping**

Characteristics	n	(%)
<b>Predictors</b>		
<i>Environmental</i>	4	21%
<i>Meteorological</i>	7	37%
<i>Population</i>	6	32%
<i>Entomological</i>	2	11%

CONTINUE

**Table III: The list of distinct characteristics from the selected studies which highlights the unique aspects of each study, such as the types of predictors analyzed, data sources, geographical coverage, and outcomes, providing a comparative overview of their contributions to dengue risk mapping. (CONT)**

Characteristics	n	(%)
<b>Model types</b>		
<i>Integrated Nested Laplace approximation methods (INLA)</i>	2	13%
<i>LASSO regression</i>	1	7%
<i>Boosted Regression Trees</i>	1	7%
<i>Random Forest (RF)</i>	2	13%
<i>J48</i>	1	7%
<i>Spatially Varying Coefficient (SVC)</i>	1	7%
<i>Random Tree</i>	1	7%
<i>Kernel Density Estimation (KDE)</i>	1	7%
<i>Logistic regression</i>	1	7%
<i>Inverse distance weighted</i>	1	7%
<i>Poisson regression</i>	1	7%
<i>Analytical Hierarchy Process (AHP)</i>	1	7%
<i>Generalized Linear Mixed Model (GLMM)</i>	1	7%
<b>Type of risk level</b>		
<i>Categorical</i>	6	60%
<i>Continuous</i>	4	40%
<b>Type of risk map</b>		
<i>Descriptive</i>	1	8%
<i>Predictive</i>	9	75%
<i>Early Warning System (EWS)</i>	2	17%

### Type of study model for dengue

All included studies in this review were retrospective in nature, primarily relying on secondary data obtained from health surveillance systems, including dengue case records. These studies utilized a diverse range of determinants for predictive modelling and risk mapping, incorporating environmental, meteorological, demographic, and entomological factors. The temporal coverage of the dengue-related datasets in these studies varied widely, ranging from one to eleven years, with an average and median duration of five years. This retrospective approach enabled researchers to analyse historical data and identify trends and patterns in dengue incidence and risk factors, contributing to a better understanding of the dynamics of dengue transmission and spread.

### Descriptive epidemiology studies

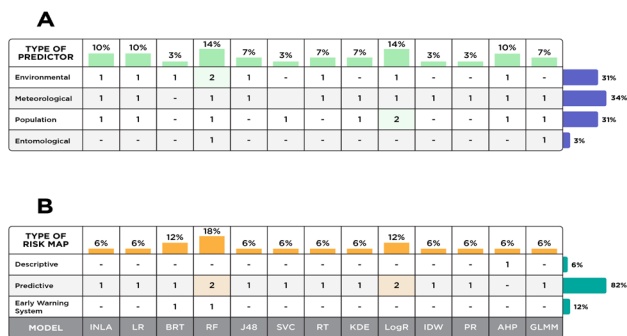
In the analysed studies, descriptive epidemiological approaches were commonly employed, with sixty percent of the studies utilizing population distribution and density as key variables in modelling dengue risk. These data were typically sourced from national censuses, providing valuable information on the spatial

distribution of populations at risk. A unique approach was observed in Singapore (12), where cellular network subscriber movement patterns were utilized to assess neighbourhood connectivity. This innovative method allowed researchers to establish a 'connectivity-weighted transmission potential,' providing insights into the risk of dengue spread between areas based on human movement patterns. Additionally, demographic factors such as age and gender, as well as housing characteristics like building age, were considered in studies in Singapore and Subang, Malaysia (12,13). Population density emerged as a common variable in several studies (13, 14, 15, 16, 17, 18), consistently linked to increased dengue risk across different geographical contexts. These findings underscore the importance of considering demographic and environmental factors in understanding and predicting dengue transmission dynamics.

### Analytical Epidemiology Studies

#### i. Agent based modelling

Meteorological factors emerged as pivotal elements in the development of dengue fever transmission models, with 60% of the reviewed studies incorporating them. Notably, rainfall consistently surfaced as a primary climatic predictor across multiple studies (13,14,18, 19,20), while relative humidity also played a significant role (12,13,18,20). These variables were instrumental in delineating spatial and temporal patterns of dengue risk. Additionally, mean temperature, minimum and maximum temperature, the number of rainy days, and air pressure were identified as important climatic predictors in several studies (12,13,19,20). Overall, meteorological factors were recognized as key influencers in 34% of the analysed models, underscoring their significance in dengue transmission risk assessment (Fig. 2). Environmental variables played a crucial role in understanding the conditions conducive to vector survival and circulation. These factors, including land use, elevation, vegetation, and surface water indicators such as the Normalized Difference Vegetation Index (NDVI), were incorporated into seven out of ten studies. Residential data emerged as a common predictive element, featured in multiple studies (14,15,17,19), alongside forested areas and water bodies, which were considered in three studies each (14,15,18). NDVI, indicative of potential breeding habitats, was utilized in two studies (12,17). Fig. 2 illustrates that 30% of the reviewed models incorporated environmental predictors, with exceptions noted in the studies by Dom et al. (2017) and Sriklin et al. (2021). Notably, the Random Forest model was utilized in 14% of the models, as demonstrated in studies by Ong et al. (2018) and Hnusuwan et al. (2020).



**Fig.2: Predictors relationship with modelling integration which outlines the key predictors (environmental, meteorological, demographic, and entomological) used in dengue risk models, showing how they are integrated into different modelling approaches and their relative influence on prediction accuracy.**

Entomological factors are critical for dengue fever forecasting and mapping, yet they were the least utilized predictors, featured in only 3% of the analysed models. Noteworthy studies by Jaya et al. (2016) in Bandung, Indonesia, and Ong et al. (2018) in Singapore highlighted the significance of entomological data. Jaya et al. found a significant association between the

larva-free index and dengue risk in southwest Bandung, while Ong et al. focused on the breeding percentage (BP) of key mosquito species in Singapore. Despite their importance, entomological predictors were infrequently integrated, with Random Forest and Generalized Linear Mixed Models (GLMM) being applied in these cases.

Population-based predictors emerged as the second most prevalent category, included in approximately 31% of the models (Fig. 2). Logistic regression was the most common statistical method employed with population-based predictors, prominently featured in two relevant studies. This underscores the significance of population dynamics alongside environmental factors in dengue risk modelling.

ii. Spatial temporal modelling

Diverse spatial-temporal modelling techniques were employed for dengue risk mapping, with many studies adopting a combination of methodologies (Table IV). These models integrated reported dengue cases with environmental, meteorological, population, and entomological predictors to assess dengue likelihood in specific geographical areas.

**Table IV: Overview of modelling approach in the systematic review which presents a comprehensive summary of the different modelling approaches (e.g., spatial, temporal, spatiotemporal, machine learning) applied in the studies.**

ID/Type of methods	1	2	3	4	5	6	7	8	9	10	Total
<b>Type of spatial model</b>											
<i>Spatial analysis of case</i>	√	√	√	√	√	√	√	√	√	√	10
<i>Spatial autocorrelation</i>	√	√			√		√		√	√	6
<i>Integrated Nested Laplace approximation methods (INLA)</i>		√								√	2
<i>LASSO regression</i>									√		1
<i>Boosted Regression Trees</i>	√										1
<i>Random Forest (RF)</i>			√					√			2
<i>J48</i>			√								1
<i>Spatially Varying Coefficient (SVC)</i>		√									1
<i>Random Tree</i>			√								1
<i>Kernel Density Estimation</i>							√				1
<i>Logistic regression</i>						√					1
<i>Inverse distance weighted</i>					√						1
<i>Poisson regression</i>					√						1
<i>Analytical Hierarchy Process</i>				√							1
<i>Generalized Linear Mixed Model (GLMM)</i>		√									1
<b>Type of risk level</b>											
<i>Categorical risk level</i>		√	√	√	√		√	√			6
<i>Continuous risk level</i>	√					√			√	√	4
<b>Type of maps</b>											
<i>Descriptive</i>				√							1
<i>Predictive maps</i>	√	√	√		√	√	√	√	√	√	9
<i>Early Warning System</i>	√							√			2

A fundamental distinction existed between models and indices: while models applied variables separately, indices utilized composite scores derived from the dataset. Spatial analysis, encompassing cluster detection and spatial autocorrelation, emerged as a prevalent approach. Cluster detection facilitated the identification of areas with high concentrations of dengue cases, offering valuable insights into localized outbreaks. Concurrently, spatial autocorrelation quantified the likelihood of correlation between proximate observations, providing crucial information about the spatial distribution of dengue risk across the study area. Various modelling methods and techniques were employed across the reviewed studies to predict dengue risk and prevalence. Integrated Nested Laplace Approximation (INLA) was utilized in studies by Bett et al. (2019) and Jaya et al. (2016), providing a sophisticated Bayesian framework for spatial analysis. Logistic regression, a traditional yet robust method, was applied in research by Shafie (2011) and Dom et al. (2017), offering insights into the relationship between predictor variables and dengue outcomes. Innovative approaches were also observed, such as the use of Lasso regression by Chen et al. (2018) in Singapore to identify key predictive factors for dengue outbreaks. Boosted Regression Trees (BRT), as employed by Cheong et al. (2014), facilitated the analysis of complex variable relationships, enhancing predictive accuracy.

Additionally, machine learning algorithms like Random Forest models were selected in studies by Ong et al. (2018) and Hnusuwan et al. (2020), providing flexibility and robustness in handling large datasets. Decision tree algorithms, such as J48, were implemented in risk prediction models, with Hnusuwan et al. (2020) employing it alongside Generalized Linear Mixed Models (GLMM) and Spatially Varying Coefficient (SVC) for risk mapping in Thailand. Less frequently utilized methods, including Random Tree and Kernel Density Estimation, also contributed to the diverse landscape of modelling techniques employed in dengue research. Risk levels were commonly represented on a scale from zero to one, with some studies categorizing risk into various levels to aid in interpretation and decision-making.

**Assessment between model types and the alignment of their objectives with the outcomes observed within the studies**

The analysis of selected articles, as depicted in Fig. 3, identifies six primary research objectives and ten distinct outcomes across the studies. The development of dengue risk maps emerged as the most common objective, accounting for 25% of the models. Notably, Integrated Nested Laplace Approximation (INLA) and Random Forest models were predominantly employed for this purpose, showcasing their versatility and effectiveness

in risk mapping. Spatiotemporal autocorrelation was the focus of 22% of the models, also dominated by INLA and Random Forest methods, while approaches like KDE and Logistic Regression were excluded. This finding underscores the growing preference for advanced statistical and machine learning methods in capturing spatial and temporal dependencies in dengue data. Methodological development constituted 18% of the objectives, where INLA emerged as the most frequently used method. However, alternative techniques such as AHP, J48, and Random Tree were notably absent, suggesting potential areas for methodological diversification. For dengue prediction and policy-oriented risk interventions, accounting for 13% of the models, methods like INLA, LASSO Regression, and Poisson Regression were employed, reflecting their applicability in predictive analytics and informing public health strategies. Dengue outbreak detection accounted for 8% of the objectives, with INLA, LASSO Regression, and Poisson Regression being the primary methods utilized, highlighting their effectiveness in identifying outbreak dynamics.

TYPE OF MODELS	OBJECTIVES						FINDINGS									
	O1	O2	O3	O4	O5	O6	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
INLA	2	1	2	1	1	2	1	1	2	2	1	2	2	1	1	2
LASSO Regression	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Random Forest	2	1	2			1	1		2	1		2	2	2	2	2
KDE	1	1		1	1	1	1		1	1		1	1	1	1	1
Logistic Regression	1	1	1	1			1	1				1	1	1		1
IDW	1	1	1	1	1	1	1		1	1		1	1	1		1
Poisson Regression	1	1	1	1	1	1	1		1	1		1	1	1		1
AHP	1		1	1					1	1		1	1			
J48	1		1						1			1	1	1	1	1
Random Tree	1		1						1			1	1	1	1	1
SVC	1		1			1			1	1		1	1			1
GLMM	1		1			1			1	1		1	1			1
BRT	1	1	1	1		1			1			1	1	1	1	1

**Fig.3: Model types and the alignment between the studies objectives and findings which categorizes the various model types (e.g., statistical, machine learning, and hybrid models) employed in the selected studies and analyzes how well these models align with the research objectives and their reported findings.**

Regarding study outcomes, the focus was primarily on geospatial mapping, identifying significant predictors, and generating risk indicators, each representing 15% of the total objectives. INLA and Random Forest models consistently outperformed others in these areas, further reinforcing their dominance in dengue risk modelling. Importantly, all models, except LASSO Regression, successfully produced dengue risk maps, with INLA and Random Forest remaining the most prevalent methods.

For constructing dengue prediction models, which represented 11% of the objectives, a variety of methodologies were employed. However, Random Forest was the most frequently used method, whereas techniques like J48, SVC, and GLMM were notably

underutilized, indicating potential for exploration in future studies.

## DISCUSSION

Our analysis reaffirms the central role of environmental variables, such as land use, elevation, Normalized Difference Vegetation Index (NDVI), and altitude, in assessing dengue risk. These factors consistently emerge as significant predictors across multiple studies, highlighting their potential to guide targeted interventions by identifying high-risk areas. This aligns with existing research that emphasizes the ecological determinants of dengue transmission (21, 22, 23). However, limited availability of environmental data in some studies raises concerns about model comprehensiveness. To enhance public health strategies, future research should prioritize integrating diverse environmental factors to improve model precision and inform interventions such as strategic larval control and urban planning.

Residential factors, particularly those influencing human-mosquito interactions, have been extensively studied in dengue research (24,25). While the use of NDVI to identify potential vector habitats is commendable (26), the underrepresentation of water bodies in certain models represents a critical gap. Water bodies serve as key breeding sites for *Aedes* mosquitoes, and their inclusion in risk models can refine intervention strategies, such as larvicide application in water storage areas or community-led efforts to eliminate standing water.

Our findings underscore the utility of remote sensing techniques for acquiring environmental data over large geographical areas. These technologies enable continuous monitoring of environmental changes, essential for dynamic dengue risk mapping (27). Public health programs could harness remote sensing tools to design adaptable control strategies, ensuring rapid responses to shifting risk patterns. Moving forward, interdisciplinary collaboration among epidemiologists, entomologists, and environmental scientists will be pivotal in integrating environmental and anthropogenic factors into robust risk models.

The integration of meteorological variables in dengue risk models, such as precipitation, humidity, and temperature, highlights their importance in shaping dengue transmission dynamics (12,14,19). Rainfall and relative humidity influence mosquito habitats and survival, while temperature accelerates virus incubation, mosquito biting rates, and lifespan (28, 29, 30). These findings have direct implications for public health strategies, such as aligning vector control efforts with weather forecasts or deploying early warning systems during high-risk climatic conditions.

Dengue transmission is shaped by a complex interplay

of factors, including vector control initiatives, population density, and socio-economic conditions (31, 32, 33). While meteorological predictors enhance risk assessments, public health strategies must adopt a comprehensive approach, incorporating urbanization trends and socio-behavioural dynamics. For example, predictive models could inform targeted resource allocation in densely populated or socio-economically vulnerable areas to improve the efficacy of vector control and outbreak response measures.

Demographic factors, such as age, gender, and housing characteristics, add valuable context to dengue prediction models (13,34). However, the urban-centric focus of most studies limits their applicability in rural settings, where transmission dynamics may differ. Expanding research to balance urban and rural contexts will improve the generalizability of findings and help tailor interventions to diverse populations. For instance, community-based awareness campaigns in rural areas could complement predictive mapping to mitigate dengue risk effectively.

Entomological factors remain underrepresented in many studies, yet their inclusion is vital for refining predictive models. Metrics such as breeding percentage (BP) provide actionable insights into transmission dynamics, enabling more targeted control strategies, such as focusing on high-breeding zones for intensive interventions. Incorporating entomological data into predictive tools could bridge critical gaps in current public health approaches.

Finally, diverse spatial analysis methodologies, including statistical and machine learning approaches, have proven invaluable in uncovering dengue risk patterns and informing interventions (35,36). Predictive maps and early warning systems facilitate timely outbreak detection, enabling health authorities to act pre-emptively. For instance, deploying risk maps in conjunction with public health campaigns could guide door-to-door mosquito control efforts or optimize resource distribution during outbreaks. Moving forward, leveraging these methodologies through interdisciplinary collaboration will not only advance our understanding of dengue epidemiology but also enhance the real-world applicability of public health responses.

### Major gaps

While this review provides valuable insights into various aspects of dengue risk mapping, it is essential to acknowledge several inherent limitations that require careful consideration in interpreting the findings and charting future research directions.

A significant limitation lies in the reliance on secondary data sources, which may introduce biases and inaccuracies due to variations in data collection methodologies, as well as disparities in spatial and

temporal resolutions. These limitations can compromise the reliability and robustness of dengue risk assessments derived from such data. Furthermore, the concentration of many studies on specific geographical areas presents a challenge to the broader applicability of their findings. This focus often overlooks long-term trends in dengue transmission, hindering our understanding of the disease's evolution on a larger scale. It is imperative to broaden the geographic scope of research efforts to capture the diversity of dengue transmission dynamics across different regions.

Moreover, the methodologies and assumptions underpinning dengue risk models play a crucial role in the accuracy of predictions. However, the application of these models across diverse regions without appropriate adjustments may fail to account for the unique dengue transmission patterns inherent to each area. Future research should aim to develop more adaptable and context-specific modelling approaches to improve the reliability of predictions.

Another notable gap is the tendency of some studies to focus solely on linear correlations between risk factors and dengue incidence, overlooking the complex, non-linear interactions that may exist. Understanding these intricate relationships is essential for accurately assessing dengue risk and guiding effective intervention strategies. Furthermore, there is a need to shift focus from solely predicting risk to addressing the practical implications of these predictions in formulating dengue control and prevention strategies. Bridging the gap between theoretical risk assessment and practical application is crucial for translating research findings into actionable measures that can mitigate the burden of dengue on affected communities.

## CONCLUSION

This systematic review of ten studies published between 2011-2022 reveals several key findings about dengue risk mapping approaches. Environmental and meteorological factors emerged as the predominant predictors in dengue risk models, accounting for 37% and 32% of the analysed studies respectively. The review identified that predictive maps were the most common type of risk visualization (75%), followed by early warning systems (17%).

The analysis demonstrated that advanced modelling techniques, particularly Integrated Nested Laplace Approximation (INLA) and Random Forest models (each 13%), have become increasingly important in dengue risk assessment. These methods showed superior performance in capturing complex spatial-temporal patterns of dengue transmission compared to traditional approaches. A significant finding was the underutilization of entomological factors in risk modeling, appearing in only 11% of studies despite

their known importance in dengue transmission. This highlights a critical gap between theoretical knowledge and practical application in current risk mapping approaches.

The review also revealed a recent surge in research activity, with 50% of the selected publications emerging in the last five years, indicating growing recognition of the importance of risk mapping in dengue prevention and control. However, the predominant focus on urban areas and reliance on secondary data sources suggests limitations in the current understanding of dengue transmission dynamics in rural and resource-limited settings.

These findings contribute to the evolving field of dengue epidemiology by synthesizing current methodological approaches and identifying critical areas for improvement in risk mapping strategies. The results underscore both the progress made in dengue risk assessment and the remaining challenges in developing comprehensive, reliable prediction models.

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