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REVIEW ARTICLE

Climate-Driven Dengue Modelling in Southeast Asia: A Scoping Review for Public Health Application

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ABSTRACT

Introduction	Dengue remains a major public health threat in Southeast Asia, with climate factors playing a significant role in its transmission. Climate-driven dengue modelling offers a valuable tool for outbreak forecasting and risk assessment. However, methodological rigour, predictive accuracy, and applicability vary across studies. This review aimed to map climate-driven dengue modelling approaches in Southeast Asia and evaluate their public health applicability.
Methods	A scoping review was conducted in accordance with the JBI framework and PRISMA-ScR guidelines. Studies focusing on climate-driven dengue prediction models were identified from PubMed, Scopus, and Web of Science. A total of 20 studies (N = 20) met the eligibility criteria. Eligible studies included those conducted in Southeast Asia that incorporated at least one climatic predictor into a dengue model and were published in English. Data extraction included model types, predictors, and model performance.
Results	The studies were included and categorized into four themes, Short-Term Forecasting, Long-Term Forecasting, Risk Mapping, and Climate–Transmission Simulation Models. Temperature, rainfall, and humidity were the most used climatic variables. Short-term models demonstrated high predictive accuracy (80%–95%). Long-term and simulation models offered insights into seasonal dynamics and intervention scenarios. Risk mapping enhanced spatial targeting, particularly when integrating land-use or mobility data. Across all themes, reliance on internal validation and inconsistent performance reporting limited generalisability.
Conclusions	These models showed significant potential to improve surveillance and outbreak preparedness in Southeast Asia. Strengthening external validation, integrating socio-environmental predictors, and fostering regional collaboration through platforms such as the ASEAN Centre for Public Health Emergencies and Emerging Diseases (ACPHEED) are essential to scaling model use for public health decision-making.
Keywords	Dengue Modelling; Climate; Public Health Application; Southeast Asia; Early Warning Systems; Long-Term Forecasting; Risk Mapping; Simulation Models

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INTRODUCTION

Dengue fever is a significant public health concern in Southeast Asia. In 2023 alone, more than 6.5 million infections were reported globally, resulting in 6,800 deaths. Southeast Asian countries, including Indonesia, the Philippines, Thailand, and Malaysia, accounted for a significant proportion of these cases.[1] Malaysia reported nearly 130,000 dengue cases in 2023, marking a 60% increase compared to the previous year.[2] This persistent and escalating burden underscores the urgent need for effective surveillance and prediction tools to guide timely intervention.

Climatic factors, including temperature, rainfall, and humidity, play a crucial role in shaping the dynamics of dengue transmission. These variables affect mosquito breeding, survival, and viral replication within the vector. Higher temperatures can accelerate virus replication, while rainfall increases the availability of breeding sites; however, excessive rain may disrupt mosquito habitats due to flooding.[3,4] Humidity levels above 60% are conducive to mosquito longevity, thereby extending the transmission window.[5] As Southeast Asia faces increasing climate variability, predictive modelling has gained prominence as a tool to anticipate dengue outbreaks and inform proactive public health interventions.

Climate-driven dengue prediction models, which incorporate climatic and environmental parameters into algorithmic or statistical frameworks, have demonstrated promising potential in outbreak forecasting. These models utilise a range of statistical, spatial, machine learning, and hybrid approaches, demonstrating predictive accuracies of up to 95% in some settings.[6] Their applications include early warning systems, risk mapping, forecasting, and optimising response strategies.[7] Despite the growing number of such models, few reviews have systematically mapped their climatic predictors, methodological strengths, and real-world public health utility in the Southeast Asia context. Moreover, the limited use of structured appraisal frameworks has made it difficult to assess the quality and consistency of reported findings.

This scoping review addresses that gap by mapping the current landscape of these models in Southeast Asia. It also aims to evaluate their strengths, limitations, and practical applications in public health settings. By providing a comprehensive synthesis, this review will guide future research, enhance model validation, and support integration of predictive tools into dengue surveillance systems across the ASEAN region.

METHODS

Study Design

This scoping review was conducted in accordance with the Joanna Briggs Institute (JBI) methodology for scoping reviews, structured around the Population, Concept, and Context (PCC) framework.[8] The reporting follows the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Reviews) checklists to ensure transparency and completeness.

To assess methodological quality, the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) checklist was used to evaluate model development, validation, and performance.[10] For studies involving clustered or hierarchical data, the TRIPOD-Cluster extension was applied. These tools helped identify strengths, such as innovative modelling and high accuracy, as well as limitations, including the lack of validation tests.[11]

Eligibility Criteria

The eligibility criteria for this review were determined using the JBI PCC framework. The population includes studies examining dengue transmission, incidence, outbreaks, or dengue-related risk in human populations. The concept focused on incorporating climate-driven predictors, such as temperature, rainfall, and humidity, or environmental data, into any form of dengue modelling approach.[12] The context includes studies conducted in Southeast Asia (Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, Vietnam).[13] Studies were eligible for inclusion if they incorporated at least one climatic variable into a dengue modelling framework, were published in English, and focused on any of the eleven Southeast Asian countries.

Search Strategy

A comprehensive literature search was conducted on 30th November 2024 using PubMed, Scopus, and Web of Science to retrieve published articles from their inception until the search date. These three databases were selected because they are widely recognised and commonly used in academic research. Keywords used included dengue, prediction model, climate, temperature, humidity, and environmental data. Boolean operators and MeSH terms were applied where applicable. Although the search strategy included broad modelling-related terms (e.g., prediction models, forecasting, GIS), additional relevant modelling approaches such as spatiotemporal analysis, risk mapping, and simulation models were also captured during screening because they incorporated climatic predictors and met the PCC eligibility criteria. All identified articles were screened independently by two reviewers in two stages. The whole search equation for each database is presented in Supplementary Table 1.

Source of Evidence Selection
Following the search, Rayyan software was utilized to compile and organise the bibliography and eliminate duplicate references. Two reviewers independently reviewed titles and abstracts to evaluate and select evidence, using the inclusion criteria to select potential studies. Then they examined the full text of the studies. Any disagreements between the two reviewers were settled by consensus.

Data Charting
Two reviewers independently extracted the data from the articles using a standardised form that captured the information in the selected studies, following the JBI guidelines and the template. According to the review questions, the initial template was designed to include information about the population, concept, context, methodology, type of modelling, and results. Any disagreement about 10% or more of the extraction process was resolved by consensus. The complete data extraction form included the following key elements: author and year, location of study, objectives, study design, model type, climatic predictors, outcome measures, results of climatic predictors, performance, findings, strengths, and limitations for each model.

Data Synthesis
Extracted data were synthesised thematically based on four primary public health application domains. *Short-term forecasting* included models developed for early warning systems. *Long-Term Forecasting* comprises models that predict seasonal or annual dengue trends. *Risk Mapping* refers to spatial visualisations highlighting areas with elevated dengue vulnerability. Finally, *Climate-Transmission Simulation Models* integrate climatic and transmission dynamics to simulate dengue incidence under different scenarios, supporting public health planning.

Each study was analysed to identify shared climatic predictors (e.g., temperature range 25-35°C, rainfall lag 2-4 months), model type, and performance metrics (e.g., accuracy, sensitivity, AUC). Findings were synthesised through narrative analysis, supported by tabulated summaries that highlighted patterns, methodological gaps, and model applicability for public-health practice.

Bias and Limitations
Potential publication bias was acknowledged, as studies with negative or non-significant model outcomes may be underrepresented in indexed databases. Selection bias may also exist due to language restrictions and database choice. These limitations were mitigated by utilising multiple databases, conducting independent screening, and employing transparent inclusion criteria.

RESULTS

A total of 20 articles were included in this scoping review after screening against the eligibility criteria outlined in Figure 1. The studies were conducted across Southeast Asia, with the majority focused in Malaysia (14 studies), followed by Indonesia (3 studies), Singapore (2 studies), and Vietnam (1 study). These studies employed various modelling approaches, including statistical models, machine learning techniques, spatial models, and hybrid models, to predict dengue outbreaks (Supplementary Table 2-3)

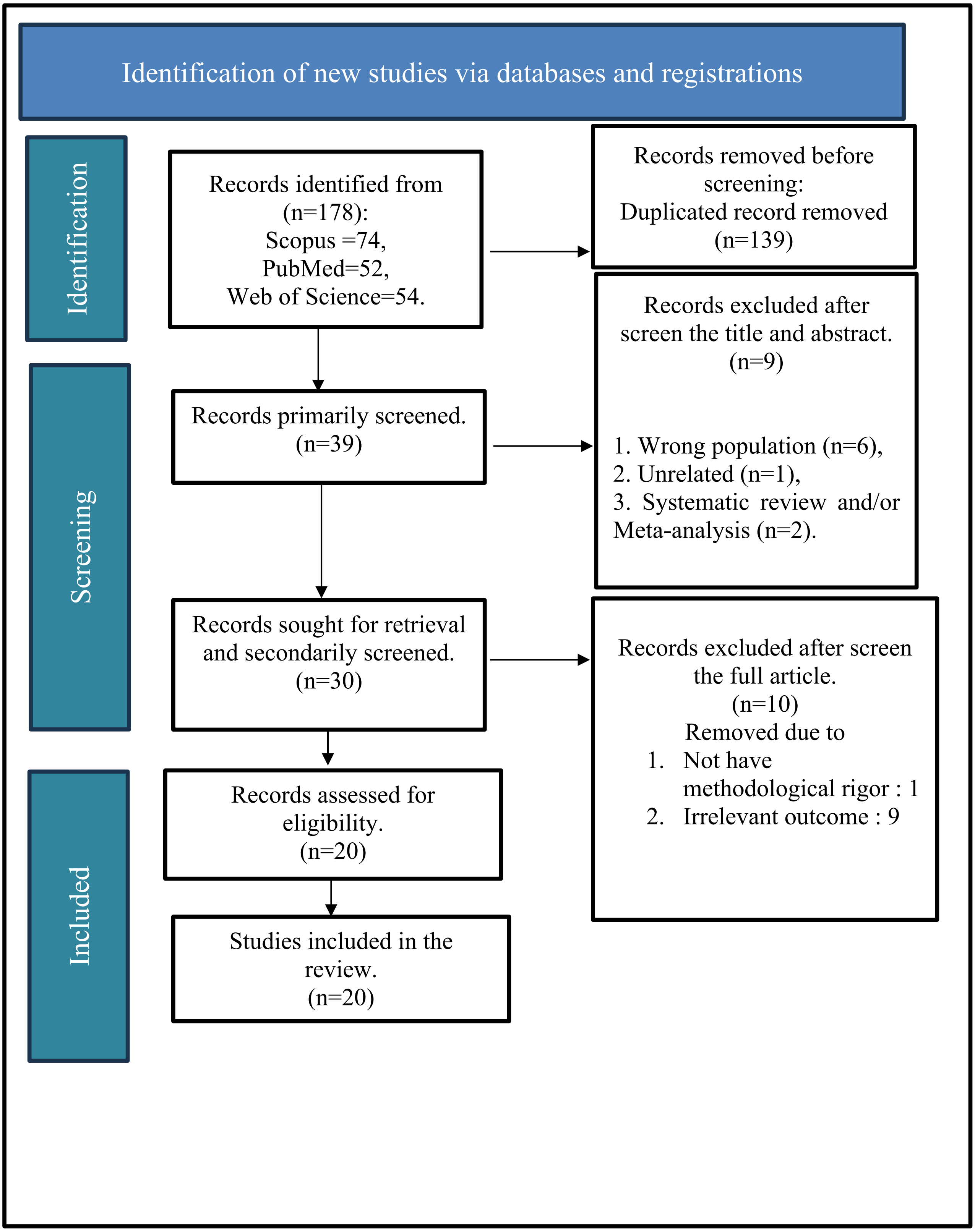

Figure 1 PRISMA flow diagram illustrating the searching and selection process.

TRIPOD and TRIPOD-CLUSTER Appraisal

The TRIPOD appraisal demonstrated adherence ranging from 86% to 100% across the studies (Supplementary Table 4). High adherence was observed in studies, such as Lu et al,[33] with 100% adherence. Among the studies, 90% (18 studies) defined predictors, specified models, and reported statistical methods and model performance metrics. However, 50% failed to address missing data, and 40% lacked details on supplementary materials. For TRIPOD-Cluster, adherence ranged from 85% to 96%, with six studies having the highest scores (Supplementary Table 5). Most studies clearly defined clusters and predictors reported statistical analysis methods, and model development. Limitations included insufficient reporting of cluster sample sizes and external validation in the studies, as well as inadequate handling of missing data in all 10 studies.

Overall, strong adherence was observed in defining predictors, statistical methods, and model performance. Gaps were present, as many studies did not effectively handle missing data and lacked external validation, highlighting areas for improvement.

Overview of Included Studies

The models were grouped into four primary themes based on their public health applications: Short-Term Forecasting, Long-Term Forecasting, Risk Mapping, and Climate-Transmission Simulation Models (Supplementary Table 2-3).

Short-Term Forecasting (Early Warning Systems)

Six studies focused on models that predict dengue within one to four weeks, thereby supporting the development of early warning systems.[14–19] The most accurate approaches used machine learning, with one study reporting 92% accuracy using a customised climate index[17] and another achieving 95% accuracy using an IoT-based Random Forest Model.[15] Models integrating mobility data also demonstrated strong performance, with accuracy reaching 93.5% in some cases.[16] In general, accuracies above 80% suggest these models are reliable for short-term outbreak detection. However, most studies relied only on internal validation and required complex computations, which may make routine implementation challenging.[14–19]

Long-Term and Seasonal Forecasting

Five studies projected dengue trends over months or across monsoon seasons.[20–24] Early statistical approaches, as reported in 2008, utilised multiple linear regression to forecast up to six months and identified relative humidity as the only significant climatic predictor.[20] Another study employed autoregressive methods combined with climate variables to capture seasonal variation and lag effects, highlighting minimum temperature and high rainfall as predictive factors.[21] More recent approaches applied advanced deep learning techniques such as attention-based long short-term memory (LSTM) models that effectively captured spatial and temporal dependencies in dengue trends.[23,24] These models demonstrated good predictive accuracy, with RMSE values around 3.0, indicating minimal deviation between predicted and observed case counts. A similar model, based on a generalised additive framework, also showed climate-driven variability in dengue incidence, albeit with modest explanatory power.[22] However, these models tended to be data- and computation-intensive. Furthermore, most were not tested beyond the original dataset, limiting their use for policy planning across different regions.[20–24]

Risk Mapping

Six studies used spatial modelling to identify high-risk areas.[25–30] Early GIS-based models that relied solely on climate variables reported limited predictive value.[25,27] However, when climatic data were combined with environmental, demographic, or mobility factors, performance improved significantly.[29,30] For example, one study using hierarchical Bayesian spatial modelling achieved prediction accuracy of up to 90%,[29] while another found that incorporating human mobility data enhanced village-level dengue cluster prediction.[30] Overall, these risk mapping studies effectively identified hotspots and informed targeted interventions; however, many studies did not report formal model accuracy, and external validation was generally lacking.[25–30]

Climate-Transmission Simulation Models

Three studies used hybrid climate–transmission models to simulate dengue incidence under varying climatic scenarios.[31–33] Two studies applied coupled statistical and mechanistic frameworks, achieving approximately 90% accuracy for short-term forecasts, while enabling the simulation of transmission dynamics under different climatic conditions.[31,32] These models are valuable for scenario-based public health planning but require extensive data and technical expertise. Another study proposed a district-level clustering model using rainfall and clustering methods; however, the absence of reported accuracy metrics limits confidence in its predictive reliability.[33]

Across all categories, temperature and rainfall were the most used climatic predictors. Short-term models offered predictive performance, while long-term and risk mapping models offered valuable insights into planning and targeted interventions. Risk mapping and simulation studies increasingly integrate mobility and land-use data to improve spatial precision.

DISCUSSION

This scoping review identified four major functional applications of climate-driven dengue models in Southeast Asia. While climatic factors such as temperature, rainfall, and humidity were used across all model types, their predictive significance varied by geographical and technical context.

Short-term forecasting models, particularly those using machine learning, demonstrated effective learning and practical value in early outbreak detection. With accuracies frequently exceeding 80% to 90%, these models enable health authorities to anticipate outbreaks with reasonable confidence.[34] For example, a model with 90% accuracy would correctly forecast dengue incidence nine out of ten times, which is highly valuable for initiating timely vector control activities.[16,17] However, in decision-making contexts, precision must be balanced with sensitivity to false negatives, given the potential public health consequences of missing early signals of an outbreak.[35]

Long-term and seasonal models contribute meaningfully to strategic planning by capturing climate-driven trends and inter-seasonal patterns.[36] Yet, their computational demands and limited external testing reduce their immediate utility for routine surveillance, particularly in resource-constrained settings.[37] Risk mapping models, especially those integrating mobility or demographic data, provide spatially explicit insights that can guide targeted interventions.[38] However, inconsistent performance reporting limits comparison across studies and reduces utility for public health policy makers.[26,28,29]

Simulation models offer a powerful tool for scenario-based planning, particularly under conditions of climatic uncertainty.[39] By combining deterministic transmission models with climate forecasts,[40] these hybrid approaches enable policymakers to test the impact of interventions under future environmental conditions. These innovations are especially relevant in the context of climate change, where shifting disease transmission dynamics necessitate adaptable predictive tools.

Implications for Public Health Practice and Policy

Climate-based models have clear potential to enhance surveillance and decision-making in Southeast Asia. Nonetheless, real-world uptake remains limited due to model complexity, data dependency, and insufficient external validation. Regional collaboration is crucial to addressing these challenges. The ASEAN Centre for Public Health Emergencies and Emerging Diseases (ACPHEED) offers an existing platform for integrating climate-based early warning systems into cross-border surveillance frameworks.[41] Embedding such models within ACPHEED's operational structure would enhance regional preparedness and resilience, particularly in climate-sensitive and highly mobile border regions.

Strengths and Limitations

This review highlights considerable innovation in climate-based dengue modelling, including the integration of advanced machine learning techniques and multiple datasets. However, most models were tested only within their development dataset and lacked external validation, which limited comparisons across different contexts.[26,29,33] Inconsistent reporting of performance metrics and the absence of standardised benchmarks further hindered model evaluation.[18] The limited integration of socio-environmental and vector data also reduces practical applicability.[19] These gaps underscore the need for more comprehensive, externally validated, and operationally feasible modelling approaches.

Recommendation

Future research should focus on developing operationally feasible models that can be integrated into existing surveillance systems, especially in low and middle-income country settings in ASEAN. External validation across different regions and seasons is crucial for improving reliability. Expanding datasets to include non-climatic factors such as vector indices, urbanisation patterns, and mobility data may enhance model performance.[42] Regional efforts to harmonise modelling standards, share data, and build technical capacity under initiatives such as those by ACPHEED will be critical to advancing climate-based dengue modelling approaches.

CONCLUSION

Climate-based dengue prediction models have demonstrated significant potential to enhance surveillance, early warning, and targeted control efforts across Southeast Asia. Short-term forecasting models, with reported accuracy ranging from 80% to 95%, offer the most promise for real-time outbreak prediction and rapid response. In contrast, risk mapping and simulation approaches provide valuable tools for intervention planning and policy evaluation. To maximise their public health impact, future efforts should focus on improving external validation, simplifying complex modelling frameworks, and strengthening regional collaboration through platforms such as the ASEAN Centre for Public Health Emergencies and Emerging Diseases (ACPHEED) to support the integration of models into routine surveillance practices across ASEAN countries.

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Author's contribution
S.N.A. conceptualised, drafted the manuscript, and designed the study. S.N.A. and M.R.R. conducted the article review and appraisal. N.S. and M.H.J. provided critical revisions, supervised the study of design and implementation. Finally, N.S. approved the final manuscript for submission.

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Ethical approval
This scoping review adhered to ethical principles and guidelines for research synthesis. As it involved the analysis of publicly available data and previously published studies, no ethical approval was required. However, all included studies were assessed for ethical compliance, ensuring they had obtained necessary ethical approvals from their respective institutional review boards (IRBs) or ethics committees. This process ensured the integrity and ethical rigour of the studies synthesised in this review.

Conflict of interest
There is no conflict of interest for this study.

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Supplementary

Table S1 Search Strategy based on Three Databases

SCOPUS	TITLE-ABS-KEY("dengue" OR "dengue fever" OR "Aedes aegypti" OR "Aedes albopictus") AND TITLE-ABS-KEY("prediction model" OR "forecasting" OR "machine learning" OR "statistical model" OR "GIS" OR "climate-driven") AND TITLE-ABS-KEY("climate" OR "temperature" OR "rainfall" OR "humidity" OR "environmental data") AND TITLE-ABS-KEY("Malaysia" OR "Brunei" OR "Cambodia" OR "Indonesia" OR "Laos" OR "Myanmar" OR "Philippines" OR "Singapore" OR "Thailand" OR "Timor-Leste" OR "Vietnam" OR "Southeast Asia ")
PUBMED	(("Dengue" [Mesh] OR "Dengue Fever" [Mesh] OR "Aedes aegypti" [Mesh] OR "Aedes albopictus" [Mesh] OR "dengue" OR "dengue fever" OR "Aedes aegypti" OR "Aedes albopictus")) AND (("Forecasting" [Mesh] OR "Machine Learning" [Mesh] OR "Models, Statistical" [Mesh] OR "Geographic Information Systems" [Mesh] OR "prediction model" OR "forecasting" OR "machine learning" OR "statistical model" OR "GIS" OR "climate-driven")) AND (("Climate" [Mesh] OR "Temperature" [Mesh] OR "Rain" [Mesh] OR "Humidity" [Mesh] OR "Environmental Monitoring" [Mesh] OR "climate" OR "temperature" OR "rainfall" OR "humidity" OR "environmental data")) AND (("Malaysia"[Mesh] OR "Brunei" OR "Cambodia"[Mesh] OR "Indonesia"[Mesh] OR "Laos"[Mesh] OR "Myanmar"[Mesh] OR "Philippines"[Mesh] OR "Singapore"[Mesh] OR "Thailand"[Mesh] OR "Timor-Leste"[Mesh] OR "Vietnam"[Mesh] OR "Southeast Asia"[Mesh]))
WOS	TS=("dengue" OR "dengue fever" OR "Aedes aegypti" OR "Aedes albopictus") AND TS=("prediction model" OR "forecasting" OR "machine learning" OR "statistical model" OR "GIS" OR "climate-driven") AND TS=("climate" OR "temperature" OR "rainfall" OR "humidity" OR "environmental data") AND TS=("Malaysia" OR "Brunei" OR "Cambodia" OR "Indonesia" OR "Laos" OR "Myanmar" OR "Philippines" OR "Singapore" OR "Thailand" OR "Timor-Leste" OR "Vietnam" OR "Southeast Asia ")

Table S2 Characteristics of included studies

Author	Location	Objective	Study Design	Model Type	Climatic Predictors	Outcome Measures
Halide & Ridd[20]	Indonesia	To develop a statistical model for predicting monthly Dengue Haemorrhagic Fever (DHF) cases using climatic and epidemiological data	Retrospective ecological time-series study	Multiple Linear Regression (MLR) with lagged climatic variables	• Temperature • Rainfall • Relative humidity • Niño 3.4 Index	Predicted monthly DHF cases (1-12 months)
Shafie[25]	Malaysia	To develop a spatial model to predict high-risk areas for DF and DHF using environmental and land-use factors	Spatial ecological case-control study	GIS spatial modelling and logistic regression	• Temperature • Rainfall	Spatial risk map for DF/DHF
Dom et al[22]	Malaysia	To develop a temporal model for predicting dengue cases using climate variables	Ecological time-series study	Autoregressive Integrated Moving Average (ARIMA)	• Temperature • Rainfall • Relative humidity	Prediction accuracy using RMSE and significant lag structures
Dom et al[27]	Malaysia	To assess dengue transmission risks using climatic and environmental indicators through remote sensing and GIS	Observational ecological study	GIS and Remote Sensing	• Temperature • Rainfall • Humidity	Environmental association with dengue hotspots: spatial risk distribution
Azid et al[27]	Malaysia	To develop a GIS-based dengue distribution map and determine whether climatic factors were associated with dengue incidence from 2008 to 2011	Ecological time-series study with spatial GIS mapping	Spatial (GIS) with simple linear regression	• Temperature • Rainfall • Relative Humidity	Spatial distribution and correlation coefficients
Risva et al[29]	Indonesia	To assess DHF vulnerability levels based on environmental variables	Cross-sectional ecological study with GIS-based spatial analysis	Spatial (GIS) with weighted factor scoring	Rainfall	DHF vulnerability (low, medium, high)
Koh et al[15]	Singapore	To develop an improved dengue prediction model and assess the usefulness of lagged precipitation data	Time-series study	Machine Learning (AR(2) autoregressive model, Bayesian Neural Network AR model, Poisson regression model)	Rainfall	Prediction accuracy using Mean Squared Error (MSE), Forecast selection accuracy. Correlation analysis

Raja et al[19]	Malaysia	To develop and validate machine learning to predict dengue outbreaks using climatic variables and vector indices	Ecological study	Bayesian Network machine learning model	• Temperature • Rainfall	Prediction accuracy (%) for forecasting Aedes population at 7, 14 and 30 days, used as a proxy for dengue outbreak risk
Bett et al[30]	Vietnam	To develop a spatiotemporal statistical model for forecasting monthly dengue incidence and generating dengue risk maps using climatic and land-cover predictors.	Ecological study	Hierarchical Bayesian spatial model (INLA) with BYM spatial effect and AR(1) temporal autocorrelation	• Temperature, • Rainfall	Theil's coefficient for model validation, prediction accuracy measured by visual fit between observed versus predicted peaks; generation of risk map
Him et al[34]	Malaysia	To develop new hybrid dengue incidence rate (DIR) forecasting models by combining the Negative Binomial Generalised Additive Model (GAM) with Fuzzy C-Means (FCM) and district-level clustering.	Ecological time-series study (Jan 2010–Aug 2015)	Negative Binomial GAM + FCM	Rainfall	Deviance (D) Akaike and Bayesian Information Criteria (AIC, BIC)
Tao et al[17]	Singapore and Malaysia	To develop a sparse space-time autoregressive (SSTAR) model to characterise human connectivity and improve short-term dengue forecasting across interconnected regions.	Ecological time-series analysis using weekly dengue incidence	Sparse Space–Time Autoregressive Model (SSTAR) compared with STAR and AR models	• Temperature • Rainfall • Humidity	Forecast error metrics (1–4 week ahead prediction error); shock-response analysis; comparative performance vs STAR and AR models
Nejad & Varathan[18]	Malaysia	To identify significant climatic risk factors and develop machine learning models for dengue prediction, including a new TempeRain Factor (TRF)	Ecological time-series analysis (2010-2019)	Machine Learning models (Custom Metric)	• Temperature • Rainfall	Prediction accuracy (%) Model comparison metrics such as precision, recall, and F-measure
Masrani et al[23]	Malaysia	To model the relationship between weather variables and dengue incidence using a Generalised Additive Model	Retrospective Ecological time-series study (weekly	Generalised Additive Model (GAM)	• Rainfall • Temperature • Wind Speed	Variability explained R^2

		(GAM) and identify significant climatic risk factors.	data, 2016–2018)			
Yip et al[20]	Malaysia	To develop a Bayesian spatio-temporal early warning system (EWS) incorporating mesoscale and synoptic climatic drivers (including ENSO indices) to detect dengue outbreaks.	Ecological time-series study (weekly data, 2013–2019)	Negative binomial Bayesian spatio-temporal hierarchical models (Poisson, NB, NB + spatial, NB + dynamic, NB + spatial + dynamic)	• Temperature • Rainfall • Ozone • Vertical velocity (omega) • Niño4 (central Pacific warming) • Niño1+2 (coastal South America SST)	• Weekly dengue hospital admissions • Prediction accuracy using RMSE, MAE, CRPS, 95% coverage (CVG) • Sensitivity and specificity of EWS alerts.
Ismail et al[16]	Malaysia	To develop a high-accuracy dengue outbreak forecasting model (>90%) for use in an early warning system using IoT-based environmental data.	Experimental field-based weekly time-series study (81 weeks of primary data collection)	Machine Learning (Random Forest, ANN, SVM)	Temperature Rainfall Humidity (RH)	Prediction accuracy using MAPE
Majeed et al[24]	Malaysia	To develop a deep learning model with spatial attention to predict dengue cases across states.	Retrospective ecological time-series study (2010–2021 monthly data)	Machine Learning (LSTM with Spatial Attention Neural Network)	• Rainfall, • Temperature • Humidity (RH)	Prediction accuracy using RMSE
Majeed et al[25]	Malaysia	To develop and validate attention-based LSTM models for medium-term dengue forecasting (1-6 months) using climatic, temporal, and geographic predictors.	Retrospective ecological time-series study (2011–2016 monthly data	Machine Learning (Attention-based LSTM)	• Temperature • Rainfall	Prediction accuracy using RMSE
Ramadona et al[31]	Indonesia	To develop a mobility-aware Bayesian model to forecast village-level dengue clusters one month in advance.	Spatiotemporal ecological time-series using monthly dengue case data (2013-2020)	Bayesian Spatio-temporal	• Temperature • Rainfall	Prediction accuracy using MAE and Log Score)

Lu et al[32]	Malaysia	To develop and validate a coupled ARIMAX–SI-SIR model to forecast dengue incidence using climate data	Retrospective ecological time-series using weekly data (2014-2019)	Hybrid (ARIMAX + SI-SIR)	Temperature Rainfall Humidity	Prediction accuracy using Mean Magnitude of Relative Error (MMRE)
Lu et al[33]	Malaysia	To develop a hybrid MLR–LSTM–SI-SIR model to forecast dengue cases based on climate-driven mosquito biting rate	Retrospective ecological time-series using weekly data (2014-2020)	Hybrid (MLR + LSTM + SI-SIR)	Temperature Rainfall Humidity	Prediction accuracy using MAE and MAPE, forecast horizon up to 60 weeks

Table S3 Climatic Predictor, Model performance, Findings, Strengths, and Limitations with public health application

Author	Climatic Predictors Result				Others	Model Performance	Findings	Strength	Limitation
	Temperature	Rainfall	Humidity	Wind Speed					
Halide & Ridd[21]	Not significant	Not significant	✓	-	Niño 3.4 Index: Not significant	> 50% for 6 months accuracy. Correlation r= 0.84	1)Relative humidity: 61% to 94%, lagged effect of 3–4 months predicted DHF 6 months ahead. 2) Temperature: Not significant 3) Rainfall: Not significant	Simple model with low computation requirements. Effective cross-validation	• Predictive ability declined > 6 months of forecasting • No external validation.
Shafie,[25]	Not significant	Not significant	-	-	-	70.3% Accuracy	1) Temperature: Not significant 2) Rainfall: Not significant The final model relied on environmental and demographic predictors.	Environmental factors predicted dengue risk, and GIS highlighted high-risk zones	Not primarily a climate-driven model with no external validation
Dom et al[22]	✓	✓	Not significant	-	-	83.14% Accuracy	1) Temperature: Min temp 25–27°C associated with dengue increase; A lag of 5 weeks is significant. 2) Rainfall: Annual rainfall exceeding 2600 mm is associated with higher	Accurately captured seasonal climatic trends.	No external validation.

							case counts; a lag of 2–3 months is significant. 3) Relative humidity: Not significant		
Dom et al[27]	✓	✓	?	-	-	Not Available (descriptive spatial association only)	Temperature: > 28.5 °C → higher dengue incidence Rainfall: High rainfall and very high temperature → highest risk Humidity: Humidity generally ≥80%, correlated seasonally	Integrated remote sensing and GIS data effectively.	Not a forecasting model, no accuracy metrics, with no external validation
Azid et al[28]	Not significant	Not significant	Not significant	-	-	Correlation Coefficients R^2=0.057 (poor)	Rainfall, temperature, and humidity showed no significant correlation with dengue cases in Cheras, Malaysia, over a four-year study period (2008–2011).	High-resolution GIS mapping with strong integration of environmental layers	Not a climate-driven model with no external validation
Risva et al[29]	-	✓	-	-	-	Not available (evaluated descriptively via GIS vulnerability maps)	High vulnerability in areas with dense populations, frequent rainfall, and poor drainage.	Integrated multi-factor climatic and environmental data with GIS mapping	Model validation not performed. No external validation
Koh et al[15]	Not significant	✓	Not significant	-	-	64% Accuracy	Strong negative correlation between once-differenced dengue counts and once-differenced rainfall lagged 3 weeks .	Improved dengue forecast accuracy using lagged total precipitation, supported by a robust Bayesian neural-network model–comparison algorithm	Short time-series dataset with risk of overfitting in neural network models. No external validation.
Raja et al[19]	✓	✓	-	-	-	79-84% Accuracy	Predictive accuracy of 79%-84% using temperature and rainfall, along with larval counts and mosquito populations.	Bayesian network models improved Aedes population prediction for outbreaks	• Data timeliness and format inconsistencies with limited real-time applicability

									• No external validation.
Bett et al[30]	✓	✓	-	Not significant		Theil's coefficient = 0.22, indicating a good forecast.	Minimum temperature and rainfall, lagged by 2 months, were significant predictors. Low-altitude and urban areas showed a higher risk; most land-cover classes were significant, except for wetlands.	Bayesian hierarchical models effectively captured spatial-temporal trends.	High dependency on provincial data quality. • No external validation.
Him et al[34]	-	✓	-	-	-	Best performance Model C (district-clustered dataset) and Model E (FCM-clustered dataset). Lowest D, AIC, and BIC values (e.g., Model E: D = 6.088, AIC = 748.266, BIC = 785.734).	Rainfall and the number of rainy days up to a 3-month lag were strong predictors of dengue incidence. Hybrid modelling using Negative Binomial GAM, combined with district clusters or FCM clusters, significantly improved model fit	Novel hybrid model with strong predictive capability.	No model validation using forecasting accuracy (No RMSE/MAPE)
Tao et al[17]	✓	Often not significant	✓	-	Human mobility and connectivity were the strongest predictors, more influential than climate	93.55% accuracy for 3 weeks ahead	Mobility drove the spread of dengue, with 50-week shock persistence; SSTAR reduced forecast error by 56%, while climate had a limited influence.	Combined human mobility and climatic factors effectively.	Computationally complex No external validation
Nejad & Varathan,[18]	✓	✓	-	-	TempeRain	92.35% prediction accuracy	TempeRain factor improved predictive accuracy to 92.35% Minimum Temperature: Correlation coefficient (PCC): 0.499 at lag 5 weeks. Cumulative Rainfall:	Introduced an integrated climatic index (TRF) and rigorously compared five	No external validation. .

							PCC: 0.0071 at lag 2 weeks. Mean Temperature: PCC: 0	machine learning models, demonstrating strong predictive performance from accessible surveillance and weather data.	
Masrani et al[23]	✓	✓	-	✓	-	R^2 = 8.2% moderate	Dengue incidence peaked at a maximum temperature of ~33°C, a mean temperature of 26–28°C, and daily rainfall of 20–30 mm, while cases declined when wind speed exceeded 5 m/s.	Captured inter-monsoon effects effectively.	Low explanatory power, passive surveillance data subject to underreporting, and no external validation
Yip et al[20]	✓	✓		-		Best model: NB + dynamic (Model D) RMSE = 44.72 MAE = 28.92 CVG = 100% Sensitivity = 94.12% Specificity = 62.96%	1. Niño1+2 (coastal South America SST): 2. Cooling is associated with a −2.26% decrease in dengue (lag 28 weeks). 3. Rainfall: Small positive effect (RR 1.009 per mm). 4. Temperature: Mild negative effect (RR <1) 5. Vertical motion (omega): Mild positive effect. 6. Ozone: Negative association (RR 0.968 per 10 ppb).	Robust hierarchical Bayesian framework accounting for spatial-temporal dependence.	• Model complexity limits scalability. • Dependent on hospital admission data, possibly underestimating the actual burden. Serotype dynamics not included
Ismail et al[16]	✓	Included, but no mention of significant	Included, but no mention of significant	-	Air Pollution Index	95% Accuracy (using Random Forest)	1) Rainfall (Lag-4): Moderate correlation (r = 0.665); >50 mm/day reduces larvae. **2)** Random Forest achieved 95% accuracy (92% without entomological data). The IoT-based e-Dengue system enables 4-week forecasting with real-time alerts, supporting community dengue control	Achieved high accuracy for outbreak prediction.	• No external validation. • High cost and logistical burden to collect entomological data

Majeed et al[24]	✓	✓	✓	-		Accuracy not reported	Temperature, rainfall, and humidity as predictors in an SSA-LSTM model with spatial attention. Best performance at 4–5 month lags (RMSE = 3.17), outperforming all other models.	Enhanced predictions with LSTM using spatial attention.	High computational complexity. • No external validation
Majeed et al[25]	✓	✓	-	-		Accuracy not reported	Rainfall (mm/day) and land surface temperature (LST, °C) as significant predictors in dengue modelling, with the SA-LSTM model achieving RMSE 3.008 for 4 4-month lookback period	Introduces a temporal attention mechanism that enhances LSTM memory for handling long dependencies.	Limiting the applicability of the weekly outbreak response. No external validation
Ramadona et al[31]	✓	✓	-	-	-	MAE = 0.522 and Log Score = 1.561	Temperature and rainfall were not significant factors in dengue clustering on their own. However, when combined with human mobility data, model performance improved significantly (log score reduced from 1.748 to 1.561; MAE from 0.676 to 0.522	Integrated human mobility and climatic predictors effectively.	No external validation. Validation was limited to internally held-out data only.
Lu et al[32]	✓	✓	✓	-	-	89%-90.37% for 4 weeks' accuracy	Temperature, humidity, and rainfall (precipitation predict dengue outbreaks, achieving 8.01% MMRE with a coupled SI-SIR and ARIMAX model for 4-week forecasts.	Combined deterministic and statistical models for policy assessment.	High model complexity. No external validation.
Lu et al[33]	✓	Not significant	✓	-	-	Accuracy 82.91%-86.88%	(MAPE ~13-17%) lead time 20-60 weeks. Temperature and humidity are significant Rainfall is not substantial.	Integrated multiple models for long-term predictions.	Computationally intensive. No external validation

Table S4 TRIPOD Adherence Assessment

No	TRIPOD Adherence Assessment	Halide & Ridd[21]	Dom et al[27]	Raja et al[19]	Koh et al[15]	Nejad & Varathan[18]	Ismail et al[16]	Majeed et al[24]	Majeed et al[25]	Lu et al[33]
1	Title and Abstract	✓	✓	✓	✓	✓	✓	✓	✓	✓
2	Background and Objectives	✓	✓	✓	✓	✓	✓	✓	✓	✓
3	Source of Data	✓	✓	✓	✓	✓	✓	✓	✓	✓
4	Participants	✓	✓	✓	✓	✓	✓	✓	✓	✓
5	Outcome Definition	✓	✓	✓	✓	✓	✓	✓	✓	✓
6	Predictors	✓	✓	✓	✓	✓	✓	✓	✓	✓
7	Sample Size	✗	✓	✓	✓	✓	✓	✓	✓	✓
8	Missing Data	✗	✗	✗	✗	✓	✗	✓	✓	✓
9	Statistical Analysis Methods	✓	✓	✓	✓	✓	✓	✓	✓	✓
10	Model Development	✓	✓	✓	✓	✓	✓	✓	✓	✓
11	Model Specification	✓	✓	✓	✓	✓	✓	✓	✓	✓
12	Model Performance	✓	✓	✓	✓	✓	✓	✓	✓	✓
13	Validation (Internal or External)	✓	✓	✓	✓	✓	✓	✓	✓	✓
14	Results (Participants)	✓	✓	✓	✓	✓	✓	✓	✓	✓
15	Results (Model Performance)	✓	✓	✓	✓	✓	✓	✓	✓	✓
16	Results (Validation)	✓	✓	✓	✓	✓	✓	✓	✓	✓
17	Discussion (Interpretation)	✓	✓	✓	✓	✓	✓	✓	✓	✓
18	Discussion (Limitations)	✓	✓	✓	✓	✓	✓	✓	✓	✓
19	Implications	✓	✓	✓	✓	✓	✓	✓	✓	✓
20	Supplementary Material	✗	✗	✗	✗	✗	✗	✗	✗	✓
21	Funding	✗	✗	✗	✓	✓	✓	✓	✓	✓
22	Ethics Approval	✓	✓	✓	✗	✓	✓	✓	✓	✓
	Adherence percentage (%)	86	86	86	86	95	91	95	95	100

Table S5 TRIPOD-CLUSTER Adherence Assessment

No	TRIPOD Assessment	Shafie[25]	Dom et al[21]	Risva et al[29]	Bett et al[30]	Him et al[34]	Tao et al[17]	Masrani et al[23]	Yip et al[20]	Ramadona et al[31]	Lu et al. (2024a)
1	Title and Abstract	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2	Background and Objectives	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3	Source of Data	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4	Participants	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
5	Outcome Definition	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
6	Predictors	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
7	Sample Size	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓
8	Missing Data	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗
9	Statistical Analysis Methods	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
10	Model Development	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
11	Model Specification	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
12	Model Performance	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
13	Validation (Internal or External)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
14	Results (Participants)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
15	Results (Model Performance)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
16	Results (Validation)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
17	Discussion (Interpretation)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
18	Discussion (Limitations)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
19	Implications	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
20	Supplementary Material	✗	✗	✗	✓	✗	✓	✗	✓	✓	✓
21	Funding	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓
22	Ethics Approval	✗	✗	✓	✓	✓	✓	✓	✓	✓	✗
23	Cluster Definition	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
24	Cluster-level Predictor Specification	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
25	Cluster Sample Size	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓
26	Cluster-level Model Performance	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
27	Cluster-level Validation	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Tripod Adherence (%)	89	89	85	96	93	96	96	96	96	96