Predictor and Modeling for Identifying Risk of Dengue Infection: A Systematic Review

Dessy Triana[1,2*], Martini Martini[3], Ari Suwondo[3], Muchlis Achsan Udji Sofro[4], Suharyo Hadisaputro[4], Awal Prasetyo[4]

[1]Department of Parasitology, Faculty of Medicine and Health Sciences, University of Bengkulu, Indonesia
[2]Doctoral Program of Medicine and Health Sciences, Faculty of Medicine, University of Diponegoro, Indonesia
[3]Faculty of Public Health, University of Diponegoro, Indonesia
Faculty of Medicine, University of Diponegoro, Indonesia
*Correspondence: dessy.triana@unib.ac.id

Abstract: Dengue is a global health problem. There has been an increase in dengue cases more than 15 times over the last two decades. Therefore, effective tools for surveillance, prevention, and control are needed. This review aimed to provide a systematic overview of the predictors and modeling approaches to generate dengue risk maps. Studies references is a Systematic Review that follows the guidelines for systematic reviews from PRISMA. Researchers searched electronic databases such as PubMed, Scopus, and ScienceDirect. Keywords based on Population, Intervention, Comparison, Outcome (PICO) formulation. Studies were organized by inclusion and exclusion criteria and evaluated using an evidence-based critical assessment checklist adapted for a cross-sectional study using the Newcastle Ottawa scale. Various predictors and models were used to create a dengue risk map, and no specific pattern was identified in the combination of predictors or models. The most widely and commonly used predictors for demographic and socioeconomic categories are land cover, age, education, housing conditions, and income level. Environmental categories are rainfall and temperature, which are significant predictors. Generally, the model is divided into statistical and expert-based approaches. Most available dengue risk maps are based on descriptive and retrospective data. Despite the limitations, the risk map facilitates decision-making in public health. Mobile devices can be optimized to describe dengue transmission dynamics through human movement from dengue serological profile data.

Keywords: dengue modeling; risk mapping; spatial distribution; dengue prediction; systematic review

1. Introduction

Dengue fever is an arboviral disease transmitted by *Aedes aegypti* and *Aedes albopictus* as the primary and secondary vectors found in tropical and subtropical areas. The transmission is influenced by mosquito vector density, virus serotype, and human population susceptibility (1–3).

Demographic changes, urbanization, inadequate water supply, migration, and transportation cause a global increase in the incidence of fever, and around 3.6 billion people are at risk of infection. Furthermore, the spread is also supported by climate change due to environmental and changes in immunological profiles. This is supported by the presence of vectors and the availability of habitats for breeding (4–6).

The World Health Organization is committed to tackling dengue through the Global Strategy for Dengue Prevention and Control 2012-2020 and the Road Map for Neglected Tropical Diseases (NTDs) from 2021 to 2023. The target is to reduce the mortality rate or CFR from 0.8% in 2020 to 0% in 2030. To meet the target, 5 strategies have been set by WHO as the main pillars in dengue control, namely diagnosis and case management, integrated surveillance and outbreak preparedness, sustainable vector control and vaccination, and operational research and information systems (7–9).

According to the Epidemiological Triangle concept, factors influencing dengue disease occurrence include an imbalance between the host, the cause, and the environment. Host factors include the body's immune response and age, while environmental factors include geographical conditions, demographics, population mobility, customs, socio-economics, and mosquito density as vectors of disease transmission (4–6,9).

Many dengue-endemic countries lack the health systems and data collection tools for extensive disease surveillance. Surveillance tools, such as incident maps, are very useful for improving public health preparedness. They have been developed and become important in the last decade. Transmission and development of dengue cases show dynamic and inherent spatial and temporal patterns. The non-homogeneous character of the dengue predictor adds to the complexity and general requirements for data input (8,10,11)..

Modeling assessment is applicable in this setting to provide a targeted and adaptable approach to addressing widespread data and resource limitations (8). Accurate assessment of global, regional, and country health situations is essential for evidence-based decision-making for public health. Furthermore, vulnerability assessments can be useful in health and well-being applications to assess the impacts of climate change and natural disasters. The understanding can significantly contribute to effective monitoring, prevention, and control strategies (12). Mapping dengue susceptibility from various factors is needed to predict the occurrence of increased cases or outbreaks (13,14).

The challenge of vulnerability assessment is synthesizing social and environmental differences to communicate and measure the implications of a particular hazard. Measures of exposure and vulnerability are often multidimensional, and indicators are used to simplify and integrate various measures into a composite index. Indicators are useful for summarizing large amounts of data into a format useful to decision-makers (15). Vulnerability assessment is a novel way to conceptualize the complex network of factors and disease interactions. It reduces the focus on the likelihood of harm occurring and analyses the various factors that influence exposure, susceptibility, and ability to cope and recover from the disease (10). This systematic review addresses research gaps caused by the lack of a structured overview of available methods, relevant predictors, modeling approach, and types of dengue risk maps. This systematic review aimed to synthesize the existing evidence about the approach, accuracy, strengths, and limitations of modeling for identifying risk of dengue infection.

2. Methods

2.1 Data Sources and Search Strategy

The systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-analyses Guidelines (PRISMA) (20). The search was initiated through three electronic databases: PubMed, Scopus and ScienceDirect. Database by Population, Intervention, Comparison, Outcome (PICO), namely P: endemic area of dengue, I: predicted area of vulnerability, C: level of endemicity, O: level of comparison of the area with a level of vulnerability to dengue. Based on the PICO, a research question arises, "How is the vulnerability in dengue-endemic areas predicted using a modeling approach?". The search included all articles published up to February 2022, using Boolean Operators (AND, OR) to combine the search terms "dengue modeling," "dengue susceptibility," "dengue mapping," and "dengue distribution.

To reduce the possibility of selection bias, articles were independently selected by experts in dengue modeling. Initially, 39,238 publications were found using the search term, and the selected reference list was screened for relevant articles based on inclusion criteria through the EndNote application (n=46). Finally, 15 articles were included for systematic review (Figure 1), and the detailed study was included in the supplementary file (S1).

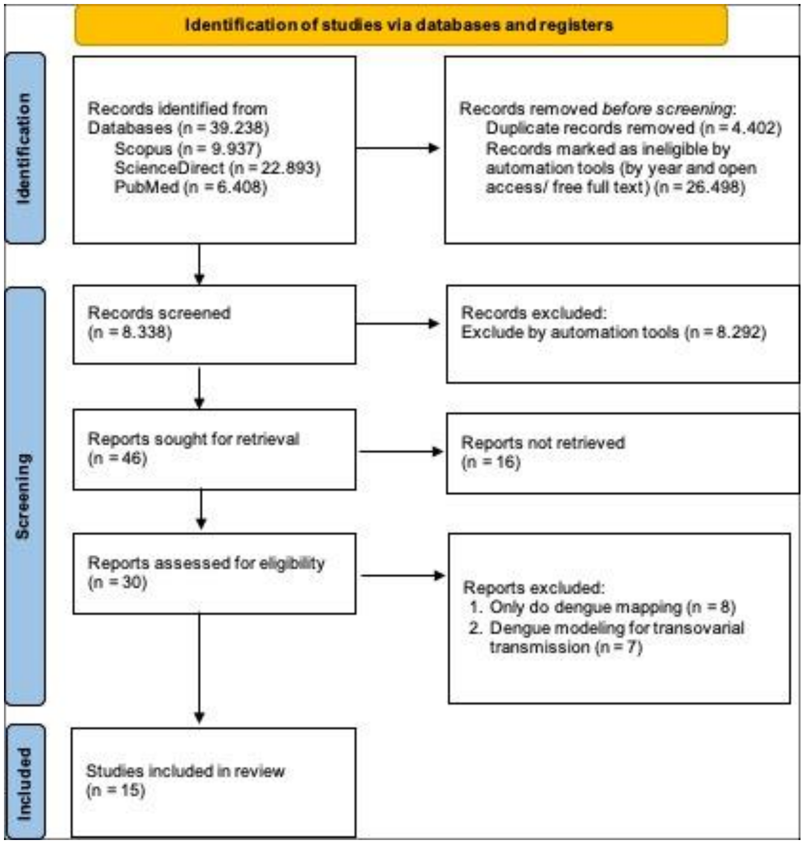

Figure 1. Flowchart of study selection process.

2.2 Ethic Approval

All procedures performed in this study were approved by the ethical standards of the institutional or national research committee.

2.3 Eligibility Criteria

The inclusion criteria for the literature were determined before electronic retrieval: (1) the literature published in 10 years lastly; (2) the literature focus on modeling dengue risk; (3) the literature could be accessed or full text; (4) articles published and written in English; (5) empirical studies using quantitative or qualitative or mixed research method.

2.4 Quality Assessment

First, the PRISMA protocol was utilized to evaluate this systematic review's quality. Second, the quality of the published articles was assessed using a checklist Newcastle-Ottawa Scale adapted for cross-sectional studies (Table 3) (16).

3. Results

3.1. Study Description

Fifteen studies met the eligibility criteria and were included in this review, and the selected references are listed in Table 1. The details of all studies are included in Table 2.

All literature that meets the condition conducted evaluation validity using Newcastle-Ottawa Scale adapted for cross-sectional studies. The quality of the literature can be seen in Table 3.

Table 1. List of publications selected for the systematic review

ID	Selected studies
(1)	Benedum C, Seidahmed OME, Eltahir EAB, Markuzon N. Statistical modeling of the effect of rainfall flushing on dengue transmission in Singapore. Reiner RC, editor. PLoS Negl Trop Dis. 2018 Dec 6;12(12):1–18.
(2)	Cahyorini, Azhar K, Veridona G. Dengue Hemorrhagic Fever vulnerability indicators valuation due to climate change in Semarang City. In: IOP Conference Series: Earth and Environmental Science. 2019. p. 1–9.
(3)	Dickin SK, Schuster-Wallace CJ. Assessing changing vulnerability to dengue in northeastern Brazil using a water-associated disease index approach. Glob Environ Chang. 2014;29(1):155–64.
(4)	Dickin SK, Schuster-Wallace CJ, Elliott SJ. Developing a vulnerability mapping methodology: applying the water-associated disease index to dengue in Malaysia. PLoS One. 2013;8(5): 1-11.
(5)	Dom NC, Ahmad AH, Latif ZA, Ismail R. Integration of GIS-based model with epidemiological data as a tool for dengue surveillance. Environ Asia. 2017;10(2):135–46.
(6)	Eisen L, Eisen RJ. Using geographic information systems and decision support systems for the prediction, prevention, and control of vector-borne diseases. Annu Rev Entomol. 2011;56(2):41–61.
(7)	Hagenlocher M, Delmelle E, Casas I, Kienberger S. Assessing socioeconomic vulnerability to dengue fever in Cali, Colombia: Statistical vs expert-based modeling. Int J Health Geogr. 2013;12(36):1–14.
(8)	Jain R, Sontisirikit S, Iamsirithaworn S, Prendinger H. Prediction of dengue outbreaks based on disease surveillance, meteorological and socio-economic data. BMC Infect Dis. 2019;19(1):1–16.
(9)	Lowe R, Cazelles B, Paul R, Rodó X. Quantifying the added value of climate information in a spatio-temporal dengue model. Stoch Environ Res Risk Assess. 2016;30(8):2067–78.
(10)	Majid NA, Razman MR, Zakaria SZS, Nazi NM. Geographical dengue incident analysis using Kernel density estimation in Bandar Baru Bangi , Selangor , Malaysia. Eco Env Cons. 2021;27(2):1–9.
(11)	Nuraini N, Fauzi IS, Fakhruddin M, Sopaheluwakan A, Soewono E. Climate-based dengue model in Semarang, Indonesia: Predictions and descriptive analysis. Infect Dis Model. 2021; 6:598–611.
(12)	Pham NTT, Nguyen CT, Vu DT, Nakamura K. Mapping of dengue vulnerability in the Mekong Delta region of Vietnam using a water-associated disease index and remote sensing approach. APN Sci Bull. 2018;8(1):9–15.
(13)	Rodrigues HS, Monteiro MTT, Torres DFM. Bioeconomic perspectives to an optimal control dengue model. Int J Comput Math. 2013;90(10):2126–36.
(14)	Wongkoon S, Jaroensutasinee M, Jaroensutasinee K. Spatio-temporal climate-based model of dengue infection in Southern, Thailand. Trop Biomed. 2016;33(1):55–70.
(15)	Zafar S, Shipin O, Paul RE, Rocklöv J, Haque U, Rahman MS, et al. Development and comparison of dengue vulnerability indices using gis-based multi-criteria decision analysis in lao pdr and Thailand. Int J Environ Res Public Health. 2021;18(9421):1–25.

Table 2. Study Characteristic

No	Author/Year	Design Research	Model	Result	Limitation
1.	Benedum et al., 2018 (23)	Cross-Sectional	Statistical-based	Logistic regression statistical modelling on the effect of rainfall (PLUM Model) on dengue transmission in Singapore.	The model does not measure human, vector, and viral components that have a role in dengue susceptibility.
2.	Cahyorini et al., 2019 (17)	Cross-Sectional	Expert-based	Dengue vulnerability index from the climate component and the incidence of floods in Semarang City, Indonesia.	Analyzing dengue susceptibility from the environment. It does not measure the components of human susceptibility, vectors, and viruses involved.
3.	Dickin et al., 2014 (11)	Cross-Sectional	Expert-based	The Water-associated Disease Index model (WADI) assesses dengue susceptibility in Brazil.	The dengue vulnerability model is based on environmental exposures such as water access, land surface, climate and waste management, and human vulnerability. It does not include vector components and viruses causing dengue disease.
4.	Dickin et al., 2013 (10)	Cross-Sectional	Expert-based	Development of a regression model on the components of social factors in the form of community and natural environment susceptibility to dengue susceptibility in Malaysia.	The dengue susceptibility index measures the components of environmental exposure and human susceptibility. It does not measure the vector component of dengue susceptibility.
5.	Dom et al., 2017 (21)	Cross-Sectional	Statistical-based	Spatio-temporal with Geographic Information System (GIS) method based on epidemiological data as a predictive model for surveillance using forecasting models in	Mapping dengue risk areas based on population density/population of an area, environment, climate, and socioeconomic. It does not involve vector components and

				Malaysia.	viruses that cause dengue.
6.	Eisen et al., 2011 (22)	Cross-Sectional	Statistical-based	Geographic Information Systems (GIS) map vector-borne diseases by interpolating environmental and socioeconomic factors (Spatial Risk Interpolation Models and Space-Time Risk Models).	Mapping of vector-borne diseases from environmental, socioeconomic, and vector variables. It does not measure human vulnerability.
7.	Hagenlocher et al., 2013 (20)	Cross-Sectional	Mixed	The dengue susceptibility index is based on an expert-based versus statistical-based spatial modelling approach. It measures Colombia's socioeconomic components and demographic indicators using the MOVE Framework.	The resulting susceptibility index does not measure vector and viral components as an indicator of dengue susceptibility.
8.	Jain et al., 2019 (26)	Cross-Sectional	Statistical-based	Predictors of dengue outbreak based on weather and socioeconomic factors in Thailand.	Mapping predictions of dengue outbreak areas based on socioeconomic and weather factors.
9.	Lowe et al., 2016 (29)	Cross-Sectional	Statistical-based	Dengue Spatio-temporal model using the Bayesian Framework statistical method based on weather and climate.	Dengue modelling is based on climate and weather factors.
10.	Majid et al., 2021 (18)	Cross-Sectional	Statistical-based	Modelling and mapping dengue cases using Kernel Density Estimation based on population density in Malaysia.	Modelling the distribution of dengue based on population density and land use change does not analyze other factor components.
11.	Nuraini et al., 2021 (27)	Cross-Sectional	Statistical-based	Using the Autoregressive Distributed Lag (ARDL) statistical model in Semarang, Indonesia, the Host-vector model to determine	This model does not provide a good prediction for the long term, influenced by the non-statistically significant value of the correlation

				dynamic dengue transmission.	between infection and climatic factors.
12.	Pham et al., 2018 (15)	Cross-Sectional	Expert-based	The use of the WADI-Dengue model in Vietnam on the components of social factors in the form of community and individual vulnerability in Vietnam.	The WADI-Dengue model is in the form of host vulnerability (human), namely community and individual vulnerability.
13.	Rodrigues et al., 2013 (28)	Cross-Sectional	Statistical-based	Mathematical modelling for humans and dengue vectors uses the ODE System (Ordinary Differential Equation).	Mathematical modelling does not include environmental and climatic factors in dengue disease transmission.
14.	Wongkoon et al., 2016 (24)	Cross-Sectional	Statistical-based	The Spatio-temporal distribution of dengue cases in Thailand is based on rainfall, temperature, and relative humidity components.	The Spatio-temporal distribution of dengue cases is only based on weather factors and does not look at other factors.
15.	Zafar et al., 2021 (19)	Cross-Sectional	Expert-based	Development and comparison of several dengue susceptibility models, namely the Shannon's Entropy (SE) model, the Water-associated Disease Index (WADI), and the Best-Worst Method (BWM).	The analysis of dengue vulnerability in Thailand and Laos is from environmental and human factors, namely, population, social, the physical environment, and environmental health.

Table 3. Newcastle-Ottawa Scale adapted for Cross-sectional Studies

No	Author (s)/Year	Selection[a]				Comparability	Outcome[b]		Total Score
		1	2	3	4		1	2	
1	(Benedum et al., 2018)	*		*	**	**	**	*	9
2	(Cahyorini et al., 2019)			*	**	**	**	*	8
3	(Dickin et al., 2014)	*		*	**	**	**		
4	(Dickin et al., 2013)	*		*	**	**	**	*	9
5	Dom, 2017)			*	**	**	*		6
6	(Eisen et al., 2011)				**	**	*	*	6
7	(Hagenlocher et al., 2013)	*			**	**	**	*	8
8	(Jain et al., 2019)	*	*		**	**	**	*	9
9	(Lowe et al., 2016)	*	*		**		**	*	7
10	(Majid et al., 2021)		*		**	**	**	*	8
11	(Nuraini et al., 2021)				**	**	**	*	7
12	(Pham et al., 2018)	*			**	**	**	*	8
13	(Rodrigues et al., 2013)	*			**	**	**	*	8
14	(Wongkoon et al., 2012)	*			**	**	*	*	7
15	(Zafar et al., 2021)	*			**	**	**	*	8

[a]: (1) Representativeness of the sample, (2) Sample size, (3) Non-respondents, (4) Risk factor
[b]: (1) Assessment of outcome, (2) Statistical test.

Cross-sectional Studies:
Very Good Studies: 9-10 points
Good Studies: 7-8 points
Satisfactory Studies: 5-6 points
Unsatisfactory Studies: 0 to 4 points

3.2. Study Design

All studies were retrospective within a certain period and used secondary data on dengue cases using an average of nine years (Fig. 2). In addition to reported dengue cases, significant predictors for modeling included variables such as population, demographics, socioeconomic status, climate, environment, dengue virus, and entomology.

3.3. Predictor

Population, demographic and socioeconomic data

Most studies totalling 9 of 15 used population distribution and density to describe and model the risk of developing dengue fever (Table 2). In general, population density data comes from the national census as observed in 5 studies. Social predictors, such as education level, unemployment and poverty rates, sanitation, and access to clean water, are used to assess environmental conditions and hygiene. These data were found in 6 studies (10,11,17–20).

Climate Data

Most studies included climate predictors in the modeling (12 of 15). The most widely used predictors were rainfall and air temperature (10,11,15,17,19,21–26), while two studies used relative humidity (25,27). This climate variable describes the spatial and temporal risk of dengue transmission.

Environmental Data

Environmental information includes data on housing quality and land cover. This predictor is widely used to describe the environment supporting vectors' breeding and survival.

The data type is in the form of a survey through remote sensing. These environmental predictors were used in 12 studies through remote sensing (10,11,15,17,19,21–26).

Entomology Data

A total of three studies used entomological predictors to form the model. Entomological predictor data is in the form of vector density and susceptibility data. The vector density data uses a mathematical model, not using primary data collected from the field. The data only uses reproduction number, biting rate, and vector mortality rate predictions (22,27,28).

3.4. Modeling Approach

The modeling approaches used in the studies varied from mathematical models, statistical methods, geography, ecology, and indices used to generate dengue risk maps (Table 2). Reported dengue cases are used with selected predictors to estimate the risk of DHF in a geographic area. The map is based on the calculated value of the predictor selected. Methodologically, models were distinguished from indices to derive risk estimates. The model uses individual variables, while the index uses a combination of variables calculated from the available data.

Model

The spatial analysis aimed at detecting dengue clusters and hotspots was the most commonly used approach in 9 of the 15 studies to generate risk maps. Cluster detection identifies concentrated areas of dengue cases rather than a randomly distributed geographic display. This modeling identifies the hotspots most likely to require public health intervention. Logistic regression, multinomial, general linear, and general additive models are common approaches used to calculate risk levels and create maps. The ecological niche is also commonly used to model environmental suitability for dengue cases and can cover a wide and diverse area, such as a country scale (10,11,15,18–20,22,24,29).

Index

The index was used in 5 of 15 literature studies, and the use is easier to implement because it does not require further calculations. The risk level calculated from the model or index is an estimate from 0 to 1, with a predictive result of "0" indicating no risk and "1" confirming the risk. The risk categories range from 3 to 5, with gradations from low to high. Index modeling is seen from several predictor components, namely population, demography, socioeconomic, climate, and environment. A model has not been found that includes all components of dengue predictors with vector components and viruses causing dengue disease (10,11,15,17,19,20).

The regional vulnerability was modelled to dengue through a statistical and expert-based approach. Approaches based on statistical methodologies are commonly used, and many perform dengue analysis mathematically. Statistical or mathematical modeling approaches include the Spatial Risk Interpolation Model and Space-time Risk Model (22), Autoregressive Distributed Lag (ARDL) Models (27), Ordinary Differential Equation System (28), Empirical Bayes Method (21,29), and Estimation of Kernel Density (18,21).

The expert-based approach is relatively complex but capable of producing predictive vulnerability maps, including social, economic, and environmental dimensions. Modeling through an expert-based approach includes the *Water-associated Disease Index* (WADI) model (8,10,11,15,17), Shannon's Entropy (SE) model (19), and *the Best-Worst Method* (BWM) (19), as shown in Figure 2.

No	Publication's Characteristic	Model Type	Categories of Predictors						
			Population	Socio-Economic	Demography	Climatology	Environment	Entomology	Total
Mathematical/Statistical Modeling									
1	Eisen/2011	Spatial-risk Interpolation Models, Space-time Risk Models.				x	x	x	3
2	Nuraini/2021	Autoregressive Distributed Lag Models.	x			x			2
3	Rodrigues/2013	Ordinary Differential Equation System (ODE System).	x					x	2
4	Benedum/2018	Logistic regression statistics, PLUM Model.				x	x		2
5	Dom/2017	Empirical Bayes Smoothing Method, Kernel Density Estimation							
6	Majid/2021	Kernel Density Estimation	x						1
7	Wongkoon/2012	Poisson Regression Model				x	x		2
8	Lowe/2016	Generalized Linear and Additive Models (GLMM/GAMs)				x	x		2
9	Jain/2019	Generalized Additive Models (GAMs)				x	x		2
Expert-based Modeling									
1	Zafar/2021	Water-associated Disease Index (WADI), Shannon's Entropy (SE), the Best-Worst Method (BWM).	x		x	x	x		4
2	Pham/2018	Water-associated Disease Index (WADI)	x		x	x	x		4
3	Hagenlocher/2013	Methods for the Improvement of Vulnerability Assessment in Europe (MOVE Framework)	x	x			x		3
4	Dickin/2014	Water-associated Disease Index (WADI)	x		x	x	x		4
5	Cahyorini/2019	Water-associated Disease Index (WADI)	x			x	x		3
6	Dickin/2013	Water-associated Disease Index (WADI)	x		x	x	x		4

Figure 2. Characteristic of reviewed articles indicating model type and predictor categories use for risk mapping

4. Discussion

Predictor

Various predictors were used to creating dengue risk maps, and no pattern was associated with any particular approach.

Population, demographic, and socioeconomic data

Demographic data are used to develop risk maps at a local scale, such as a village or city. Socioeconomic and demographic data are used as proxies for mobility or population density, housing conditions, and potential vector exposure. In the publications reviewed, the predictor associated with poor housing conditions is a reliable indicator of increased dengue incidence (10,11,17,19,20,22). Several maps depict where dengue cases have occurred, and an approach mainly based on population data was used. These descriptive maps are useful for visualizing disease hotspots and areas with an increased risk of dengue fever at a given time and space (10,11,17,19,20,26,28).

Climate and environmental data

Climate and weather data were beneficial for creating predictive risk maps, and almost all publications had a climate and environmental data component (12 of 15 studies). These findings indicate that this predictor has high resolution and is a prerequisite for predictive map generation for early warning. Even though temporal pure dengue modeling has yielded good estimates of the general dengue situation in several studies, this review suggests that map generation is at higher resolutions. Other factors, such as human movement, population density, or housing conditions, play a role in the occurrence of dengue cases (30).

Entomological Data

Adult vector abundance and oviposition correlated more with dengue disease (31). Catching adult mosquitoes is rare because it is more complex and expensive. Entomological indices such as a house, container, and Breteau index are commonly used to examine the effectiveness of vector control measures rather than evaluate vector density (32).

Pupae and adult indices can provide more reliable predictions, but the evidence is limited. Entomological surveys are resource-intensive and expensive, and it is essential to establish their relevance in risk mapping (32).

Modeling Approach

The modeling approaches used in the publications reviewed varied from statistics, geography, and ecology to genetics. Cluster detection for dengue cases and hotspot analysis are often used as starting points to generate risk maps. The approach in statistics uses surveillance data collected from the district level for risk mapping, including general additive models, general linear models, kernel estimates, or Bayesian frameworks. Niche modeling and maximum entropy algorithms are commonly used in ecology, while weighted regression and kriging are used in geography.

Approaches based on statistical methodologies are very commonly used, and many conduct profile analyses of dengue fever in the research area (18,21–23,26–28,33). Some research is more complex and mathematically involved, allowing the development of predictive maps. This approach has been used to describe potential areas of dengue occurrence on a global scale (34). However, expert-based or index-based modeling approaches have not been widely published but are simpler to implement in the community. Some of the possibilities are due to the complexity of the factor components and require a lot of costs (35).

Modeling with Statistical Approach

Spatial-risk Interpolation Models

The spatial-risk interpolation method is useful for converting point-based data into a smooth surface interfering risk in unsampled areas. This method is most useful at fine spatial scales but unreliable outside the geographic area. Software like *ArcGIS®* has a vast capacity for interpolation modeling, and spatial dependence for vector presence or dengue incidence rates was observed at a fine spatial scale. For example, areas with high vector presence or disease incidence often border other areas with high vector or disease incidence. The similarity in the response variables decreases with increasing distance. Moreover, a kriging or other type of interpolation model generates a smooth interpolated map of the response variables (22).

Space-time Risk Models

This space-time risk model is used to explore spatial groupings. Exploration is conducted by considering spatial and temporal interactions. For example, dengue susceptibility modeling vectors or cases are useful for identifying risk patterns. The risk is an outbreak with a rapid increase in cases and an explosive spread within the affected area. This modeling can assist in identifying the underlying factors that regulate vector spread or occurrence of dengue cases. It is more sensitive than purely spatial or temporal models in detecting local outbreaks (36,37). Therefore, the output can be used as an early warning system and guide vector control or surveillance activities (22).

Autoregressive Distributed Lag Models (ARDL Models)

It is an analytical tool model in econometrics. This linear regression model considers the long-term and short-term effects of the dependent variable on a change in the value of the explanatory variable (38). The ARDL is a model that uses past and present time data, consisting of independent and dependent variables. The autoregressive model implies that the lag value affects the model. It has distributed the lag component in the form of the predictor variables.

Ordinary Differential Equation System (ODE System)

A differential equation with an unknown function is a function of a single independent variable. In its simplest form, this unknown function is real or complex, but it can be a vector or a matrix function. It is an ordinary differential equation but uses an optimal control approach in an epidemiological model (28).

Predictive Flushing-Mosquito Model (*PLUM Model)*

This model aims to make daily predictions and identify common flushing conditions that lead to overflows. It is a flood early warning system that uses rainfall thresholds to predict the occurrence of floods (39). The PLUM model operates by identifying a set of variables and thresholds associated with flushing. Furthermore, it was developed using entomological observations and rainfall data. The proposed approach identifies rainfall thresholds associated with a higher possibility of flushing (23).

Generalized Additive Models (GAMs)

Generalized Additive Models (GAMs) combine additive and Generalized Linear Models (GLMs). Generalized additive models simultaneously the different effects of each independent variable. Each effect can be estimated using smoothing or mathematical functions, leading to GAM as a semiparametric model (40). The high correlation between predictor variables can cause singularity problems in statistical models. The model only checks for collinearity and adjusts the function, and ensures one variable can be produced using other combinations called concurvity checking (26).

Modeling with an Expert-Based Approach

Water-associated Disease Index (WADI)

This model is an objective approach developed by Dickins in 2013 by dividing the components of factors influencing dengue susceptibility in an area into two components. The components include using an ecological health model that combines environmental/ecological and social health determinants to detect and visualize vulnerabilities using a map format (8,10,11).

The WADI-Dengue model is an ecological health model creating a framework that integrates the environmental, health, and characteristics of the particular population under research to understand vulnerability. This contributes to public health interventions and strategies that can reduce the burden of water-related diseases. It can be implemented with limited data or technical input, which is critical for decision-making in low-resource settings. The areas most susceptible to dengue were identified and mapped by key factors representing exposure, individual susceptibility, and community susceptibility to dengue transmission (8).

The WADI-Dengue model is widely used to map dengue susceptibility in Vietnam, Brazil, Jamaica, Bhutan, India, Malaysia, and Thailand. In Indonesia, the full implementation of the WADI-Dengue model has not been carried out. Only a few component factors have been implemented (17). This model offers an easy implementation with objective calculations through the weighting of factor components. Meanwhile, the weakness is that the scope of measurement is limited in assessing the area's susceptibility to dengue, such as vector components and viruses as the cause of the disease (10,19).

Shannon's Entropy (SE)

This model was developed in 2017 and is a method to determine an area's vulnerability, namely Shannon's Entropy (SE), which is a modification of the WADI-Dengue model with the addition of an adaptive capability component consisting of access to health facilities and socioeconomic status (19,41). The adaptive capacity indicator reflects the population's ability to cope with or prevent dengue outbreaks. The SE-Dengue method uses probability theory to measure the amount of information stored in the form of data. This suggests that a more comprehensive distribution will contain more uncertainty than a sharply peaked distribution. However, it is more challenging to implement because the calculations are different. According to probability theory, when the sub-class indicators are identical, then the sub-classes will be mutually exclusive (19,42).

The Best-Worst Method (BMW)

The Best-Worst Method (BMW) developed by Rezaei in 2015 is a subjective approach to mapping vulnerabilities. In its development, this method has been criticized for two reasons, namely, the subjective approach is highly biased by the opinion of decision-makers and comparing indicators between different domains, such as exposure to sensitivity/vulnerability (19,43,44).

Methods for the Improvement of Vulnerability Assessment in Europe (MOVE) Framework

This method was designed in 2013 by Birkmann and developed in the European research project MOVE (Methods for the Improvement of Vulnerability Assessment in Europe). This framework conceptualizes the complex and multidimensional nature vulnerability of society and its inhabitants at different spatial and temporal scales. The MOVE framework characterizes vulnerability through three main factors, namely (1) vulnerability, reflecting an assessment unit within the geographic range of a hazard event, (2) susceptibility, describing the predisposition of elements that are at risk of suffering losses, and (3) lack of resilience, determined by limitations in terms of access, and resource mobilization of a community or socio-ecological system in response to a particular hazard (20).

5. Conclusions

This review shows the diversity of predictors and model approaches to create dengue risk maps. The risk factors are very diverse and complex to be modelled. Therefore, mobile devices can be optimized to describe dengue transmission dynamics through human movement against serological profile data and viruses. The availability of mobile devices with geo-referencing capabilities allows speculation in integrating these factors. Despite its limitations, which depend heavily on the acquisition and availability of various quality and adequate data in terms of spatial and temporal resolution, dengue risk maps can facilitate decision-making in public health.

Author Contributions: Conceptualization and design, D.T.; methodology, M.M.; S.H.; writing—original draft preparation, D.T.; writing—review and editing, D>T.; M.M.; A. S.; M.A.U.S.; supervision, S.H.; A.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Mardihusodo SJ, Satoto TBT, Mulyaningsih B, Umniyati SR, Ernaningsih. Pupal Demographic and Adult Aspiration Survey of Residental and Public Sites in Yogyakarta, Indonesia to Inform Development of Targeted Sources Control Strategy for Dengue. Dengue Bull. 2011;35:141–51.
2. Kovats S, Ebi KL, Menne B. Methods of Assessing Human Health Vulnerability and Public Health Adaptation to Climate Change. WHO Regional Office for South-East Asia; 2003. p. 1–112.
3. WHO. Guidelines for safe recreational water. Volume 1, coastal and fresh waters. Risk Manag. 2003;1:253.
4. Arslan A, Rathor HR, Mukhtar MU, Mushtaq S, Bhatti A, Asif M, et al. Spatial Distribution and Insecticide Susceptibility Status of Aedes aegypti and Aedes albopictus In Dengue Affected Urban Areas of Rawalpindi, Pakistan. J Vector Borne Dis. 2016;53(2):136–43.
5. Kamgang B, Marcombe S, Chandre F, Nchoutpouen E, Nwane P, Etang J, et al. Insecticide Susceptibility of Aedes aegypti and Aedes albopictus in Central Africa. Parasit Vectors [Internet]. 2011;4(1):79–86. Available from: http://www.parasitesandvectors.com/content/4/1/79
6. Lima EP, Paiva MHS, De Arúajo AP, Da Silva ÉVG, Da Silva UM, De Oliveira LN, et al. Insecticide resistance in Aedes aegypti populations from Cearáe, Brazil. Parasites and Vectors. 2011;4(1):5.
7. WHO. Global Strategy for Dengue Prevention and Control 2012–2020 [Internet]. WHO. 2012. 1–34 p. Available from: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Global+strategy+for+dengue+prevention+and+control#8
8. Fullerton L, Dickin S, Schuster-Wallace CJ. Mapping Global Vulnerability to Dengue using the Water Associated Disease Index Waste to Wealth View project [Internet]. United Nations University; 2012. 1–40 p. Available from: https://www.researchgate.net/publication/273439367
9. Ministry of Health of the Republic of Indonesia. National Strategy for Dengue Prevention 2021-2025. Jakarta: Ministry of Health of the Republic of Indonesia; 2021. 1–94 p.
10. Dickin SK, Schuster-Wallace CJ, Elliott SJ. Developing a Vulnerability Mapping Methodology:

Applying the Water-Associated Disease Index to Dengue in Malaysia. PLoS One. 2013;8(5):1–11.

11. Dickin SK, Schuster-Wallace CJ. Assessing changing vulnerability to dengue in northeastern Brazil using a water-associated disease index approach. Glob Environ Chang [Internet]. 2014;29(1):155–64. Available from: http://dx.doi.org/10.1016/j.gloenvcha.2014.09.007
12. Cong NT, Nga PTT, Duoc V. Mapping Vulnerability to Dengue using the Water Associated Disease Index. Vol. 13, United Nations University (UNU-INWEH). 2014.
13. Sekarrini CE. Mapping of Dengue Hemorrhagic Fever Vulnerability Based on Geographic Information. Sumatra J Disaster, Geogr Geogr Educ. 2020;4(1):63–7.
14. Hikmawati I, Sholikhah U, Wahjono H, Martini M. Community vulnerability map in endemic areas of dengue hemorrhagic fever (DHF), Banyumas, Indonesia. Iran J Public Health. 2020;49(3):472–8.
15. Pham NTT, Nguyen CT, Vu DT, Nakamura K. Mapping of dengue vulnerability in the Mekong Delta region of Vietnam using a water-associated disease index and remote sensing approach. APN Sci Bull. 2018;8(1):9–15.
16. Moskalewicz A, Oremus M. No clear choice between Newcastle–Ottawa Scale and Appraisal Tool for Cross-Sectional Studies to assess methodological quality in cross-sectional studies of health-related quality of life and breast cancer. J Clin Epidemiol. 2020 Apr 1;120:94–103.
17. Cahyorini, Azhar K, Veridona G. Dengue Hemorrhagic Fever vulnerability indicators valuation due to climate change in Semarang City. In: IOP Conference Series: Earth and Environmental Science [Internet]. 2019. p. 1–9. Available from: https://iopscience.iop.org/article/10.1088/1755-1315/363/1/012012
18. Majid NA, Razman MR, Zakaria SZS, Nazi NM. Geographical dengue incident analysis using Kernel density estimation in Bandar Baru Bangi , Selangor , Malaysia. Eco Env Cons. 2021;27(2):1–9.
19. Zafar S, Shipin O, Paul RE, Rocklöv J, Haque U, Rahman MS, et al. Development and comparison of dengue vulnerability indices using gis-based multi-criteria decision analysis in lao pdr and Thailand. Int J Environ Res Public Health. 2021;18(9421):1–25.
20. Hagenlocher M, Delmelle E, Casas I, Kienberger S. Assessing socioeconomic vulnerability to dengue fever in Cali, Colombia: Statistical vs expert-based modeling. Int J Health Geogr. 2013;12(36):1–14.
21. Dom NC, Ahmad AH, Latif ZA, Ismail R. Integration of GIS-based model with epidemiological data as a tool for dengue surveillance. Environ Asia. 2017;10(2):135–46.
22. Eisen L, Eisen RJ. Using geographic information systems and decision support systems for the prediction, prevention, and control of vector-borne diseases. Annu Rev Entomol. 2011;56(2):41–61.
23. Benedum CM, Seidahmed OME, Eltahir EAB, Markuzon N. Statistical modeling of the effect of rainfall flushing on dengue transmission in Singapore. PLoS Negl Trop Dis. 2018 Dec;12(12):1–18.
24. Wongkoon S, Jaroensutasinee M, Jaroensutasinee K. Spatio-temporal climate-based model of dengue infection in Southern, Thailand. Trop Biomed. 2016;33(1):55–70.
25. Lowe R, Bailey TC, Stephenson DB, Graham RJ, Coelho CAS, Sá Carvalho M, et al. Spatio-temporal modelling of climate-sensitive disease risk: Towards an early warning system for dengue in Brazil. Comput Geosci [Internet]. 2011;37(3):371–81. Available from: http://dx.doi.org/10.1016/j.cageo.2010.01.008
26. Jain R, Sontisirikit S, Iamsirithaworn S, Prendinger H. Prediction of dengue outbreaks based on disease surveillance, meteorological and socio-economic data. BMC Infect Dis. 2019;19(1):1–16.
27. Nuraini N, Fauzi IS, Fakhruddin M, Sopaheluwakan A, Soewono E. Climate-based dengue model in Semarang, Indonesia: Predictions and descriptive analysis. Infect Dis Model. 2021;6:598–611.

28. Rodrigues HS, Monteiro MTT, Torres DFM. Bioeconomic perspectives to an optimal control dengue model. Int J Comput Math. 2013;90(10):2126–36.
29. Lowe R, Cazelles B, Paul R, Rodó X. Quantifying the added value of climate information in a spatio-temporal dengue model. Stoch Environ Res Risk Assess. 2016;30(8):2067–78.
30. Hii YL, Zhu H, Ng N, Ng LC, Rocklöv J. Forecast of Dengue Incidence Using Temperature and Rainfall. PLoS Negl Trop Dis. 2012;6(11):1–9.
31. Banu S, Hu W, Hurst C, Tong S. Dengue transmission in the Asia-Pacific region: impact of climate change and socio-environmental factors. Trop Med Int Health [Internet]. 2011 May [cited 2022 Sep 13];16(5):598–607. Available from: https://pubmed.ncbi.nlm.nih.gov/21320241/
32. Thomas CJ, Lindsay SW. Local-scale variation in malaria infection amongst rural Gambian children estimated by satellite remote sensing. Trans R Soc Trop Med Hyg [Internet]. 2000 [cited 2022 Sep 13];94(2):159–63. Available from: https://pubmed.ncbi.nlm.nih.gov/10897355/
33. Lowe R, Coelho CA, Barcellos C, Carvalho MS, Catão RDC, Coelho GE, et al. Evaluating probabilistic dengue risk forecasts from a prototype early warning system for Brazil. Elife. 2016 Feb;5.
34. Bhatt S, Gething PW, Brady OJ, Messina JP, Farlow AW, Moyes CL, et al. The global distribution and burden of dengue. Nature [Internet]. 2013 Apr 7 [cited 2017 Jul 30];496(7446):504–7. Available from: http://www.nature.com/doifinder/10.1038/nature12060
35. Louis VR, Phalkey R, Horstick O, Ratanawong P, Wilder-Smith A, Tozan Y, et al. Modeling tools for dengue risk mapping - a systematic review. Int J Health Geogr [Internet]. 2014;13(1):50. Available from: http://ij-healthgeographics.biomedcentral.com/articles/10.1186/1476-072X-13-50
36. Kulldorff M, Heffernan R, Hartman J, Assunção R, Mostashari F. A space-time permutation scan statistic for disease outbreak detection. PLoS Med [Internet]. 2005 [cited 2022 Feb 11];2(3):0216–24. Available from: https://pubmed.ncbi.nlm.nih.gov/15719066/
37. Gething PW, Atkinson PM, Noor AM, Gikandi PW, Hay SI, Nixon MS. A local space–time kriging approach applied to a national outpatient malaria data set. Comput Geosci. 2007 Oct 1;33(10):1337–50.
38. Nulhanuddin N, Andriyani D. Autoregressive Distributed Lag Exchange Rate and Crude Rubber Exports on Indonesia's Economic Growth. J Ekon Reg Unimal. 2020;3(2):47.
39. Martina MLV, Todini E, Libralon A. A Bayesian decision approach to rainfall thresholds based flood warning. Hydrol Earth Syst Sci. 2006;10(3):413–26.
40. Fithriasari K, Soehardjoepritika, Iriawan N. Generalized Additive Logistics In Modeling Factors Affecting Profit PT. PDC. INFERENSI. 2018;1(1):45–7.
41. Islam A, Abdullah M, Tazeen A, Naqvi IH, Kazim SN, Ahmed A, et al. Circulation of dengue virus serotypes in hyperendemic region of New Delhi, India during 2011–2017. J Infect Public Health [Internet]. 2020;13(12):1912–9. Available from: https://doi.org/10.1016/j.jiph.2020.10.009
42. Khumaidi A. Shannon's Entropy Simulation, Renyi's Entropy, and information on the Spin Wheel case. AKSIOMA J Mat dan Pendidik Mat. 2021;12(1):120–8.
43. Rezaei J. Best-worst multi-criteria decision-making method. Omega [Internet]. 2015;53(2):49–57. Available from: http://dx.doi.org/10.1016/j.omega.2014.11.009
44. Rezaei J. A Concentration Ratio for Nonlinear Best Worst Method. Int J Inf Technol Decis Mak. 2020;19(3):891–907.
45. Wongkoon S, Jaroensutasinee M, Jaroensutasinee K. Assessing the temporal modelling for prediction of dengue infection in northern and north-eastern, Thailand. Trop Biomed. 2012 Sep;29(3):339–48.