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The application of geographic information system for dengue epidemic in Southeast Asia: A review on trends and opportunity

Cipta Estri Sekarrini[1], Sumarmi[2], Syamsul Bachri[2], Didik Taryana[2] and Eggy Arya Giofandi[3]

Abstract

The infectious disease dengue hemorrhagic fever remains an unresolved global problem, with climatic conditions and the location of areas located at the equator more often infected with dengue fever. Various modeling approaches have been employed for the development of a dengue risk map. The geographic information system approach was used as an instrument in applying mathematical algorithms to process field vector data into a preventive objective which is studied, then the application of remote sensing provides spatial-temporal data related to land use/land cover data sources as other variable categories. Map of hotspots for dengue fever cases is used to identify the risk of dengue fever areas by applying various complex methodologies, analysis, and visualization of advanced data are needed for its application in public health. In the last 10 years, the increase in the publication of dengue hemorrhagic fever in Southeast Asia in reputable international journals has increased significantly.

Keywords

Dengue, disease dengue, epidemic, Southeast Asia

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Introduction

The viral disease of dengue fever is transmitted by mosquitoes with a rapid spread in the spread of infection transmission of disease, improper control, and severe disease.[1,2] Most of the *Aedes aegypti* and *Aedes albopictus* mosquitoes are in tropical and subtropical climates, transmission conditions are influenced by various factors including virus circulation, vector density, and population susceptibility.[3,4] The pattern of infection increases in semi-urban areas, Southeast Asia is the dominant area affected by endemic dengue hemorrhagic fever, the presence of global cases (14.11%) in 2015 with an estimated 1.8 billion people at risk of dengue.[5,6] Meanwhile, the incidence of dengue fever is reported with an estimated 50–100 million cases each year, and the number of epidemics that occur increases every 3–5 years.[7] The spread is taking place rapidly in the Asia-Pacific region which is associated with globalization, developing rapidly unplanned and unregulated in urban development causing poor water storage and unsatisfactory sanitation conditions.[8]

Dengue virus infection causes various manifestations of low-grade fever, fatal shock syndrome, immunity develops after infection with one of the four viral types, and disease progression with secondary infection.[9–11] The existence of dengue is classified as one of the water-related diseases, water-related diseases account for about 10% of global diseases.[12] Cycles in the increase in the amount of shallow surface water such as water storage basins, wet areas, and

[1]Program Doctoral of Geography Education, Faculty of Social Science, State University of Malang, Malang, East Java, Indonesia
[2]Department of Geography Education, Faculty of Social Science, State University of Malang, Malang, East Java, Indonesia
[3]Department of Geography, Faculty of Social Science, State University of Padang, Padang, West Sumatera, Indonesia

Corresponding author:
Cipta Estri Sekarrinin, Department of Geography Education, State University of Malang, A21 Building 1st Floor Kampus PPG UM Malang, Malang City, East Java 65145, Indonesia.
Email: ciptaputri123123@gmail.com

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swamps are a public concern about the future disturbance of dengue mosquitoes.[13] Environmental conditions with sparse vegetation, transportation routes, low altitude, and urban development after urbanization support *Aedes aegypti* to become uncontrollable even though several criteria are found outside the environment.[14] This is also supported by information on anthropogenic growth that affects the natural environment, such as changes in land use accelerating the problem of ecosystem damage.[15–17] Most of the vector-borne diseases have a seasonal pattern in the case of vector abundance which indicates that dengue is sensitive to climatological factors.[18–21] The need for knowledge and attitudes of local residents in responding to the presence of dengue mosquitoes in controlling vectors in infected areas.[22,23]

The spatial approach provides information in a spatial angle with the disease identification method covering two classes of parametric and non-parametric categories. Non-parametric method of spreading no statistical distribution of spatial disease levels by applying local information in the form of weighted disease levels from neighboring areas looking at the boundaries between spatial regions as well as the opposite category.[24] Some studies on disease geography are categorized into three classes related to the ecological environment, disease clusters, and disease distribution. Geographic information system-based disease mapping information depends on the interests of researchers in sharpening directions regarding patterns, risk factors, and causes of disease in spatial relationships in the research area.[25,26] One of them is calculating population genetics in estimating distribution through spatial autocorrelation analysis with several cases in eastern Thailand, there is a relationship from spatial autocorrelation up to 1 km of the active spread of *Aedes aegypti*.[27,28] Several important factors affect DENV (dengue virus) transmission, where climate variables are kept to a minimum to maintain DENV transmission with seasonal fluctuations in parameters acting as determinants of strength and period of transmission. An understanding of the climatological interactions and the temporal-spatial distribution of infectious diseases has stimulated research interest in infectious disease epidemic modeling.[29–31] An understanding is needed to understand the relationship in estimating future health impacts.[32]

The ability to map the accessibility of health services relying on the application of Euclidean buffers yields results that would be useful, but the lack of investigation of alternative approaches such as the option of applying kerne density estimation to assess health care availability in Nicaragua and combined with algebraic procedures in geographic information systems.[33] The fuzzy logic approach helps to identify the biogeographical interaction of vector diseases in the risk of dengue fever to establish a biogeographical framework for the location of the disease.[34] Currently, dengue risk mapping has focused on future scenarios, understanding of the distribution of dengue virus transmission is far from perfect and needs to be evaluated with additional variables and comparative methods in predicting patterns and trends of dengue fever.[11]

Design and methods

The search terms used are medical, biogeography, geographic information systems for medical, dengue modeling using geographic information systems, spatial-temporal dengue outbreaks, the environment of the *Aedes aegypti* mosquito, the influence of climate on dengue outbreaks, and books related to the application of geographic methods for health. The researchers examined excerpts from the included papers focused on peer-reviewed papers related to the development of geographic technology in the application of health problems.

(E.g. Geographical epidemiology)

Spatial epidemiology identifies and distributes spatial variations in transmission risk through map visualization and exploratory analysis through interpretation of geographic points of view in epidemiological research.[35] When individuals make a diagnosis of transmission, the need for data to address events can be assumed to be an aggregate of events, either country, department, or whatever, then the relative risk measurement using the standard of mortality and mobility ratios gives an analogous result. As long as epidemiological spatial analysis means data in the form of the same spatial unit, separate, and can run without geographic information systems with all the methods discussed consider health data to be superior to area-based data.[36] Application of geographic information system with spatial analysis and spatial statistics as a tool to increase exploration of global factors and points. Spatial analysis tools are becoming available for exploration of transmission relevant to the surrounding environment, with the application of factor X as an investigation case and factor Y as a mathematical nomenclature variable through the spatial point related to the incidence of y as a determinant risk factor for diagnosing the transmission environment.[35]

(E.g. Spatial transmission diffusion)

A phenomenon related to the geomedical use of geographic information systems or remote sensing began to trend around the 1990s, the existence of standardized geography diffusion models began to provide a means to track concepts in geomedical development and began to adopt innovations over a period of time through scientific publications.[37] The introduction of diffusion transmission is the movement of locations without using a network or system for interaction from the beginning of existence. The descriptions of expansion, contact and diffusion of shared configuration or use of change are adapted from contact innovations in which individual relationships exist.[38] The exploratory analysis investigates the understanding of disease patterns to select a more appropriate analysis and further resolving doubts that arose in early stage investigations.[36] Several approaches have been used in the design of spatial diffusion statistical modeling ranging from simple models through single parameters based on normal, binomial, or Poisson distributions to multivariable regression models with distributions covering the number of exposure variables that relate the probability of an outcome to the intensity of exposure of the value of one or more variables.[39]

Result

This study shows a significant growth of dengue hemorrhagic fever publications related to the Southeast Asian region. Various mapping tools are increasingly being used related to vector control, *Aedes aegypti* mosquito surveillance, and public health. Several studies related to control programs have used geographic information systems as monitoring daily surveillance data. The results of the research that have been implemented are shown in Table 1 regarding the risk assessment of dengue fever using geographic information systems and spatial statistics for the

Table 1. Characteristics of the study area.

Urban/Rural	Findings	Country
Urban	Data were collected from 2014 to 2016 related to address, gender, age, and anonymous code. Geocoding kernel density method was applied in determining the cluster of events with the southern and southeastern areas is riskier. The data was about 60% of the total data in the city of Bandung obtained from type B hospital information.[40]	Indonesia
Urban	An observational approach with cross-sectional spatial analysis found that women aged <25 years had a 54% higher percentage than men 46%. The cluster information occurred in March-April 2018 with a transmission radius of three km^2.[41]	Indonesia
Rural	One of the stages carried out in-depth is an interview approach with questions related to the environment and demography linked through secondary data analysis. The risk category was found in children and students. The highest cases reached (78.7%) of the 61 cases found (4.9%) resulted in death.[42]	Indonesia
Urban	The application of the random forest algorithm and ordinary least squares (OLS) regression is carried out statistically, if non-stationary through the geographically weighted regression stage. The obtained values of R2 for the regression ranged from 0.364 to 0.671 and the k-means clustered dataset ranged from 0.395 to 0.945. The results of the GWR model between 0.675 and 0.876 resulted in a logical classification of the GIS grouping analysis.[43]	Philippines
Rural	The information approach was processed using a spatial mean center approach, standard distance, directional distribution analysis, and average nearest neighbor. The distance between events in 2008 was about 22,085 m and for the 2009 case with a distance of 20,318 m. Small-scale transmission with the presence in 2008 the ratio of nearest neighbors 0.225698 and *z*-score −55.444729 and in 2009 the spatial point of dengue cases found the ratio of nearest neighbors 0.264112 and *z*-score −45.748278. Information was related to the factors affecting the distribution pattern and direction of transmission.[44]	Malaysia
Urban	Climate and vegetation variables from 2008 to 2015 were used to predict the incidence of dengue fever through the autoregressive integrated moving average (ARIMA) model. The finding of quadratic correlation reached 0.869.[45]	Philippines
Urban	Dengue fever outbreaks were analyzed through 3 spatial statistics, namely, Moran's I, Average Nearest Neighborhood (ANN), and Kernel Density to see the spatial distribution of cases. There is an average distance of 264.91 m with regional housing locations as identified places.[46]	Malaysia
Urban	The application of fuzzy techniques with epidemiological, environmental, and socio-economic approaches provides a level of model accuracy into four categories, namely positive predictive value (PPV) = 0.780, Negative Predictive Value (NPV) = 0.938, Sensitivity = 0.547, and Specificity = 0.978 with the application of the F0 measure. ,5. Mitigation effectiveness can increase as predictive modeling advances for more precise mitigation and planning consequences management.[47]	Philippines
Urban	The information found during the spatial-temporal period of at-risk groups is concentrated in the southeast and central regions. The clusters formed seven groups ($p < 0.001$) with the most at-risk cluster of 3.94 ($p < 0.001$, about 14% of the total population). Findings from all clusters are 71.4% in the same month for 3 years.[48]	Malaysia
Urban	Ecological and sociodemographic approaches were tested with multivariate and univariate logistic regression. The spatial statistical description of commercial areas mixed with residential and densely populated areas resulted (aOR = 2.23 and $p = 0.009$), while the findings in the sociodemographic model with the highest risk were >45 years old (aOR = 3.24, $p = 0.003$). Communities that apply clean environmental management have the smallest value (aOR = 1.91, $p = 0.035$).[49]	Thailand

control of infectious disease prevention in the Southeast Asian region.

Discussion

The application of geographic information systems in the world of health provides a broad overview of contributions, ranging from case visualization which is used as a tool in spatial epidemiology to help identify disease events and interventions. Case visualization is loaded into a simple display that can be accessed by civilians and health workers to find out information about risks around and the position of the address through the use of global position system input to the web to form health geo-information.

Collection of citation analysis to obtain article quality is sometimes unreliable because published articles still have lower citations. The author's behavior of citing articles is motivated by various reasons, such as methodology, the correct variables produce useful study results. Researchers sometimes cite other papers for the opposite reason, regarding flawed or problematic methods and results. Therefore, it cannot be refuted as an indicator of a good article. Although there are no limitations regarding the results of the literature in the use of keywords and terms in producing relevant case studies. The use of ambiguous language related to technical terms such as climatology, environment, modeling, risk, and dengue mapping, in the literature studied was limited or resulted in bias in the search results.

The review is deliberately focused on studies of utilizing geographic information systems for dengue risk in the Southeast Asian region by linking health problems with existing problems in society, while a number of studies dealing with entomological risks are still minimally considered in the review.

Conclusion

This review has demonstrated the diversity of variables and modeling approaches for the creation of dengue fever risk maps. The growth related to the use of geographic information systems in dengue hemorrhagic fever modeling in reputable international journal publications, increasing both the quality and quantity of publications require various strategies for using variables. The pattern of analysis that is less standardized shows that the field of dengue risk mapping modeling will continue to develop, marked by high variability. Improving the ability of structured training interventions, providing learning references, training for writing that is supported by an academic atmosphere, and policies that encourage the renewal of variability encourage publication of publications. Despite the various limitations, dengue risk maps become a powerful tool to improve surveillance to prediction which depends on the acquisition of availability of good quality data requirements in terms of spatial and temporal resolution.

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Author contributions

CES, designed and interpretation of data, conceptual, literature survey, analysis, and drafting the article; S, involved and contribute to conceptual, critical reviewing and final approval of the version to be submitted; SB, involved and contribute to conceptual, critical reviewing and final approval of the version to be submitted; DT, involved and contribute to conceptual, critical reviewing and final approval of the version to be submitted; EAG, interpretation of data, conceptual, literature survey, analysis, and drafting the article.

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Significance for Public Health

This research has a novelty in helping reduce the transmission of dengue hemorrhagic fever with a spatial perspective, the endemic outbreak of dengue hemorrhagic fever which is transmitted from the aedes aegypti mosquito can be estimated using spatial technology of geographic information systems. This is important to explain regarding the development and opportunities of health information in controlling the Aedes aegypti mosquito outbreak in Southeast Asia. this will assist practitioners and health policy makers in making decisions in estimating the emergence of mosquito habitats.

Availability of data and materials

All data generated or analyzed during this study are included in this published article.

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