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Spatial Clustering and Determinants of Dengue Incidence Among the Young Population of Northern Thailand During the COVID-19 Pandemic

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ABSTRACT

Dengue infection remains a significant public health concern in Thailand, particularly among young populations. The emergence of COVID-19 introduced additional complexity to disease surveillance and control efforts. This study aimed to determine the spatial clustering and determinants of dengue incidence among individuals under 25 years of age in Northern Thailand during the COVID-19 pandemic. Ecological analysis was conducted across 103 districts in eight northern provinces. District-level dengue incidence rates of individuals under 25 years of age for 2021 were calculated and analyzed using global Moran's I and local indicators of spatial association (LISA) to detect spatial clustering. Bivariate LISA was employed to explore spatial correlations between dengue incidence and sociodemographic, environmental, and health service factors. Spatial regression models were applied to identify significant predictors while accounting for spatial dependence. There were 18 districts (17.48%) with dengue incidence rates higher than the national target. Global Moran's I indicated a positive spatial autocorrelation (Moran's I = 0.087), and LISA identified significant high-high clusters in two remote border districts. Bivariate LISA analysis revealed significant positive spatial associations between dengue incidence and the proportion of the population under 25 years of age, COVID-19 morbidity rate, and minimum, maximum, and average rainfall. In contrast, significant negative spatial associations were observed with the proportion of the urban population, COVID-19 fatality rate, and both minimum and average temperatures. Given the low spatial dependence observed, the ordinary least squares model was considered appropriate and identified the number of schools, the ratio of village health volunteers to households, and average temperature as significant determinants of dengue incidence ($R^2 = 0.102$). These findings indicated the need for geographically targeted health planning strategies and community design, school-based vector control, and climate-informed surveillance strategies. Integrated and resilient public health systems are essential for managing concurrent health threats.

Keywords: dengue incidence, young population, clustering, sociodemographic, environment, health service

INTRODUCTION

Dengue infection is one of the most widespread mosquito-borne viral diseases in tropical and subtropical regions, with Southeast Asia accounting for a substantial proportion of the global burden. In Thailand, dengue remains endemic, and children and young adults (individuals under 25 years of age) have consistently represented a disproportionately high number of reported cases in Thailand, particularly in endemic regions of the north region (Thisyakorn et al., 2022). The emergence of the COVID-19 pandemic disrupted routine public health functions, including vector control, mobility patterns, access to care, and disease surveillance (Roster et al., 2024; Yek et al., 2022). These disruptions might have uniquely affected younger populations, especially students and adolescents, due to prolonged school closures, increased time spent at home, and reduced access to health education and prevention activities (Bialy et al., 2024). Such factors likely altered exposure patterns and care-seeking behaviors, contributing to shifts in dengue transmission among youth during this period (Brady & Wilder-Smith, 2021; Liyanage et al., 2021).

Despite this significance, few studies have specifically examined the spatial epidemiology of dengue among youth during the COVID-19 pandemic, especially in the northern provinces of Thailand, where both vector ecology and population distribution vary considerably. Existing research has largely focused on general population models or aggregated case data without disaggregating by age or examining contextual risk factors relevant to young people's environments, such as proximity to schools, urban-rural variation, or community-level health services (Hnusuwan et al., 2020; Phanitchat et al., 2019; Saita et al., 2022). Understanding how sociodemographic, environmental, and health system factors shape these spatial variations is essential for building responsive, dengue area-based surveillance and control strategies amid emerging health crises (Rahman et al., 2021; Romeo-Aznar et al., 2024; Zheng et al., 2019).

Therefore, these gaps need to be addressed by focusing specifically on individuals under 25 years of age, integrating geospatial methods to identify spatial clustering and determinants of dengue incidence across 103 districts in Northern Thailand during the COVID-19 pandemic, in particular in 2021. By incorporating spatial autocorrelation measures and spatial regression models, the research aims to produce actionable insights that account for demographic-specific vulnerabilities and spatial heterogeneity, both of which are essential for effective area-based public health planning and disease control during the overlapping health crisis.

RESEARCH MATERIALS AND METHODOLOGY

Study areas

This study was conducted in Northern Thailand, comprising eight provinces: Chiang Mai, Chiang Rai, Mae Hong Son, Lamphun, Lampang, Phayao, Phrae, and Nan. These provinces are characterized by mountainous terrain and extensive forest cover. The unit of analysis was at the district level, encompassing a total of 103 districts (Figure 1). The region features diverse topographical and ecological conditions that may influence the transmission dynamics of dengue fever. Population density across districts varied, ranging from 3.98 to 302.09 persons per square kilometer (Office Statistics Registration System, Ministry of Interior, 2021). The majority of the population resided in rural or semi-urban areas, which are interspersed with highland communities and remote settlements.

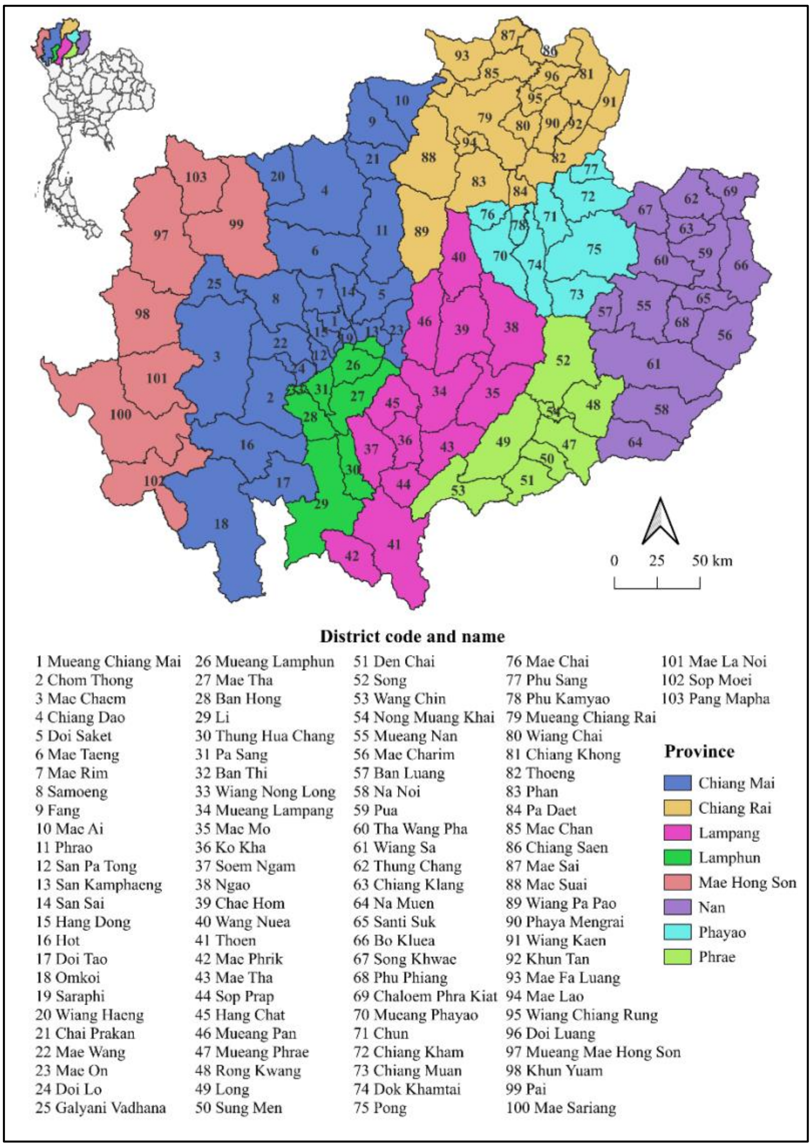
Data Preparation

The dependent variable in this study was the incidence rate of dengue infection (per 100,000 population) among individuals under 25 years of age at the district level in 2021. Data on new dengue cases diagnosed according to the 1997 WHO guidelines (World Health Organization, 1997) were obtained from the national disease surveillance system (R506). The mid-year population was also retrieved from the Bureau of Epidemiology, Department of Disease Control, Ministry of Public Health (Bureau of Epidemiology, Department of Disease Control, Ministry of Public Health Thailand, 2021). The incidence rate in each district was calculated using the number of reported all serotypes of dengue cases comprising dengue fever, dengue hemorrhagic fever, and dengue shock syndrome of individuals under 25 years of age divided by the mid-year population of each district in the same age group and then multiplied by 100,000 to standardize the measure.

The independent variables in this study in 2021 were categorized into three main groups: sociodemographic factors, environmental characteristics, and health service indicators. Sociodemographic variables included the sex ratio (male to female) among individuals under 25 years of age, the proportion (%) of the population under 25 years old, population density, and the proportion (%) of urban population. These data were sourced from the Bureau of Registration Administration, Ministry of Interior (Bureau of Registration Administration, Ministry of Interior, n.d.). Additionally, the nighttime light (NTL) in 2021 was obtained from SNPP/VIIRS satellites using Google Earth Engine, with a spatial resolution of approximately 500 meters. To account for differences in district area, NTL values were normalized by calculating the average of NTL per square kilometer and aggregated at the district level using zonal mean statistics. NTL was used as a proxy for urbanization and economic activity (Puttanapong et al., 2022).

Figure 1

Map of 103 Districts in 8 Provinces in Northern Thailand



Environmental variables, including rainfall, temperature, and Normalized Difference Vegetation Index (NDVI), were derived from satellite sources via Google Earth Engine for the year 2021. Rainfall data were obtained from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset, with a spatial resolution of approximately 5 km. Land surface temperature and NDVI were derived from the Terra MODIS sensor at a 1 km resolution. Minimum, maximum, and average values of each environmental variable were computed for each district using zonal statistics based on district boundaries. Additional environmental indicators comprised the proportion (%) of households with poor hygiene, the number of higher education institutions, schools, and nurseries. These data were sourced from the Basic Needs Data platform by the Community Development Department, the Ministry of Interior (Community Development Department, Ministry of Interior, 2021), and the Educational Information Center, Ministry of Education (Educational Information Center, Ministry of Education, 2021).

Health service-related variables in each district included the ratio of village health volunteers (VHVs) to households, which was obtained from the Department of Health Service Support, Ministry of Public Health (Department of Health Service Support, Ministry of Public Health, n.d.). Data on the COVID-19 morbidity rate and the fatality rate of COVID-19 were obtained from Provincial Public Health Offices using a district-based data recording form.

Data analysis

Spatial Distribution and Clustering

The spatial distribution of dengue incidence among individuals under 25 years of age at the district level in 2021 was calculated, and a map was created using QGIS 3.28.0 (QGIS Development Team, 2023), compared to the national target (40 cases per 100, 000 population). Before assessing the spatial autocorrelation of dengue incidence across districts in 2021, the spatial empirical Bayesian (SEB) smoothed incidence was computed to solve the problem of comparing rates in different population sizes related to the problem of variance instability and spurious outliers (Deb Nath et al., 2023; Saita et al., 2022). The spatial autocorrelation based on SEB-smoothed incidence was investigated using Moran's I equation, which is defined as in Eq. (1). This measure evaluates whether the spatial distribution of a variable is clustered, dispersed, or random by comparing the value at each location with the values at neighboring locations. Moran's I ranges from -1 to +1, where positive values indicate spatial clustering of similar values, negative values suggest spatial dispersion, and values near zero imply a random spatial pattern (Li et al., 2007). For the spatial weight matrix, a fixed distance threshold of approximately 45 kilometers was used to define spatial neighbors based on Euclidean distance between district centroids. This distance ensured that all districts had at least one neighbor and avoided isolated spatial units. The threshold was determined using an incremental spatial autocorrelation test based on Global Moran's I, which identified the distance at which spatial clustering peaked. A distance-based approach was chosen over contiguity-based methods (e.g., Queen or Rook adjacency) due to the substantial variation in size, shape, and geographic isolation of administrative districts in Northern Thailand. Many remote or mountainous districts do not share borders with adjacent units, rendering contiguity-based definitions less effective. The use of a Euclidean distance threshold (approximately 45 kilometers) ensures that all districts have at least one spatial neighbor, enabling a more accurate representation of proximity-based spatial interactions across a heterogeneous landscape.

The analysis was performed using GeoDa software, which provides robust tools for spatial statistical analysis (Anselin et al., 2022). A statistically significant positive Moran's I value would indicate clustering of high or low dengue incidence rates in neighboring districts.

$$I = \frac{n \sum_i \sum_j w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{(\sum_i \sum_j w_{ij}) \sum_i (x_i-\bar{x})^2} \quad (1)$$

Where n is the number of spatial units (districts); x_i is the value of the variable at location i; x_j is the value of the variable at location j (the neighbor of location i); $\bar{x}$ is the mean of the observed value; w_{ij} is the spatial weight between locations i and j.

In addition to Moran's I, LISA were applied to detect the presence and location of local clusters of dengue incidence based on SEB-smoothed incidence as in Eq. (2). LISA statistics assess the degree of spatial association around individual spatial units, enabling the identification of statistically significant local patterns that may not be evident through global measures. The results classified districts into four types of spatial clusters: High-High (hotspots), where districts with high dengue incidence are surrounded by similarly high-incidence district neighbors; Low-Low (cold spots), where districts with low incidence are surrounded by low-incidence district neighbors; and the spatial outliers High-Low and Low-High, which represent districts with values that contrast with those of their surrounding areas (Anselin, 1995).

$$I_i = \frac{\sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (2)$$

Where x_i is the value of the variable at location i; x_j is the value of the variable at location j (the neighbor of location i); $\bar{x}$ is the mean of the observed value; and w_{ij} is the spatial weight between locations i and j.

Bivariate Local Moran's I

To further explore spatial relationships between two distinct variables, bivariate local Moran's I was employed. This method extends the traditional LISA by measuring the spatial association between the value of one variable at a given location and the values of a second variable in neighboring locations as in Eq. (3). In this study, bivariate LISA was applied to examine local spatial correlations between dengue incidence and potential explanatory variables, including sociodemographic, environmental, and health service factors. The analysis identified spatial clusters where high (or low) values of the dengue incidence co-occur with high (or low) values of an independent variable in adjacent districts. The analysis was performed using GeoDa software, with spatial relationships defined by a fixed-distance spatial weight matrix based on Euclidean distance, using a threshold of approximately 45 kilometers. Statistical significance was assessed using 999 random permutations, with a significance level set at $p < 0.05$.

$$I_i^B = (x_i - \bar{x}) \sum_j w_{ij}(y_j - \bar{y}) \quad (3)$$

Spatial regression

To examine the spatial determinants of dengue incidence at the district level, accounting for spatial dependence, the spatial regression models included variables that demonstrated statistical or marginal significance ($p < 0.100$) in the bivariate spatial correlation analysis and showed no evidence of multicollinearity. Three regression approaches were employed: ordinary least squares (OLS), spatial lag model (SLM), and spatial error model (SEM) (Anselin, 1988; Anselin & Bera, 1998). These models enabled the identification of key sociodemographic, environmental, and health service-related factors associated with spatial variations in dengue incidence.

The OLS model served as the baseline for comparing and verifying the spatial model. The general form of the OLS model is Eq. (4).

$$Y = \beta_0 + \beta X + \varepsilon \quad (4)$$

where Y is the dependent variable, X is a matrix of explanatory variables, β_0 is the intercept, β is the regression coefficient of X, and ε is the error term.

To address spatial autocorrelation, the SLM incorporates a spatially lagged dependent variable as an additional predictor. The SLM equation is defined as Eq. (5).

$$Y = \beta_0 + \beta X + \rho W y + \varepsilon \quad (5)$$

where ρ is the spatial autoregressive coefficient, and Wy is the spatial lag of the dependent variable, based on a spatial weight matrix W.

The SEM assumes that spatial dependence is present in the error terms rather than in the dependent variable itself. The SEM equation is defined as Eq. (6).

$$Y = \beta_0 + \beta X + \lambda W \xi + \varepsilon \quad (6)$$

where λ is the spatial autoregressive coefficient in the error component, and $W\xi$ is the spatial error.

Both SLM and SEM were estimated using a spatial weight matrix constructed based on Euclidean distance, with a fixed distance threshold of approximately 45 kilometers. Model performance was compared using diagnostic indicators, including the Akaike Information Criterion (AIC), log-likelihood, coefficient of determination (R^2), and Lagrange Multiplier (LM) tests. Statistical significance was considered at $p < 0.05$.

Ethical approval

This study was reviewed and exempted from a full ethical review by the Human Research Ethics Committee of Thammasat University, Thailand. The exemption was granted under approval number 015/2566, dated May 16, 2023.

RESULTS

Spatial Clustering of Dengue Incidence

In 2021, the dengue incidence among individuals under 25 years of age in Northern Thailand was 43.59 per 100,000 population. Spatial distribution exhibited substantial variation across districts. Based on the national dengue control target (40 cases per 100,000 population), the majority of districts (85 out of 103) met the national target. However, seven districts (6.8%) reported incidence rates exceeding four times the national target, with the highest burden concentrated in the western region, particularly in Mae Hong Son Province, and in parts of northern Chiang Rai and Nan Province (Figure 2a).

The Global Moran's I statistics for dengue incidence was 0.087, indicating a positive spatial autocorrelation across districts in 2021 (Figure 3). LISA analysis revealed significant spatial clustering of dengue incidence across districts. Out of the 103 districts, 22 districts (21.4%) exhibited statistically significant local spatial autocorrelation ($p < 0.05$). Among these, the most notable clusters were two High-High districts located in the remote western border area of Mae Hong Son Province, Sop Moei and Mae Sariang, highlighting zones of elevated incidence surrounded by similar high-incidence neighbors. In contrast, Low-Low clusters were observed in several central and eastern districts, particularly in Lampang, Phrae, and Nan, where both local and neighboring districts reported low dengue incidence. Low-High outliers, primarily found in northern Chiang Rai Province, indicate districts with relatively low dengue incidence surrounded by high-incidence neighbors (Figure 2b and Table 1).

Figure 2

Distribution of Dengue Incidence (a) and LISA Clusters (b) in Northern Thailand, 2021

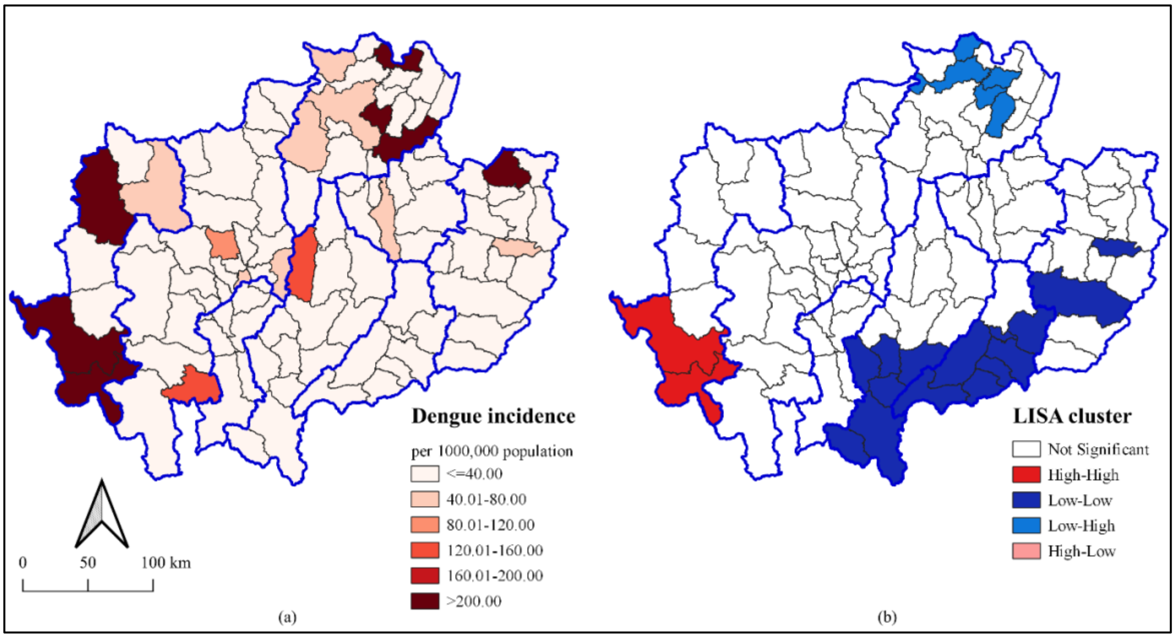


Figure 3

Moran's I Scatterplot of SEB Dengue Incidence in 2021

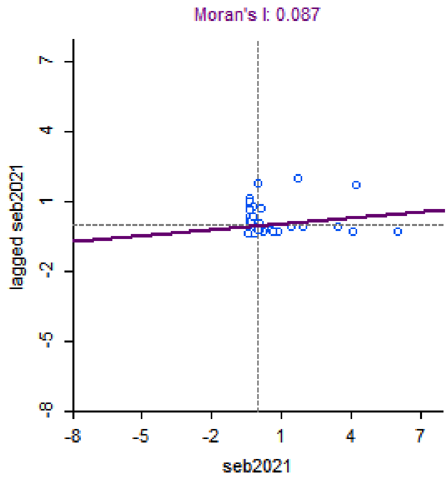


Table 1

Dengue Cluster by District and Province

Cluster	District	Province
High-High	Mae Sariang	Mae Hong Son
High-High	Sop Moei	Mae Hong Son
Low-Low	Soem Ngam	Lampang
Low-Low	Thoen	Lampang
Low-Low	Mae Phrik	Lampang
Low-Low	Mae Tha	Lampang
Low-Low	Ko Kha	Lampang
Low-Low	Sop Prap	Lampang
Low-Low	Mueang Phrae	Phrae
Low-Low	Long	Phrae
Low-Low	Den Chai	Phrae
Low-Low	Wang Chin	Phrae
Low-Low	Nong Muang Khai	Phrae
Low-Low	Sung Men	Phrae
Low-Low	Rong Kwang	Phrae
Low-Low	Wiang Sa	Nan
Low-Low	Santi Suk	Nan
Low-High	Wiang Chiang Rung	Chiang Rai
Low-High	Doi Luang	Chiang Rai
Low-High	Mae Sai	Chiang Rai
Low-High	Mai Chan	Chiang Rai
Low-High	Phaya Mengrai	Chiang Rai

Spatial Determinants of Dengue Incidence

Among sociodemographic variables, the proportion of the population under 25 years old showed a significant positive spatial correlation with dengue incidence (I = 0.190, p = 0.001); meanwhile, the proportion of urban population was negatively associated (I = –0.110, p = 0.003). The minimum, maximum, and average rainfall showed statistically significant positive spatial correlations with dengue incidence (I = 0.084, 0.107, and 0.089, respectively; $p < 0.05$), while minimum and average temperature were negatively associated (I = –0.120 and –0.141; p = 0.004 and 0.002, respectively). Regarding health service factors, the COVID-19 morbidity rate was positively associated with dengue incidence (I = 0.107, p = 0.024), whereas the COVID-19 fatality rate exhibited a significant negative spatial relationship (I = –0.076, p = 0.016) (Table 2).

Among key spatial determinants of dengue incidence, the bivariate LISA analysis revealed distinct spatial clustering patterns between dengue incidence and several explanatory variables. High-High clusters, indicating districts with both high dengue incidence and high values of the explanatory variable in surrounding neighbors, were most frequently observed in the northernmost districts of Chiang Rai Province (e.g., Mae Chan, Mae Sai, Phaya Mengrai, and Wiang Chiang Rung) and the western border districts of Mae Hong Son Province (Sop Moei and Mae Sariang). These clusters were consistent across multiple variables, suggesting overlapping vulnerabilities. In contrast, Low-Low clusters were concentrated in central and eastern districts such as Ko Kha, Soem Ngam, and Sop Prap in Lampang; Rong Kwang and Den Chai in Phrae; and Ban Luang in Nan areas characterized by low dengue incidence and correspondingly low levels of explanatory variables in neighbors (Figure 4 and Table 3).

All three models (OLS, SLM, and SEM) were estimated using a spatial weight matrix based on a 45 km Euclidean distance threshold. However, tests for spatial dependence, including Global Moran's I and LM diagnostics, indicated no significant spatial autocorrelation in the residuals (p-values > 0.262), suggesting that the data did not exhibit strong spatial dependence (Table 4).

As such, the use of spatial regression models may not be strictly necessary in this context. Nonetheless, for comparative purposes, both the SLM and SEM were assessed. The SEM demonstrated slightly better model fit, with the lowest AIC (1259.89), highest log-likelihood (–624.943), and marginally improved R^2 (0.108). Across all models, the ratio of VHVs to households, the number of schools, and average temperature were statistically significant predictors of dengue incidence. Specifically, higher VHV-to-household ratios and a greater number of schools were positively associated with dengue incidence, while higher average temperature was negatively associated with dengue incidence (Table 5).

Table 2

Bivariate Moran's I Between Sociodemographic, Environmental, Health Services Related Factors, and Dengue Incidence

Factors	I	p	Factors	I	p
Sociodemographic factors			**Environmental factors**		
Sex ratio (male to female)	0.013	0.380	Minimum rainfall	0.084	0.027*
% of population under 25 years old	0.190	0.001*	Maximum rainfall	0.107	0.014*
Population density	-0.030	0.241	Average rainfall	0.089	0.021*
% of urban population	-0.110	0.003*	Minimum temperature	-0.120	0.004*
NTL	-0.011	0.102	Maximum temperature	-0.048	0.109

Table 2 (Continued)

Factors	I	p	Factors	I	p
Health services			Average temperature	-0.141	0.002*
Ratio of VHVs to households	-0.051	0.093	Minimum NDVI	-0.012	0.394
COVID-19 morbidity rate	0.107	0.024*	Maximum NDVI	-0.061	0.083
COVID-19 fatality rate	-0.076	0.016*	Average NDVI	-0.040	0.180
			Proportion of poor hygiene households	0.064	0.082
			Number of higher education institutions	-0.035	0.192
			Number of schools	0.061	0.078
			Number of nurseries	0.028	0.249

Note. * p<0.05

Figure 4

Bivariate LISA Cluster Map of Dengue Incidence and Significant Explanatory Variables

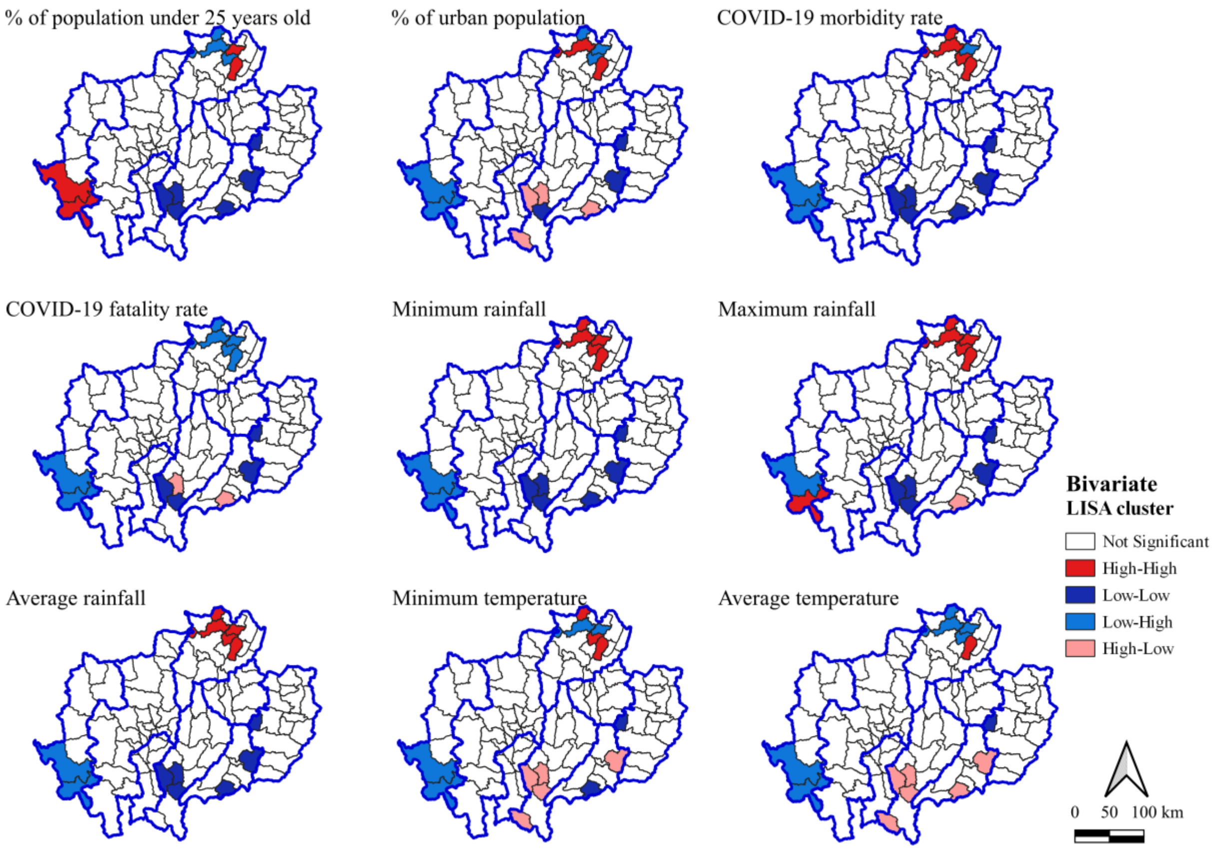


Table 3

Districts Within Significant Bivariate LISA Clusters Between Dengue Incidence and Key Determinants, Northern Thailand, 2021

b	Cluster	District	Province	Cluster	District	Province
% of population under 25 years old	H-H	Phaya Mengrai	Chiang Rai	L-L	Ko Kha	Lampang
		Doi Luang	Chiang Rai		Soem Ngam	Lampang
		Mae Sariang	Mae Hong Son		Sop Prap	Lampang
		Sop Moei	Mae Hong Son		Rong Kwang	Phrae
					Den Chai	Phrae
					Ban Luang	Nan
	L-H	Mae Chan	Chiang Rai	H-L	-	-
		Mae Sai	Chiang Rai			
		Wiang Chiang Rung	Chiang Rai			
% of urban population	H-H	Mae Chan	Chiang Rai	L-L	Sop Prap	Lampang
		Phaya Mengrai	Chiang Rai		Rong Kwang	Phrae
					Ban Luang	Nan
	L-H	Mae Sai	Chiang Rai	H-L	Ko Kha	Lampang
		Wiang Chiang Rung	Chiang Rai		Soem Ngam	Lampang
		Doi Luang	Chiang Rai		Mae Phrik	Lampang
		Mae Sariang	Mae Hong Son		Den Chai	Phrae
		Sop Moei	Mae Hong Son			
COVID-19 morbidity rate	H-H	Mae Chan	Chiang Rai	L-L	Ko Kha	Lampang
		Mae Sai	Chiang Rai		Soem Ngam	Lampang
		Phaya Mengrai	Chiang Rai		Sop Prap	Lampang
		Wiang Chiang Rung	Chiang Rai		Rong Kwang	Phrae
					Den Chai	Phrae
					Ban Luang	Nan
	L-H	Doi Luang	Chiang Rai	H-L	-	-
		Mae Sariang	Mae Hong Son			
		Sop Moei	Mae Hong Son			

Table 3 (Continued)

b	Cluster	District	Province	Cluster	District	Province
COVID-19 fatality rate	H-H	-	-	L-L	Soem Ngam	Lampang
					Sop Prap	Lampang
					Rong Kwang	Phrae
					Ban Luang	Nan
	L-H	Mae Chan	Chiang Rai	H-L	Ko Kha	Lampang
		Mae Sai	Chiang Rai		Den Chai	Phrae
		Phaya Mengrai	Chiang Rai			
		Wiang Chiang Rung	Chiang Rai			
		Doi Luang	Chiang Rai			
		Mae Sariang	Mae Hong Son			
		Sop Moei	Mae Hong Son			
Minimum rainfall	H-H	Mae Chan	Chiang Rai	L-L	Ko Kha	Lampang
		Mae Sai	Chiang Rai		Soem Ngam	Lampang
		Phaya Mengrai	Chiang Rai		Sop Prap	Lampang
		Wiang Chiang Rung	Chiang Rai		Rong Kwang	Phrae
		Doi Luang	Chiang Rai		Den Chai	Phrae
					Ban Luang	Nan
	L-H	Mae Sariang	Mae Hong Son	H-L	-	-
		Sop Moei	Mae Hong Son			
Maximum rainfall	H-H	Mae Chan	Chiang Rai	L-L	Ko Kha	Lampang
		Mae Sai	Chiang Rai		Soem Ngam	Lampang
		Phaya Mengrai	Chiang Rai		Sop Prap	Lampang
		Wiang Chiang Rung	Chiang Rai		Rong Kwang	Phrae
		Doi Luang	Chiang Rai		Ban Luang	Nan
		Sop Moei	Mae Hong Son			
	L-H	Mae Sariang	Mae Hong Son	H-L	Den Chai	Phrae
Average rainfall	H-H	Mae Chan	Chiang Rai	L-L	Ko Kha	Lampang
		Mae Sai	Chiang Rai		Soem Ngam	Lampang
		Phaya Mengrai	Chiang Rai		Sop Prap	Lampang
		Wiang Chiang Rung	Chiang Rai		Rong Kwang	Phrae
		Doi Luang	Chiang Rai		Den Chai	Phrae
					Ban Luang	Nan
	L-H	Mae Sariang	Mae Hong Son	H-L	-	-
		Sop Moei	Mae Hong Son			

Table 3 (Continued)

b	Cluster	District	Province	Cluster	District	Province
Minimum temperature	H-H	Mae Sai	Chiang Rai	L-L	Den Chai	Phrae
		Phaya Mengrai	Chiang Rai		Ban Luang	Nan
		Wiang Chiang Rung	Chiang Rai			
	L-H	Mae Chan	Chiang Rai	H-L	Ko Kha	Lampang
		Doi Luang	Chiang Rai		Soem Ngam	Lampang
		Mae Sariang	Mae Hong Son		Mae Phrik	Lampang
		Sop Moei	Mae Hong Son		Sop Prap	Lampang
					Rong Kwang	Phrae
Average temperature	H-H	Phaya Mengrai	Chiang Rai	L-L	Ban Luang	Nan
	L-H	Mae Chan	Chiang Rai	H-L	Ko Kha	Lampang
		Mae Sai	Chiang Rai		Soem Ngam	Lampang
		Wiang Chiang Rung	Chiang Rai		Mae Phrik	Lampang
		Doi Luang	Chiang Rai		Sop Prap	Lampang
		Mae Sariang	Mae Hong Son		Rong Kwang	Phrae
		Sop Moei	Mae Hong Son		Den Chai	Phrae

Note. H-H = High-High, L-L = Low-Low, L-H = Low-High, and H-L = High-Low

Table 4

Diagnostics for Spatial Dependency

Test	MI or DF	Value	p-value
Moran's I (error)	0.045 (MI)	1.122	0.262
Lagrange Multiplier (lag)	1 (DF)	0.743	0.389
Robust LM (lag)	1 (DF)	0.380	0.538
Lagrange Multiplier (error)	1 (DF)	0.539	0.463
Robust LM (error)	1 (DF)	0.176	0.675
Lagrange Multiplier (SARMA)	1 (DF)	0.919	0.632

Note. MI = Moran's I statistic and DF = Degrees of Freedom

Table 5

Spatial Regression Models of Dengue Incidence, 2021

Factors	OLS (SE)	p	SLM (SE)	p	SEM (SE)	p
COVID-19 morbidity rate	-6.542×10^{-4} (6.187×10^{-4})	0.293	-6.933×10^{-4} (6.013×10^{-4})	0.249	-7.055×10^{-4} (6.209×10^{-4})	0.256
Ratio of VHVs to households	5.332 (2.373)	0.027*	5.385 (2.306)	0.020*	5.474 (2.304)	0.018*
Number of schools	1.333 (0.643)	0.041*	1.277 (0.628)	0.042*	1.289 (0.636)	0.043*
Average temperature	-16.952 (7.705)	0.030*	-15.539 (7.604)	0.041*	-15.859 (7.849)	0.043*
ρ	-		0.115 (0.151)	0.447	-	
λ	-		-		0.107 (0.156)	0.495
F-statistic	2.794		-		-	
R^2	0.102		0.109		0.108	
Log likelihood	-625.134		-624.874		-624.943	
AIC	1260.277		1261.754		1259.891	

Note. SE = standard error, ρ = spatial autoregressive coefficient, λ= spatial error coefficient, R^2 = coefficient of determination, AIC = Ake's Information Criterion and * $p<0.05$.

DISCUSSION

During the COVID-19 pandemic in 2021, few districts in Northern Thailand had higher dengue incidence among individuals under 25 years than the national target, which were in the border area. This was in line with a positive global spatial autocorrelation in the LISA cluster map, which identified specific high-high clusters, particularly in the west district of Mae Hong Son, a remote, mountainous border area adjoining Myanmar. A concentrated spatial burden of dengue incidence might be influenced by limited access to healthcare during the pandemic and ecological conditions conducive to *Aedes* mosquito breeding. The remoteness of Mae Hong Son and the challenges in surveillance efforts during the crisis might also contribute to delayed outbreak detection and under-resourced vector control, amplifying disease clustering in these areas (Lu et al., 2023). These might point to the need for spatial planning approaches that address the vulnerabilities of peripheral regions. The low-high clusters in the northern district of Chiang Rai Province might indicate areas where preventive measures are effective, despite proximity to high-burden districts. These areas are risk zones that serve as critical targets for proactive vector control, community engagement, and enhanced surveillance, particularly during periods of regional outbreak expansion. Alternatively, it may reflect reporting gaps or differences in surveillance sensitivity during the COVID-19 pandemic (Rahastri & Sulistyawati, 2024; Roster et al., 2024), highlighting the need for continuous monitoring in districts even during the pandemic.

The bivariate spatial analysis revealed several contextual factors influencing dengue incidence during the COVID-19 pandemic in northern

Thailand. A higher proportion of the population under 25 years of age exhibited a significant positive spatial association with dengue incidence, especially in High-High clusters in Mae Hong Son and northern Chiang Rai. This aligns with known epidemiological trends in Thailand, where children and young adults remain particularly vulnerable due to behavioral exposure and lower immunity (Thisyakorn et al., 2022). Conversely, a higher proportion of the urban population showed a negative spatial association with dengue incidence. This may reflect benefits of urban infrastructure, more consistent vector control, and improved healthcare access in urban areas (Lindsay et al., 2017; Mani et al., 2021). Interestingly, this pattern contrasts with pre-pandemic trends in some countries where urban areas often reported higher dengue burdens, suggesting that urban-rural risk patterns may shift under overlapping health crises (Brady & Wilder-Smith, 2021). The COVID-19 morbidity rate demonstrated a positive spatial correlation with dengue incidence, suggesting that areas with high COVID-19 case burdens may have experienced interruptions in vector control, reduced community health activities, or health system strain. In contrast, the COVID-19 fatality rate showed a negative spatial correlation with dengue, likely because fatalities reflect healthcare outcomes and population vulnerability rather than disease burden. These findings reinforce the importance of syndemic-informed surveillance systems that account for simultaneous public health threats (Araujo et al., 2024; Wilder-Smith & Osman, 2020). Regarding climate variables, minimum, maximum, or average rainfall was positively associated with dengue incidence, consistent with its role in creating breeding habitats for *Aedes* mosquitoes (Xu et al., 2024). On the other hand, minimum and average temperatures had significant negative spatial correlations, particularly in highland and cooler districts, supporting evidence that cooler climates constrain mosquito survival and virus replication (Nik Abdull Halim et al., 2022). These spatial patterns highlight the interplay between demographic, climatic, and health system variables in shaping dengue risk, underscoring the importance of geographically tailored vector control and health interventions, especially in peripheral or underserved districts.

Spatial regression analysis confirmed three consistent and significant determinants of dengue incidence: the ratio of VHVs to households, the number of schools, and average temperature. A positive association was observed between the VHVs to household ratio and dengue incidence. Areas with a higher VHVs coverage tend to have a higher number of recorded cases. During the COVID-19 pandemic, VHVs in Thailand played a crucial role in the prevention and control of COVID-19, leveraging their community-based approach to health care involving proactive disease control, community education, and direct health services, which collectively helped mitigate the spread of the virus (Krassanairawiwong et al., 2021; Singweratham et al., 2024; Zaheer et al., 2022). A high VHVs coverage still could facilitate the education of dengue symptoms, collection of dengue case data, and ensure that cases are reported accurately while facing this crisis, contributing to higher, timely recorded dengue cases. This aligns with findings that emphasize the importance of robust surveillance systems in tracking dengue cases (Togami et al., 2023). This study suggests that areas with higher disease burdens may require the allocation of more VHVs to support public health responses (Bohm et al., 2024).

Schools represent high-density environments where large numbers of children and adolescents congregate during the day, providing favorable conditions for mosquito-human contact. Furthermore, school environments might inadvertently serve as breeding grounds for *Aedes* mosquitoes due to the presence of shaded areas, open containers, clogged drainage systems, and insufficient sanitation infrastructure (Ratanawong et al., 2016). In Southeast Asian schools, water storage containers, such as drums and buckets, are common breeding sites for *Aedes* mosquitoes. A study in Indonesia found that schools with poor waste management practices and uncovered water containers had higher *Aedes* indices, indicating increased mosquito breeding (Sasmita et al., 2021). This risk was compounded by the tendency of children to spend extended periods outdoors, often without protective clothing or repellent. Moreover, during the COVID-19 pandemic, intermittent school closures due to lockdown measures and reopening might have influenced local dengue dynamics by altering population movement and vector exposure patterns (Chen et al., 2022). As schools resume full operations, it is crucial to reinforce dengue prevention measures in educational settings, particularly in high-risk districts. This finding also highlighted for integration of vector-aware design principles into educational facility planning, especially in high-risk districts.

Districts with lower average temperatures tended to report higher dengue incidence among individuals under 25 years of age during the COVID-19 pandemic. Previous research indicated that dengue transmission occurs most efficiently within an optimal temperature range of approximately 21-34°C (Manna et al., 2024; Ryan et al., 2019). Within this range, mosquito survival, biting rates, and viral replication inside the mosquito are maximized. However, temperatures above this range, especially when sustained, can reduce mosquito survival, impair egg and larval development, and inhibit virus propagation, thereby lowering transmission potential (Agyekum et al., 2021, 2022). This phenomenon might explain the negative association observed in this study. Lower-altitude areas of Northern Thailand experience higher average temperatures. However, highland areas such as parts of Mae Hong Son and Chiang Rai Provinces, which have reported high dengue incidence, may still exhibit temperature conditions that are still within or close to the optimal dengue transmission range, especially during the rainy season. These highland areas might also experience unique climatic characteristics with moderate temperatures, higher humidity, and suitable breeding habitats, creating favorable conditions for localized outbreaks, since a study focused on broader trends in Thailand indicated that relative humidity and precipitation trends vary regionally (Kliengchuay et al., 2024). Climate variability associated with the El Niño–Southern Oscillation (ENSO) has also been linked to changes in dengue patterns across Asia. ENSO-related temperature shifts can influence mosquito population dynamics and expand transmission into previously cooler regions (Jing et al., 2024). This reinforces the importance of incorporating temperature trends into spatial risk models and suggests that climate-informed early warning systems could help anticipate dengue outbreaks in vulnerable districts.

Although the COVID-19 morbidity rate did not show a statistically significant association with dengue incidence in this study, the coexistence of these diseases emphasizes the importance of integrated surveillance systems capable of managing concurrent health threats (Khan et al., 2022). The pandemic might have indirectly influenced dengue patterns through disruptions in vector control, altered healthcare-seeking behavior, and changes in human mobility, leading to complex and localized effects on transmission (Chen et al., 2022). Additionally, the reallocation of public health resources toward COVID-19 might have impacted dengue case detection and reporting, particularly in under-resourced areas (Wiyono et al., 2021).

Although spatial regression models such as SLM and SEM are widely recommended for addressing spatial autocorrelation in geographic health data (Anselin, 1988), their necessity may depend on the extent of spatial dependence present in the dataset. In this study, the Global Moran's I statistics for dengue incidence were relatively low, and diagnostic tests for spatial dependence returned non-significant results, suggesting no substantial spatial autocorrelation in the residuals. Accordingly, the spatial parameters in both SLM ($\rho = 0.115$) and SEM ($\lambda = 0.107$) were statistically insignificant. While the SEM yielded a slightly better model fit, the improvements over the OLS model were marginal. Importantly, the key explanatory variables were consistently significant across all models, reinforcing the robustness of these associations. These findings support the use of the simpler OLS model in contexts where spatial dependence is weak, as it offers interpretable and statistically sound results without unnecessary model complexity. Nevertheless, the spatial lag framework retains conceptual relevance. Even when not statistically dominant, it highlights the potential for inter-district transmission dynamics influenced by human mobility, environmental continuity, and vector behavior (Pakaya et al., 2023; Soukavong et al., 2024). Therefore, incorporating spatial perspectives into disease surveillance, particularly through coordinated regional responses, can strengthen preparedness, strategic planning, and policy implementation. In regions with similar ecological and social conditions, cross-boundary strategies may be critical to controlling dengue transmission spillovers, regardless of the strength of observed spatial dependence. From a public health perspective, this underscores the need for inter-district coordination in surveillance and vector control efforts. For instance, the existing mechanism, as documented by Prasittisopin et al. (2024), should be extended to incorporate the health care program and contagion prevention. Moreover, a systematic planning approach, such as that introduced by Jiravanichkul et al. (2024), should be applied.

This study highlighted the spatial heterogeneity of dengue incidence among young people in Northern Thailand during the COVID-19 pandemic, with high-risk clusters concentrated in remote border areas. Spatial regression analysis identified key contextual factors, including the number of schools, VHVs coverage, and average temperature, as significant predictors of dengue incidence. Although spatial autocorrelation was relatively weak, these findings reinforce the value of spatial analysis for identifying place-based risk factors and informing targeted responses. Targeted responses in high-incidence areas should be accompanied by proactive measures in surrounding districts, especially in border zones where administrative boundaries may not align with transmission risk. To enhance public health resilience, spatially informed strategies are needed. In urban areas, the association with school density calls for integrating vector control into school infrastructure and neighborhood planning, including improved drainage and waste management systems. In rural and remote districts, where healthcare access is limited, expanding the capacity of community-based surveillance, particularly through VHVs, is crucial. Investments in basic environmental health infrastructure, such as sanitation and water management, can also reduce mosquito breeding sites. Both urban and rural settings would benefit from cross-sectoral collaboration and the use of geospatial data in planning, ensuring that dengue prevention measures are both context-sensitive and sustainable. These insights can support more equitable and effective health and environmental planning across diverse geographic regions.

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REFERENCES

Agyekum, T. P., Arko-Mensah, J., Botwe, P. K., Hogarh, J. N., Issah, I., Dwomoh, D., Billah, M. K., Dadzie, S. K., Robins, T. G., & Fobil, J. N. (2022). Effects of elevated temperatures on the growth and development of adult anopheles gambiae (s.l.) (Diptera: Culicidae) Mosquitoes. *Journal of Medical Entomology*, *59*(4), 1413–1420. https://doi.org/10.1093/jme/tjac046

Agyekum, T. P., Botwe, P. K., Arko-Mensah, J., Issah, I., Acquah, A. A., Hogarh, J. N., Dwomoh, D., Robins, T. G., & Fobil, J. N. (2021). A systematic review of the effects of temperature on anopheles mosquito development and survival: Implications for malaria control in a future warmer climate. *International Journal of Environmental Research and Public Health*, *18*(14), Article 7255. https://doi.org/10.3390/ijerph18147255

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Springer Science & Business Media.

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Anselin, L., & Bera, A. K. (1998). Spatial dependence in inear regression models with an introduction to spatial econometrics. *Handbook of Applied Economic Statistics*. CRC Press.

Anselin, L., Li, X., & Koschinsky, J. (2022). GeoDa, from the edsktop to an ecosystem for exploring spatial data. *Geographical Analysis*, *54*(3), 439–466. https://doi.org/10.1111/gean.12311

Araujo, J. L. B., Bomfim, R., Filho, C. I. N. S., Cavalcanti, L. P. G., Neto, A. S. L., Jr, J. S. A., & Furtado, V. (2024). The impact of COVID-19 mobility restrictions on dengue transmission in urban areas. *PLOS Neglected Tropical Diseases*, *18*(11), Article e0012644. https://doi.org/10.1371/journal.pntd.0012644

Bialy, L., Elliott, S. A., Melton, A., Ali, S., Scott, S. D., Knisley, L., & Hartling, L. (2024). Consequences of the coronavirus disease 2019 pandemic on child and adolescent mental, psychosocial, and physical health: A scoping review and interactive evidence map. *Journal of Child Health Care, 0*(0), 1–15. https://doi.org/10.1177/13674935241238794

Bohm, B. C., Morais, M. H. F., Cunha, M. d. C. M., Bruhn, N. C. P., Caiaffa, W. T., & Bruhn, F. R. P. (2024). Determining the relationship between dengue and vulnerability in a Brazilian city: A spatial modeling analysis. *Pathogens and Global Health*, *118*(2), 120–130. https://doi.org/10.1080/20477724.2023.2247273

Brady, O., & Wilder-Smith, A. (2021). What is the impact of lockdowns on dengue? *Current Infectious Disease Reports*, *23*(2), 1–8. https://doi.org/10.1007/s11908-020-00744-9

Bureau of Epidemiology, Department of Disease Control, Ministry of Public Health Thailand. (2021). *Rabop fao rawang rok 506* [National disease surveillance (R506)]. http://doe1.moph.go.th/surdata/index.php

Bureau of Registration Administration, Ministry of Interior. (n.d.). *Rabop sathiti thangkan thabian* [Official statistics registration systems]. https://stat.bora.dopa.go.th/stat/statnew/statMenu/newStat/home.php

Chen, Y., Li, N., Lourenço, J., Wang, L., Cazelles, B., Dong, L., Li, B., Liu, Y., Jit, M., Bosse, N. I., Abbott, S., Velayudhan, R., Wilder-Smith, A., Tian, H., Brady, O. J., Procter, S. R., Wong, K. L., Hellewell, J., Davies, N. G., …Tully, D. C. (2022). Measuring the effects of COVID-19-related disruption on dengue transmission in southeast Asia and Latin America: A statistical modelling study. *The Lancet Infectious Diseases*, *22*(5), 657–667. https://doi.org/10.1016/S1473-3099(22)00025-1

Community Development Department, Ministry of Interior. (2021). *Prokraem chat kep banthuek lae pramuan phon khwam champen phuenthan* [eBMN Application]. https://ebmn.cdd.go.th/#/jpt

Deb Nath, N., Khan, M. M., Schmidt, M., Njau, G., & Odoi, A. (2023). Geographic disparities and temporal changes of COVID-19 incidence risks in North Dakota, United States. *BMC Public Health*, *23*(1), Article 720. https://doi.org/10.1186/s12889-023-15571-5

Department of Health Service Support, Ministry of Public Health. (n.d.). *Chamnuan asasamak satharanasuk pracham muban rai tambon* [Number of village health volunteers, by sub-district]. https://www.thaiphc.net/new2020/content/1

Educational Information Center, Ministry of Education. (2021). *Sarasonthet dan sathan kansueksa* [Information on the number of educational institutions]. https://edustatistics.moe.go.th/school

Hnusuwan, B., Kajornkasirat, S., & Puttinaovarat, S. (2020). Dengue risk mapping from geospatial data using GIS and data mining techniques. *International Journal of Online and Biomedical Engineering (iJOE)*, *16*(11), 57–79. https://doi.org/10.3991/ijoe.v16i11.16455

Jing, C., Wang, G., Ebi, K. L., Su, B., Wang, X., Chen, D., Jiang, T., & Kundzewicz, Z. W. (2024). Emerging risk to dengue in Asian metropolitan areas under global warming. *Earth's Future*, *12*(7), Article e2024EF004548. https://doi.org/10.1029/2024EF004548

Jiravanichkul, S., Pinich, S., Sreshthaputra, A., & Jarutach, T. (2024). The development of a well-being environment and age-friendly communities assessment criteria using the analytic hierarchy process: A case of Thailand. *Nakhara: Journal of Environmental Design and Planning, 23*(3), Article 416. https://doi.org/10.54028/NJ202423416

Khan, S., Akbar, S. M. F., & Nishizono, A. (2022). Co-existence of a pandemic (SARS-CoV-2) and an epidemic (dengue virus) at some focal points in Southeast Asia: Pathogenic importance, preparedness, and strategy of tackling. *The Lancet Regional Health - Southeast Asia*, *4,* Article 100046. https://doi.org/10.1016/j.lansea.2022.100046

Kliengchuay, W., Mingkhwan, R., Kiangkoo, N., Suwanmanee, S., Sahanavin, N., Kongpran, J., Aung, H. W., & Tantrakarnapa, K. (2024). Analyzing temperature, humidity, and precipitation trends in six regions of Thailand using innovative trend analysis. *Scientific Reports*, *14*(1), Article 7800. https://doi.org/10.1038/s41598-024-57980-5

Krassanairawiwong, T., Suvannit, C., Pongpirul, K., & Tungsanga, K. (2021). Roles of subdistrict health office personnel and village health volunteers in Thailand during the COVID-19 pandemic. *BMJ Case Reports CP*, *14*(9), Article e244765. https://doi.org/10.1136/bcr-2021-244765

Li, H., Calder, C. A., & Cressie, N. (2007). Beyond Moran's I: Testing for spatial dependence based on the spatial autoregressive model. *Geographical Analysis*, *39*(4), 357–375. https://doi.org/10.1111/j.1538-4632.2007.00708.x

Lindsay, S. W., Wilson, A., Golding, N., Scott, T. W., & Takken, W. (2017). Improving the built environment in urban areas to control Aedes aegypti-borne diseases. *Bulletin of the World Health Organization*, *95*(8), 607–608. https://doi.org/10.2471/BLT.16.189688

Liyanage, P., Rocklöv, J., & Tissera, H. A. (2021). The impact of COVID-19 lockdown on dengue transmission in Sri Lanka; A natural experiment for understanding the influence of human mobility. *PLoS Neglected Tropical Diseases*, *15*(6), Article e0009420. https://doi.org/10.1371/journal.pntd.0009420

Lu, H.-Z., Sui, Y., Lobo, N. F., Fouque, F., Gao, C., Lu, S., Lv, S., Deng, S.-Q., & Wang, D.-Q. (2023). Challenge and opportunity for vector control strategies on key mosquito-borne diseases during the COVID-19 pandemic. *Frontiers in Public Health*, *11*, Article 1207293. https://doi.org/10.3389/fpubh.2023.1207293

Mani, S., Ghosh, S., Sharma, R., Ajith, A., & Prabhakaran, P. (2021). Chapter 1—controlling dengue, an urban pandemic – a case study of Delhi, India. In R. Katz & M. Boyce (Eds.), *Inoculating cities* (pp. 1–19). Academic Press. https://doi.org/10.1016/B978-0-12-820204-3.00001-2

Manna, B., Bharati, P., Paul, S., Mahata, A., Mondal, S., Mukherjee, S., Dutta, A. K., & Roy, B. (2024). Results and discussion of dengue model with temperature effects in interval environment. *SciNexuses*, *1*, 75–81. https://doi.org/10.61356/j.scin.2024.1372

Nik Abdull Halim, N. M. H., Che Dom, N., Dapari, R., Salim, H., & Precha, N. (2022). A systematic review and meta-analysis of the effects of temperature on the development and survival of the Aedes mosquito. *Frontiers in Public Health*, *10*, Article 1074028. https://doi.org/10.3389/fpubh.2022.1074028

Office Statistics Registration System, Ministry of Interior. *Chamnuan prachakon* [Population statistics]. https://stat.bora.dopa.go.th/new_stat/webPage/statByYear.php

Pakaya, R., Daniel, D., Widayani, P., & Utarini, A. (2023). Spatial model of Dengue Hemorrhagic Fever (DHF) risk: Scoping review. *BMC Public Health*, *23*(1), Article 2448. https://doi.org/10.1186/s12889-023-17185-3

Phanitchat, T., Zhao, B., Haque, U., Pientong, C., Ekalaksananan, T., Aromseree, S., Thaewnongiew, K., Fustec, B., Bangs, M. J., Alexander, N., & Overgaard, H. J. (2019). Spatial and temporal patterns of dengue incidence in northeastern Thailand 2006–2016. *BMC Infectious Diseases*, *19*(1), Article 743. https://doi.org/10.1186/s12879-019-4379-3

Prasittisopin, L., Kitkuakul, P., Chotchakornpant, K., & Rugkhapan, N. T. (2024). Implementing the sister city policy: Perspectives from Thailand. *Nakhara: Journal of Environmental Design and Planning, 23*(2), Article 413. https://doi.org/10.54028/NJ202423413

Puttanapong, N., Luenam, A., & Jongwattanakul, P. (2022). Spatial analysis of inequality in Thailand: Applications of satellite data and spatial statistics/econometrics. *Sustainability*, *14*(7), Article 3946. https://doi.org/10.3390/su14073946

QGIS Development Team. (2023). *QGIS Geographic Information System* [Computer software]. https://www.qgis.org

Rahastri, A., & Sulistyawati, S. (2024). The impact of COVID-19 on dengue cases in low-and middle-income countries: A systematic review. *International Journal of Public Health Science (IJPHS)*, *13*(4), 1560–1567. https://doi.org/10.11591/ijphs.v13i4.24454

Rahman, M. S., Ekalaksananan, T., Zafar, S., Poolphol, P., Shipin, O., Haque, U., Paul, R., Rocklov, J., Pientong, C., & Overgaard, H. J. (2021). Ecological, social, and other environmental determinants of dengue vector abundance in urban and rural areas of northeastern Thailand. *International Journal of Environmental Research and Public Health*, *18*(11), Article 5971. https://doi.org/10.3390/ijerph18115971

Ratanawong, P., Kittayapong, P., Olanratmanee, P., Wilder-Smith, A., Byass, P., Tozan, Y., Dambach, P., Quinonez, C. A. M., & Louis, V. R. (2016). Spatial variations in dengue transmission in schools in Thailand. *PLOS ONE*, *11*(9), Article e0161895. https://doi.org/10.1371/journal.pone.0161895

Romeo-Aznar, V., Telle, O., Santos-Vega, M., Paul, R., & Pascual, M. (2024). Crowded and warmer: Unequal dengue risk at high spatial resolution across a megacity of India. *PLOS Climate*, *3*(3), Article e0000240. https://doi.org/10.1371/journal.pclm.0000240

Roster, K. O., Martinelli, T., Connaughton, C., Santillana, M., & Rodrigues, F. A. (2024). Impact of the COVID-19 pandemic on dengue in Brazil: Interrupted time series analysis of changes in surveillance and transmission. *PLOS Neglected Tropical Diseases*, *18*(12), Article e0012726. https://doi.org/10.1371/journal.pntd.0012726

Ryan, S. J., Carlson, C. J., Mordecai, E. A., & Johnson, L. R. (2019). Global expansion and redistribution of Aedes-borne virus transmission risk with climate change. *PLOS Neglected Tropical Diseases*, *13*(3), Article e0007213. https://doi.org/10.1371/journal.pntd.0007213

Saita, S., Maeakhian, S., & Silawan, T. (2022). Temporal variations and spatial clusters of dengue in Thailand: Longitudinal study before and during the coronavirus disease (COVID-19) pandemic. *Tropical Medicine and Infectious Disease*, *7*(8), Article 171. https://doi.org/10.3390/tropicalmed7080171

Sasmita, H. I., Neoh, K.-B., Yusmalinar, S., Anggraeni, T., Chang, N.-T., Bong, L.-J., Putra, R. E., Sebayang, A., Silalahi, C. N., Ahmad, I., & Tu, W.-C. (2021). Ovitrap surveillance of dengue vector mosquitoes in Bandung city, West Java province, Indonesia. *PLOS Neglected Tropical Diseases*, *15*(10), Article e0009896. https://doi.org/10.1371/journal.pntd.0009896

Singweratham, N., Nawsuwan, K., Suriya, N., Oupra, R., & Lillahkul, N. (2024). Factors perceived by village health volunteers to implement the strategies of the COVID-19 control centre in Thailand. *Health Promotion Journal of Australia*, *35*(3), 683–687. https://doi.org/10.1002/hpja.798

Soukavong, M., Thinkhamrop, K., Pratumchart, K., Soulaphy, C., Xangsayarath, P., Mayxay, M., Phommachanh, S., Kelly, M., Wangdi, K., Clements, A. C. A., & Suwannatrai, A. T. (2024).

Bayesian spatio-temporal analysis of dengue transmission in Lao PDR. *Scientific Reports*, *14*(1), Article 21327. https://doi.org/10.1038/s41598-024-71807-3

Thisyakorn, U., Saokaew, S., Gallagher, E., Kastner, R., Sruamsiri, R., Oliver, L., & Hanley, R. (2022). Epidemiology and costs of dengue in Thailand: A systematic literature review. *PLOS Neglected Tropical Diseases*, *16*(12), Article e0010966. https://doi.org/10.1371/journal.pntd.0010966

Togami, E., Chiew, M., Lowbridge, C., Biaukula, V., Bell, L., Yajima, A., Eshofonie, A., Saulo, D., Do, H. T. H., Otsu, S., Cong, D. T., Ngon, M. S., Lee, C.-K., Tsuyuoka, R., Tuseo, L., Khalakdina, A., Kab, V., Abeyasinghe, R. R., Yadav, R. P., … Olowokure, B. (2023). Epidemiology of dengue reported in the World Health Organization Western Pacific Region, 2013–2019. *Western Pacific Surveillance and Response*, *14*(1), Article 1. https://doi.org/10.5365/wpsar.2023.14.1.973

Wilder-Smith, A., & Osman, S. (2020). Public health emergencies of international concern: A historic overview. *Journal of Travel Medicine*, *27*(8), 1–13. https://doi.org/10.1093/jtm/taaa227

Wiyono, L., Rocha, I. C. N., Cedeño, T. D. D., Miranda, A. V., & Lucero-Prisno III, D. E. (2021). Dengue and COVID-19 infections in the ASEAN region: A concurrent outbreak of viral diseases. *Epidemiology and Health*, *43*, Article e2021070. https://doi.org/10.4178/epih.e2021070

World Health Organization (Ed.). (1997). *Dengue haemorrhagic fever: Diagnosis, treatment, prevention and control* (2nd ed.). World Health Organization.

Xu, C., Xu, J., & Wang, L. (2024). Long-term effects of climate factors on dengue fever over a 40-year period. *BMC Public Health*, *24*(1), Article 1451. https://doi.org/10.1186/s12889-024-18869-0

Yek, C., Pacheco, A. R., Lon, C., Leang, R., & Manning, J. E. (2022). Additional considerations for assessing COVID-19 impact on dengue transmission. *The Lancet Infectious Diseases*, *22*(6), 762–763. https://doi.org/10.1016/S1473-3099(22)00293-6

Zaheer, S., Tahir, M. J., Ullah, I., Ahmed, A., Saleem, S. M., Shoib, S., & Asghar, M. S. (2022). Dengue outbreak in the times of COVID-19 pandemic: Common myths associated with the dengue. *Annals of Medicine and Surgery*, *81*, Article 104535. https://doi.org/10.1016/j.amsu.2022.104535

Zheng, L., Ren, H.-Y., Shi, R.-H., & Lu, L. (2019). Spatiotemporal characteristics and primary influencing factors of typical dengue fever epidemics in China. *Infectious Diseases of Poverty*, *8*(1), Article 24. https://doi.org/10.1186/s40249-019-0533-9