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Geospatial assessment of dengue fever risk and spatial patterns in Phayao Province, Thailand

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Abstract

This study employed geospatial approaches to assess the risk and spatial distribution of Dengue Fever (DF) and Dengue Hemorrhagic Fever (DHF) in Phayao Province, Thailand. Epidemiological data from 2016 to 2024, comprising 3,600 reported cases, were analysed alongside demographic and climatic variables. Temporal analysis revealed a major epidemic in 2023 lasting 20 weeks, coinciding with peak rainfall, with adolescents and young adults (13–24 years old) being the most affected group. Spatial autocorrelation (Moran's I) indicated significant clustering of dengue morbidity rates, with hotspots concentrated in urbanised districts such as Mueang Phayao, Dok Khamtai and Chiang Kham, while Kernel Density Estimation (KDE) highlighted shifts of hotspots toward eastern districts in later years. Local Indicators of Spatial Association (LISA) identified 24 high–high clusters in 2019, predominantly in Mae Chai District. Case-control analysis further revealed that socio-economic conditions, housing environments and inconsistent preventive behaviours influenced dengue incidence, with strong community participation linked to more effective prevention. These findings underscore the spatial heterogeneity of dengue transmission and provide geospatial evidence to guide targeted vector control, strengthen community-based interventions, and support evidence-based public health strategies in northern Thailand.

Key words: geospatial analysis; dengue fever; spatial autocorrelation; hotspot detection; public health interventions, Thailand.

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Introduction

Dengue Fever (DF) and Dengue Hemorrhagic Fever (DHF) are mosquito-borne viral infections of major public health concerns in tropical and subtropical regions, particularly in Southeast Asia (Kristiani *et al.*, 2026). Globally, approximately 390 million cases occur annually, 96 million manifesting clinical symptoms, with Asia bearing the greatest burden (Cao & Luong, 2023; WHO, 2024; Jaya *et al.*, 2025; Lim *et al.*, 2025; Kristiani *et al.*, 2026). Thailand has experienced recurrent dengue outbreaks with varying intensity across its provinces, including the northern region where Phayao Province is located. The increasing frequency and severity of dengue outbreaks in Thailand highlight the urgent need for localised risk assessment and spatial analysis to inform targeted interventions and resource allocation. Here. the disease has become hyperendemic, with multiple serotypes co-circulating and causing outbreaks almost every year. The disease burden is particularly high among children and young adults, with incidence rates exceeding 400 cases per 100,000 population in some age groups (Kaewhan *et al.*, 2025). While southern Thailand has been extensively studied for dengue risk, the northern provinces, including Phayao, remain underrepresented in spatial epidemiological research despite increasing case reports in recent years (Pakaya *et al.*, 2023). The spatial distribution of dengue is influenced by a complex interplay of environmental, climatic, socio-economic, and demographic factors (Kristiani *et al.*, 2026). Variables such as temperature, rainfall, humidity, land use, population density and water storage practices significantly affect the breeding habitats of *Aedes aegypti* and *Ae. albopictus*, the primary vectors of the dengue virus. Moreover, unplanned urbanisation, inadequate waste management and limited access to healthcare services exacerbate the vulnerability of rural communities to dengue outbreaks (Suwanbamrung *et al.*, 2021). Geographic Information Systems (GIS) have emerged as powerful tools for spatial analysis and risk mapping of vector-borne diseases. GIS enables the integration of diverse datasets to identify high-risk areas, detect spatial clusters, and support early warning systems for disease surveillance. In Thailand, recent studies have demonstrated the utility of GIS-based occurrence-intensity models in identifying dengue hotspots at sub-district levels, providing actionable insights for public health planning (Jeefoo *et al.*, 2011; Jeefoo *et al.*, 2021; Prakash Nayak *et al.*, 2025). However, most of these studies have focused on urban or southern regions, with limited attention to village-level dynamics in the northern provinces.

Phayao Province, characterised by diverse topography, rural settlements, and seasonal climatic variations, presents a unique context for dengue transmission. The lack of fine-scale spatial analysis at the village level hampers the ability of local health authorities to implement precise and timely vector control measures. Therefore, this study aims to assess the spatial distribution and risk of DF/DHF at the village level in this province using GIS-based methods. By identifying high-risk areas and associated environmental and socio-demographic factors, the study seeks to contribute to the development of localised, evidence-based strategies for dengue prevention and control. This research further aligns with the growing emphasis on community-level risk assessment and participatory approaches in public health. Integrating local knowledge with spatial data can enhance the accuracy of risk predictions and foster community engagement in vector control initiatives. The findings are expected to support health authorities in Phayao and similar settings in optimising surveillance systems, prioritising interventions, and ultimately reducing the burden of dengue in vulnerable rural populations.

Materials and Methods

Study area

Phayao Province is located in northern Thailand between 18°50’-19°45′ N latitude and 99°40’-100°40’E longitude (Figure 1). The province is characterised by the Phi Pan Nam Mountain Range, which runs north-south, and the Ing River Valley where Phayao City is situated. Approximately 51.4%of the province is forested. Phayao experiences a tropical savanna climate with distinct wet (May-October) and dry (November-April) seasons. The average annual temperature is 25.4°C, with April the hottest month and December the coolest. Rainfall peaks in August, averaging 260 mm. These climatic and geographical conditions create favourable environments for *Aedes* mosquitoes, particularly during the wet season, thereby increasing dengue transmission risk (Jeefoo *et al.*, 2021; Pakaya *et al.*, 2023). The methodology is summarised in the flowchart shown in Figure 2, comprising five main steps: data collection, preprocessing, spatial analysis, hotspot detection and interpretation.

Data preparation

Epidemiological data

Dengue case data from 2016 to 2024 were obtained from the Phayao Provincial Public Health Office (PPPHO). Records included suspected and confirmed cases, with patient demographics (age, sex, address) and dates of symptom onset and hospital consultation. Cases were reported using official Form 506, following national surveillance protocols (Bureau of Vector Borne Disease, Ministry of Public Health (MOPH).

Village data

Location and population data for 764 villages were collected from the Department of Provincial Administration. Village point locations were validated using high-resolution Thailand Earth Observation System (THEOS) satellite imagery

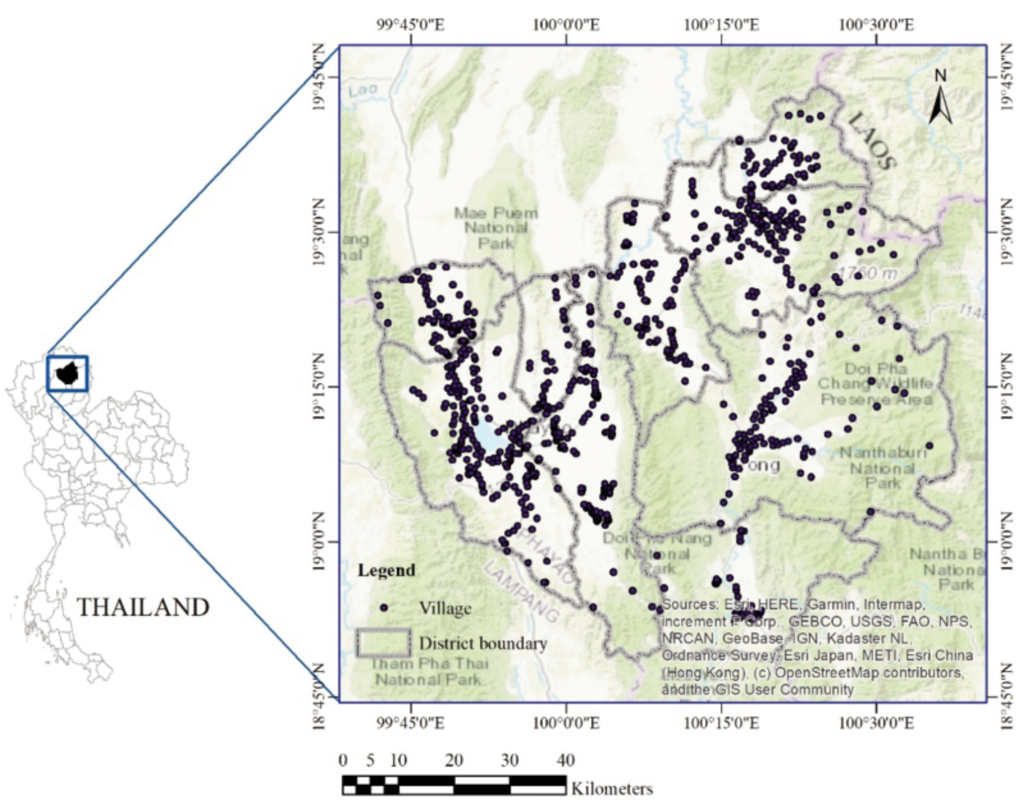

Figure 1. Location of the Phayao Province, Thailand.

(https://www.eoportal.org/satellite-missions/theos) to ensure spatial accuracy.

Climate data

Monthly rainfall (mm), temperature (°C), and relative humidity (%) from 2016 to 2024 were obtained from eight meteorological stations operated by the Thai Meteorological Department (TMD). These data were used to assess correlations between climatic variables and dengue incidence (Lim *et al.*, 2025).

Data analysis

Data analyses were performed using SPSS for statistical tests, GeoDa for spatial autocorrelation and hotspot detection and ArcGIS for spatial visualisation and map production.

General analysis

The annual dengue incidence was analysed by gender and age groups. Descriptive statistics were used to summarise demographic characteristics of the cases.

Temporal analysis

Monthly dengue cases were compared with climatic variables to identify seasonal patterns. Pearson correlation coefficients were calculated to assess associations between dengue incidence and climatic factors (rainfall, temperature, humidity) given by month and year (time t) and when lagged by one month (t−1) (Kaewhan *et al.*, 2025). This time lag between rainfall and dengue incidence was initially selected based on the biological and epidemiological characteristics of dengue transmission, including mosquito breeding cycles, viral incubation periods in the vector and the typical delay between environmental exposure and reported human cases. Rainfall contributes to the formation of breeding sites for *Aedes* mosquitoes and increases in mosquito abundance commonly precede reported dengue cases by several weeks. To further support this assumption, a cross-correlation analysis between monthly rainfall and dengue incidence was conducted to examine the strength of association across multiple temporal lags.

Spatial analysis

Spatial Autocorrelation Analysis (SAA) was conducted to detect clustering of dengue morbidity rates at the village level (Jeefoo *et al.*, 2011). Global Moran's *I* was applied to measure spatial dependence, with significance tested using 999 permutations at $\alpha = 0.01$ (Anselin *et al.*, 2006). Local indicators of spatial association (LISA) were used to identify local clusters and spatial outliers (Jepsen *et al.*, 2009). The interpretation of the indices values is presented in Table 1.

Hotspot detection

Hotspots were identified using LISA cluster maps and Moran scatterplots. Kernel density estimation (KDE) was employed to generate continuous surfaces of dengue morbidity intensity, highlighting high-risk zones (Getis & Ord, 1995; Osei & Duker, 2008).

Factors associated with the incidence of DF/DHF

To investigate factors associated with DF/DHF incidence in Phayao Province, a retrospective case-control study was conducted between August and October 2025. Thirty-three DF/DHF patients registered at the Phayao Provincial Public Health Office (PPPHO) were matched (1:2 ratio) with 65 controls without the disease based on age, sex, and village of residence. Socio-demographic and environmental data were collected through field surveys and structured interviews. Data were analysed using chi-square, t-tests, and binary logistic regression to identify significant risk factors (Suwanbamrung *et al.*, 2021).

Results

General analysis

Between 2016 and 2024 (Table 2), a total of 3,600 dengue cases were reported in Phayao Province, comprising 1,890 females (52.5%) and 1,710 males (47.5%). The highest incidence occurred in 2023, with 1,305 cases, while the lowest was recorded in 2021 (41 cases). Female patients consistently outnumbered males, reflecting patterns observed in other endemic regions (Lim *et al.*, 2025). Age distribution analysis revealed that the 13-24year old group had the highest incidence (24.6%), followed by the 0-12year old group (18.9%) and the 25-36years group (18.5%). Individuals aged over 37 years accounted for 38% of cases. These findings highlight the vulnerability of younger populations, particularly adolescents and young adults, to dengue infection (Kaewhan *et al.*, 2025). Disease distribution based on age of the patients was also determined. The age distribution of dengue cases observed was

Table 1. Numeric scales of Moran's *I* ratio.

Spatial patterns	Moran's *I*
Clustered pattern in which adjacent or nearby points show similar characteristics	1 > E(I)
Random pattern in which points do not show particular patterns of similarity	1 ~ = E(I)
Dispersed pattern in which adjacent or nearby points show different characteristics	1 < E(I)

E(I) = ~ (1) / (n - 1), with n denoting the number of points in the distribution.

Table 2. Number of dengue cases in Phayao Province classified by gender over the years 2016-2024.

Gender	Year									Percentage (%)
	2016	2017	2018	2019	2020	2021	2022	2023	2024	
Male	96	44	77	189	111	26	58	635	474	47.5
Female	106	39	96	219	130	15	43	670	572	52.5
Total	202	83	173	408	241	41	101	1,305	1,046	3,600

Source: Phayao Provincial Public Health Office (PPPHO).

different from the general population age distribution in the province (Figure 3). The highest incidence was in the 13-24year old age group with a percentage of 24.6% (321 cases), while incidence in the 0-12year old age group was 18.9% (246 cases) and DF/DHF incidence in the 25-36year old age group was 18.5% (242 cases). In the population older than 37 years, the incidence was only 38.0% (496 cases).

Temporal analysis

In 2023, there were 1,305 suspected dengue patients. The epidemic lasted 20 weeks from 1st of May till 30th of September, coinciding mainly with the rainy season. There were as many as 2,935 cases dengue cases spread throughout the province, affecting 81.53% of the 0.65% of the total population. Approximately 45% of the cases occurred from 1st to 4th week of August, with the highest number occurring in Chiang Kham District (335 cases) and the second highest in Mueang Phayao District (224 cases). Most cases were in August 2023, with 371 cases, while February 2023 had the lowest number with only one case. The comparison of temporal distribution of dengue cases for years 2016 to 2024 is shown in Figure 4. The temporal distribution of dengue across the province, with the highest incidence occurring during the rainy season, showed a similar trend each year. The epidemiological pattern of dengue corresponded to the three seasonal cycles. Disease patterns highlighted critical months from May to September, coinciding with the rainy season. The peak incidence was reported in August 2023, with more than 371cases. Dengue outbreaks generally occurred in the early part of the rainy season, when humidity was above average (Jeefoo *et al.*, 2011). Rainfall, temperature and relative humidity began to rise in May, leading to outbreaks during June to August, when rainfall and humidity were high. Subsequently, the number of cases declined in September, even though the rainfall and relative humidity reached their highest levels, while the temperature showed a decrease. To examine the relationship between case numbers and climatic conditions, the Pearson correlation coefficients between dengue cases and climatic variables were calculated at the same time of occurrence and with one□month lag, to show how climatic parameters influenced the vector populations. The highest correlation for rainfall was observed in 2021, with values of 0.8095 at the same time of occur-

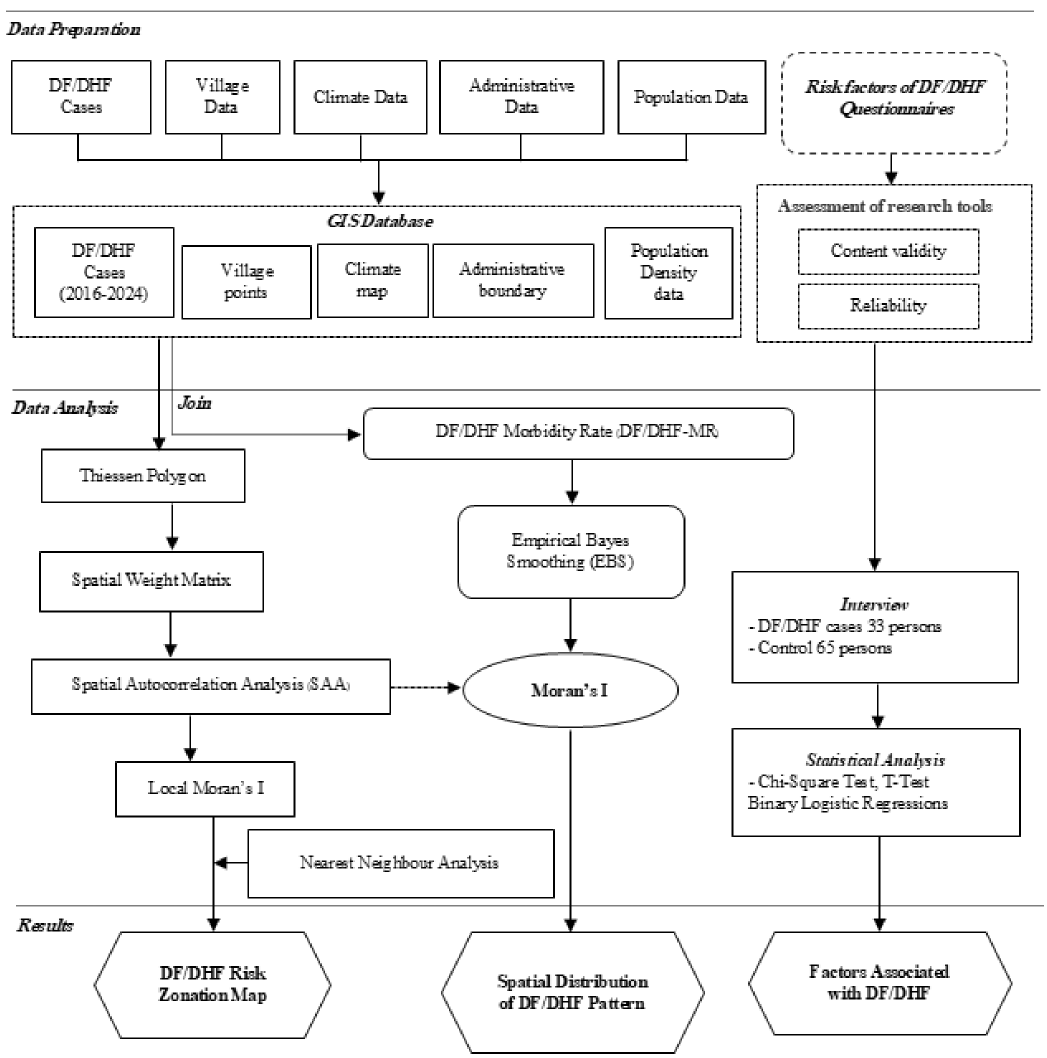

Figure 2. Flowchart of the methodology applied.

rence and 0.8269, with one-month lag (Table 3). In 2019, the temperature) showed strong correlations of 0.6515 and 0.7566 at the same time and with one-month lag, respectively. The relative humidity demonstrated the highest correlation in 2022 at the same time of occurrence (0.8513), whereas in 2024 the strongest correlation was observed with one-month lag (0.8362).

Spatial analysis

Global spatial autocorrelation analysis by Moran's *I* revealed significant clustering of dengue morbidity rates across villages (Table 4). The values ranged from -0.013 (dispersed, 2017) to 0.285 (clustered, 2019), with most years showing positive and significant clustering ($p < 0.01$). This indicates that dengue incidence was not randomly distributed but spatially dependent, with clusters concentrated in specific districts (Anselin *et al.*, 2006).

Standard Deviational Ellipses (SDEs) and local Moran's *I* (cluster and outlier analysis) were utilised to determine the overall spatial distribution, directional trends, and extents of infected villages for each year. The SDEs indicated that dengue cases were predominantly concentrated in the urban areas of Phayao Province, specifically within the urbanised districts Mueang Phayao, Dok Khamtai, and Chiang Kham. Although the overall spatial patterns of DF/DHF clusters and outliers remained relatively consistent over the nine consecutive years, the disease exhibited a dynamic spatiotemporal trajectory (Figure 5). Originating in Mueang Phayao District in 2016, the centroid shifted northeast towards Phu Kamyao District in 2017 and eastwards to Chun District in 2018. From 2019 to 2021, the trajectory fluctuated, shifting northwest within Chun District (2019), reversing southwest to Phu Kamyao (2020) and then returning northeast to Chun (2021). Between 2022 and 2024, the movement trended generally westwards and southwestwards before ultimately shifting northwards into Dok Khamtai District in 2024. Documenting these detailed spatiotemporal shifts is essential for developing agent-based models to simulate disease dynamics across space and time.

Hotspot detection

Hotspot detection was performed using LISA for local clusters and spatial outliers and Moran's *I* statistics for global spatial autocorrelation. KDE was applied to generate continuous surfaces of disease intensity. Collectively, these methods enabled the identification of high-risk villages and spatial trends critical for targeted interventions.

Figure 6 illustrates the Moran scatterplot (panel a) and the LISA cluster map of DFMR for 2019 (panel b). The LISA map depicts statistically significant local Moran's *I* values, classified by type of spatial association. Distinct spatial clusters of Dengue Fever Morbidity Rate (DFMR) were observed across multiple years. In 2019, 24 villages were identified as hotspots (high–high clusters). The majority were located in Mae Chai district (18 villages), including Pa Faek (6 villages), Mae Chai (5 villages), Si Thoi (3 villages), Ban Lao (3 villages), and Mae Suk (1 village). Additional hotspots were found in Chiang Kham district (3 villages in Nam Waen sub-district), Mueang Phayao district (2 villages in Mae Ka sub-district), and Dok Khamtai district (1 village in Khue Wiang sub-district).

The standardised DFMR values for each village were compared with their spatial averages to detect significant outliers at the 0.01 level. KDE interpolation further highlighted spatial heterogeneity, producing continuous density surfaces of DFMR (Figure 7). These maps revealed clear spatial patterns: hotspots were concentrated in western Phayao (Mae Chai, Mueang Phayao, Dok Khamtai) during 2016, 2017, 2019, 2020, 2021 and 2022, while in 2018, 2023, and 2024, hotspots shifted towards eastern districts (Phu Sang, Chiang Kham, Chiang Muan).

Factors associated with the incidence of DF/DHF

In section 1, the findings revealed that the majority of respondents were female, with an average age situated within the middle working age group (40-60 years old). Most participants reported being married, and their highest educational attainment ranged from upper secondary school to a bachelor's degree. Agriculture

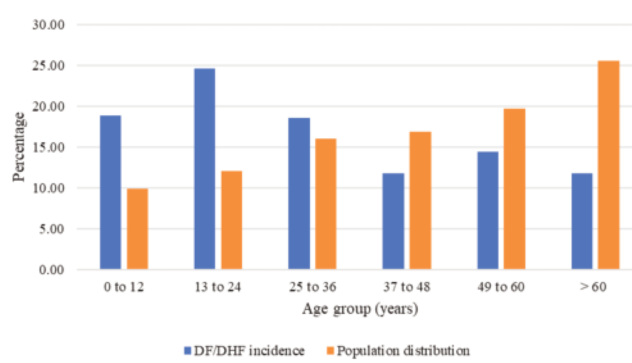

Figure 3. Dengue incidence and percentage population in different age groups in 2023.

Table 3. Pearson correlation between climate factors and dengue cases in the time series 2016-2024.

Year	RF		TEMP		RH	
	t	t-1	t	t−1	t	t−1
2016	0.4291	0.4722	0.1121	0.2505	0.6425	0.6223
2017	0.6532	0.7994	0.3019	0.6653	0.6583	0.7783
2018	0.5254	0.4765	0.4232	0.3305	0.5502	0.5173
2019	0.4490	0.3061	0.6515	0.7566	0.1694	0.2634
2020	0.4652	0.2567	0.5820	0.3044	0.5557	0.3305
2021	0.8095	0.8269	0.2207	0.2658	0.6932	0.7885
2022	0.7061	0.4410	0.5682	0.5123	0.8513	0.5622
2023	0.5056	0.7963	0.0332	0.3135	0.5932	0.7142
2024	0.4230	0.6868	0.2096	0.4753	0.4722	0.8362

RF, rainfall; TEMP, temperature; RH, relative humidity; t, time of occurrence; t-1, with one-month time lag; p<0.01.

was identified as the primary occupation, reflecting the socio-economic structure of the study area. The average monthly household income was found to be less than 20,000 Baht, indicating a relatively modest economic status among respondents. In terms of housing characteristics, the majority resided in single-story houses, with surrounding environments frequently characterised by stagnant water or fruit orchards, both of which are potential breeding grounds for mosquitoes. Regarding sources of information on dengue prevention, radio and television were reported as the most common channels, followed by printed materials, underscoring the importance of traditional media in disseminating public health knowledge within these communities (Table 5).

In section 2, the analysis revealed that dengue prevention behaviours varied significantly across districts in Phayao Province. The study of dengue prevention behaviours in Phayao Province reveals that households consistently practice personal and environmental preventive measures, such as sleeping under mosquito nets and eliminating breeding sites. However, behaviours requiring sustained effort and community involvement remain weak. Enhancing awareness and promoting collective responsibility will be crucial for long-term dengue control effectiveness (Table 6).

Districts such as Phu Kamyao, Mae Chai, and Chun demonstrated consistently high proportions of "regular practice" across nearly all behaviours, reflecting strong community discipline and participation. In contrast, Mueang Phayao showed higher proportions of "occasional practice" or "never practiced," indicating irregular or insufficient preventive actions, while in Mueang Phayao and Phu Chang, preventive behaviours such as sleeping under mosquito nets, eliminating breeding sites and using Abate sand were often reported as "occasional" or "never practiced," suggesting inconsistent implementation. The districts Dok Khamtai and Chiang Kham exhibited mixed patterns, with moderate levels of "regular practice" alongside "occasional practice," particularly in community participation and peer education. The districts Phu Kamyao, Chun and Mae Chai stood out with more than 90% of respondents reporting "regular practice" in almost all behaviours, highlighting strong community engagement and leadership, while

Table 4. Global indices of spatial autocorrelation.

Year	Moran's *I*	Pattern
2016	0.119	Clustered
2017	-0.013	Dispersed
2018	0.006	Clustered
2019	0.285	Clustered
2020	0.131	Clustered
2021	0.072	Clustered
2022	0.227	Clustered
2023	0.067	Clustered
2024	0.115	Clustered

Table 5. Section 1: general characteristics of participants.

Variable	Finding	Approximate proportion
Gender	Majority female	Female 65%, Male 35%
Age	Predominantly middle working age (40-60 years)	70%
Marital status	Mostly married	60% married, 30% single, 10% widowed/divorced
Family role	Mainly household heads	55% Household heads, 25% spouse, 20% children/relatives
Educational level	Upper secondary to bachelor's degree	40% upper secondary, 35% Bachelor's, 15% lower,10% higher than bachelor's
Main occupation	Agriculture as primary occupation	50% agriculture, 20% wage labor, 15% trade, 10% government/state enterprise, 10% others
Average monthly household income	Less than 20,000 Baht	65% < 20,000 Baht, 25% 20,001-30,000 Baht, 10% > 30,000 Baht
Housing type	Mostly single-story houses	70% single-story, 25% two-story, 5% others
Surrounding environment	Stagnant water or fruit orchards	40% stagnant water, 30% fruit orchard/rubber plantation, 20% rice field, 10% others
Sources of information of dengue prevention	Radio/television and printed materials most common	50% radio/TV, 30% printed materials, 10% village broadcast system, 10% others

Table 6. Section 2: dengue prevention behaviours.

Behavior	Regularly	Occasionally	Never
Sleeping under mosquito nets	High	moderate	Low
Elimination breeding sites	High	Moderate	Low
Advising others	Moderate	High	Low
Acting as a community leader	Low	Moderate	High
Participating in campaigns	Moderate	High	Low
Household management	High	Moderate	Low
Using Abate sand granules	Low	Moderate	High
Destroying or overturning containers	High	Moderate	Low
Storing clothes/household items properly	Moderate	High	Low
Changing water in vases	Low	Moderate	High

high proportions of "never practiced" were observed in Chiang Muan and Pong indicating the need for intensified awareness campaigns and community mobilisation. High-performing districts (Phu Kamyao, Chun, Mae Chai) can serve as models of strong community-based dengue prevention. Low-performing districts (Chiang Muan, Pong, Mueang Phayao), on the other hand, require targeted interventions, including awareness campaigns and motivational strategies. Policy recommendation: strengthening community leadership and promoting collective activities are crucial for sustaining regular preventive practices.

In section 3: community participation also varied across districts. High-performing districts (Phu Kamyao, Chun, Mae Chai) reported consistent involvement in meetings, campaigns, source reduction and knowledge dissemination reflecting strong community cohesion and leadership. Moderate participation, with inconsistent engagement across activities was observed in Dok Khamtai and Chiang Kham. In contrast, low participation was found in Mueang Phayao and Chiang Muan, particularly with regard to decision-making and financial contributions, highlighting gaps in motivation and community organisation (Table 7).

With regard to participation, the findings can be categorised into three main groups: high, moderate and low. In the districts Phu Kamyao, Chun and Mae Chai, respondents reported participation "every time" in nearly all activities, including meetings, campaigns, source reduction and knowledge dissemination. The proportion of "always participated" exceeded 90%, reflecting strong community cohesion and proactive local leadership. In the districts Dok Khamtai and Chiang Kham, participation was moderate, with most respondents indicating "occasional participation" in activities such as discussions, family mobilisation, and situation assessments. This suggests inconsistent engagement across different preventive measures. In the districts Mueang Phayao and Chiang Muan, a high proportion of "never participated" was observed, particularly in activities such as financial contributions and decision-making. This highlights limitations in motivation and community organisation.

Discussion

The spatial analysis revealed significant clustering of DF/DHF cases in urbanised districts such as Mueang Phayao, Chiang Kham and Dok Khamtai. These areas exhibited high–high clusters, indicating elevated morbidity rates surrounded by similarly high values. This finding is consistent with previous studies that demonstrated the influence of urbanisation and population density on dengue transmission (Anselin *et al.*, 2006; Jeefoo *et al.*, 2011).

Climatic factors, particularly rainfall and temperature, showed strong correlations with dengue incidence. Seasonal peaks during the rainy season highlight the role of environmental conditions in vector proliferation, aligning with earlier research that identified rainfall as a critical driver of mosquito breeding and dengue outbreaks (Pakaya *et al.*, 2023; Lim *et al.*, 2025). The temporal analysis confirmed that dengue epidemics in Phayao Province are closely linked to climatic variability, emphasising the need for climate-sensitive surveillance systems. The relationship between rainfall and dengue incidence was statistically supported by quantitative measures. Pearson's correlation analysis demonstrated a significant positive association at the one-month lag level (p <0.01), confirming that increases in rainfall precede increases in dengue cases with a short temporal delay.

Hotspot detection using LISA and KDE provided granular insights into spatial heterogeneity. The identification of persistent hotspots in the districts Mae Chai, Mueang Phayao and Chiang Kham underscores the importance of localised interventions. These findings support the utility of GIS-based methods (Getis & Ord, 1995) in identifying priority areas for vector control and resource allocation, as demonstrated by other regional studies (Osei & Duker, 2008).

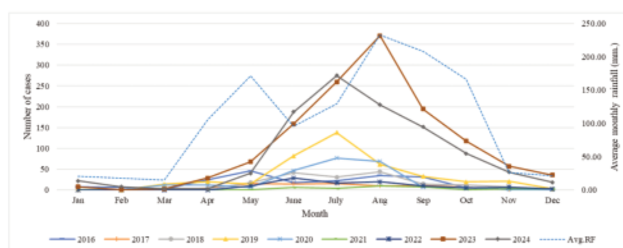

Figure 4. Number of dengue cases and average rainfall on monthly basis in the years 2016-2024.

Table 7. Section 3: community participation.

Participation Activity	High (always)	Moderate (sometime)	Low (never)
Attending community meetings	High	Moderate	Low
Joining community discussions	High	Moderate	Low
Participating in mosquito breeding site searches	Moderate	High	Low
Sharing opinions in community forums	Moderate	High	Low
Participating in decision-making	Low	Moderate	High
Joining mosquito breeding site elimination	High	Moderate	Low
Cooperating with community activities	High	Moderate	Low
Supporting knowledge dissemination	Moderate	High	Low
Donating money or resources	Low	Moderate	High
Encouraging relatives/friends to participate	Moderate	High	Low
Joining campaigns	High	Moderate	Low
Overturning unused containers/materials	High	Moderate	Low
Participating in situation assessments	Low	Moderate	Low

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Socio-demographic factors also played a significant role in dengue risk. The case-control study revealed that households with lower income, agricultural occupations, and housing environments characterised by stagnant water or orchards were more vulnerable to dengue transmission. Although only 33 cases were included in the detailed household-level analysis, this subset was not intended to represent the full epidemiological burden of dengue in the study period. Instead, it served as a focused sample for examining community-level behaviours, preventive practices, and local environmental conditions. The broader spatio-temporal analysis was conducted using the complete dataset of 3,600 cases, ensuring statistical robustness at the population level. The household survey component therefore complements, rather than replaces, the large-scale spatial analysis, providing contextual and behavioural insights that cannot be derived from surveillance data alone. Nevertheless, we acknowledge that the limited sample size may constrain statistical generalisation, and future studies should consider larger survey samples to strengthen inference. These results are consistent with

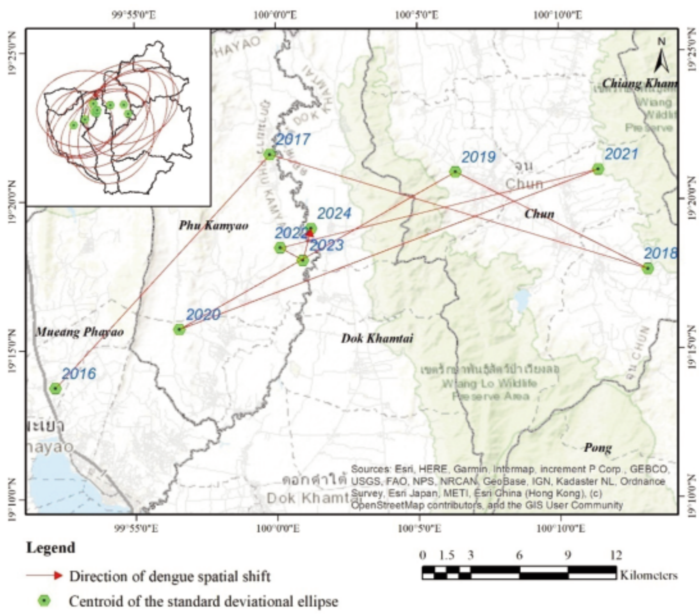
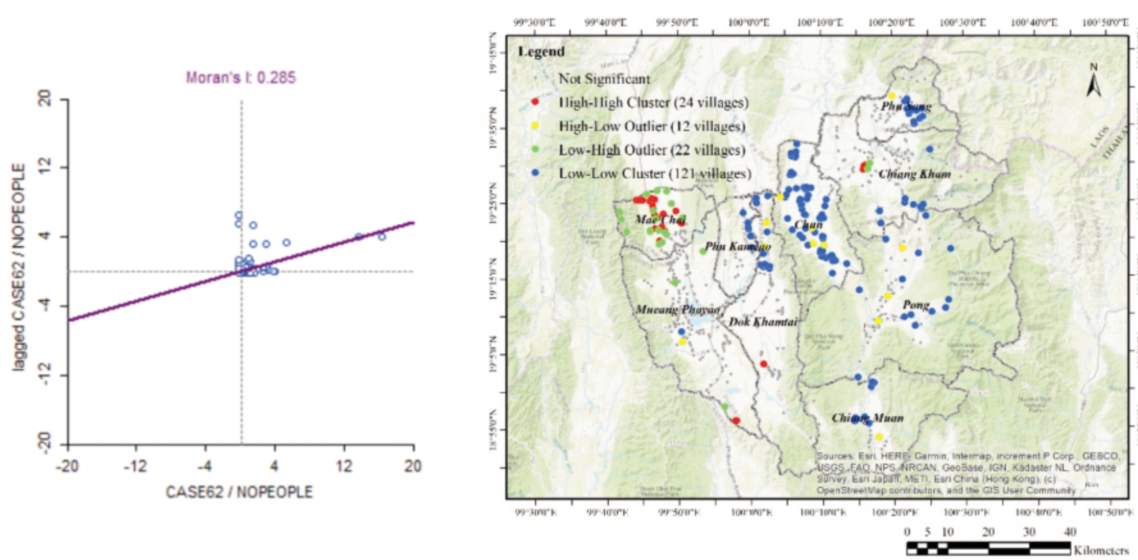


Figure 5. Standard deviational ellipses of dengue cases in Phayao Province 2016-2024. The centroid of each annual ellipse is connected chronologically to illustrate the spatiotemporal shifts and directional trends of the disease over the study period.



(a.) (b.)

Figure 6. (**a**) Moran scatter plot matrix and (**b**) LISA cluster map of DFMR (p<0.01) for the year 2019. Red and dark blue areas represent spatial clusters (areas with high dengue presence surrounded by other similarily high areas, and low dengue presence surrounded by other similarily low areas), whereas yellow and green areas indicate spatial outliers (high surrounded by low values, and low surrounded by high values).

evidence that socio-economic status and environmental conditions strongly influence vector-borne disease risk (Suwanbamrung *et al.*, 2021). Moreover, reliance on traditional media such as radio and television for dengue prevention information highlights the need to strengthen communication strategies and integrate modern digital platforms for broader outreach.

Strengths and limitations

Overall, this study demonstrates that dengue transmission in Phayao Province is shaped by a combination of climatic, spatial, and socio-demographic factors. The integration of GIS-based spatial analysis with epidemiological and environmental data provides actionable evidence for public health authorities. Strengthening community participation, improving surveillance systems, and prioritising interventions in identified hotspots are essential strategies to reduce the burden of dengue in northern Thailand. Although these important insights were gained, several limitations must also be acknowledged. First, potential underreporting of dengue cases may affect the accuracy of spatial clustering and hotspot detection. Second, the absence of real-time surveillance data limits the ability to capture dynamic transmission patterns. Third, mobility patterns and socio-economic variables were not fully integrated into the

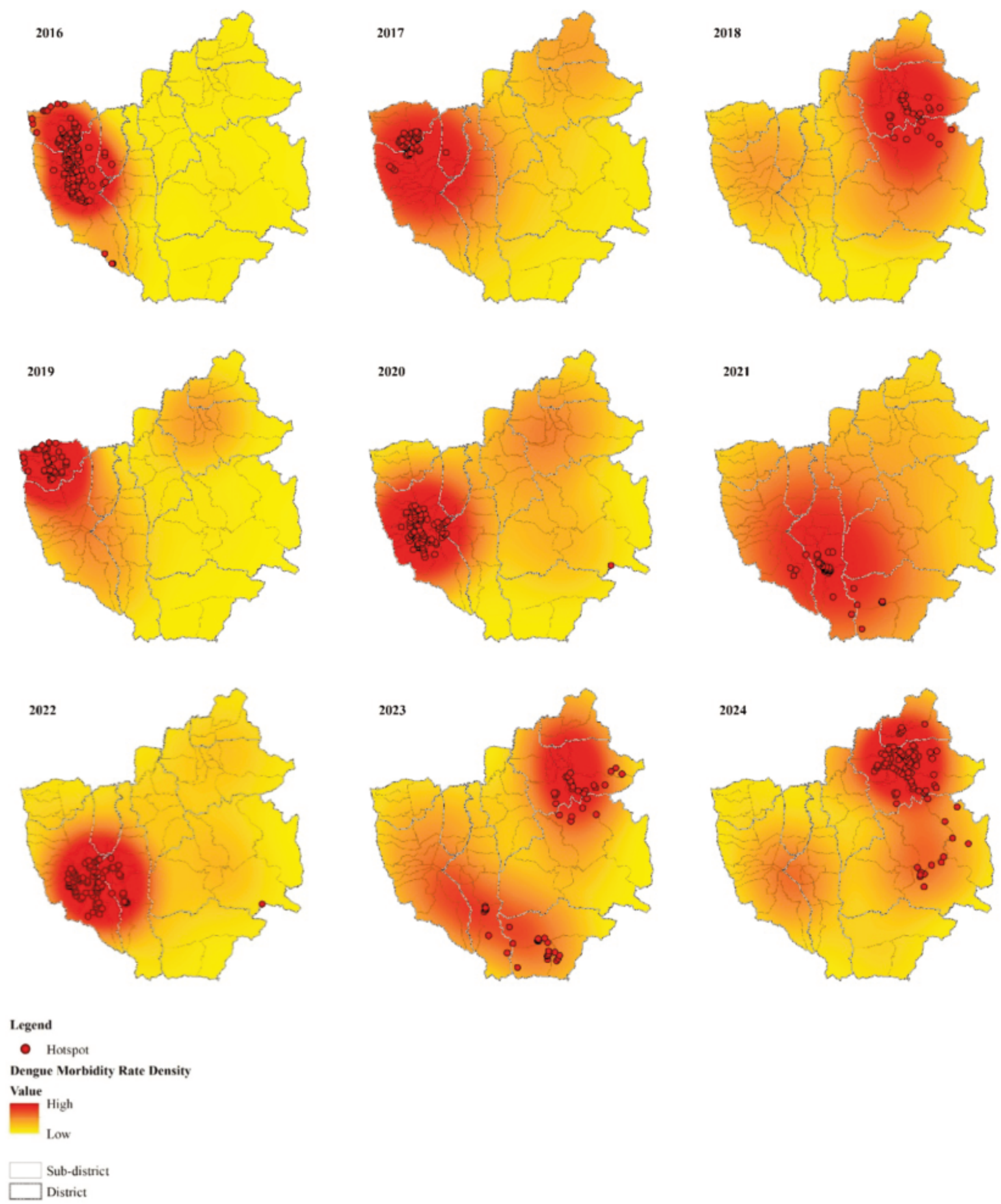


Figure 7. Dengue morbidity rate density.

spatial models, which may reduce predictive accuracy. Future research should incorporate these factors to enhance the robustness of risk assessments.

Conclusions

The utility of GIS and spatial statistical methods in assessing DF and DHF risk at the village level in Phayao Province, Thailand were demonstrated. By integrating epidemiological, climatic, and socio-demographic data, the analysis revealed significant spatial clustering of DF/DHF cases, with hotspots concentrated in urbanised districts, such as Mueang Phayao, Chiang Kham and Dok Khamtai. Temporal analysis confirmed seasonal peaks during the rainy season, underscoring the influence of rainfall and temperature on vector proliferation.

Hotspot detection using LISA and Kernel Density Estimation provided granular insights into spatial heterogeneity, enabling the identification of priority villages for targeted interventions. The case-control study further highlighted socio-demographic and environmental risk factors, including low household income, agricultural occupations and housing environments characterised by stagnant water or orchards. These findings emphasise the importance of integrating spatial analysis with community-level socioeconomic data to enhance dengue prevention strategies.

The results provide actionable evidence for public health authorities in northern Thailand. Strengthening surveillance systems, prioritising interventions in identified hotspots, and promoting community participation are essential measures to reduce the burden of dengue. Future research should incorporate real-time surveillance data, socio-economic mobility patterns, and advanced predictive models to improve the accuracy of risk assessments and support sustainable vector control programs.

References

Anselin L, Syabri I, Kho Y, 2006. GeoDa - an introduction to spatial data analysis. Geogr Anal 38:5-22.

Cao TH, Luong TBT, 2023. Spatial analysis in epidemiological studies of dengue: A systematic rereview and meta-analysis. World J Biol Pharm Health Sci 16:178-87.

Getis A, Ord JK, 1995. Local spatial autocorrelations statistics: distributional issues and application. Geogr Anal 27:286-306.

Jaya IGNM, Andriyana Y, Tantular B, Pangastuti S, Kristiani F, 2025. Spatiotemporal dengue forecasting for sustainable public health in Bandung, Indonesia: a comparative study of classical, machine learning, and Bayesian models. Sustainability 17:6777.

Jeefoo P, Tripathi NK, Souris M, 2011. Spatio-temporal diffusion pattern and hotspot detection of dengue in Chachoengsao Province, Thailand. Int J Environ Res Public Health 8:51-74.

Jeefoo P, Preedapirom W, Rojanavasu P, 2021. Risk assessment and factors associated with lung cancer using GIS in Mae Ka Subdistrict, Muang District, Phayao Province, Thailand. Int J Geoinform 17:21-33.

Jepsen MR, Simonsen J, Ethelberg JS, 2009. Spatio-temporal cluster analysis of the incidence of Campylobacter cases and patients with general diarrhea in a Danish county, 1995–2004. Int J Health Geogr 8:11.

Kaewhan S, Junpha J, Pimpeach W, 2025. The regional distribution of dengue fever in Thailand and other emerging countries in Southeast Asia: a literature review. Toxicol Environ Health Sci 17:327–34.

Kristiani F, Jaya IGNM, Irawan R, Priscilia IM, 2026. Bayesian modelling of dengue incidence with climatic drivers: comparing fixed-effects, nonlinear and dynamic approaches. Geospat Health, 21:1461.

Lim A, Ammatawiyanon L, Khurram H, Tongkumchum P, McNeil D, 2025. Spatial occurrence-intensity modeling of dengue inci-

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