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# Spatiotemporal dynamics and forecasting of dengue incidence in Northeastern Thai border provinces, 2014−2023

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## ABSTRACT

**Objective:** To identify the underexplored nature of localized, long-term spatiotemporal patterns (2014-2023) and predictive modeling feasibility in these regions. The analysis specifically explored the potential for robust forecasting of dengue incidence trends.

**Methods:** Dengue incidence trends were analyzed across five northeastern Thai provinces: Sisaket (SSK), Ubon Ratchathani (UBN), Yasothon (YST), Amnat Charoen (ACR), and Mukdahan (MDH) over a ten-year period (2014-2023). Analysis of Kruskal–Wallis *H* test followed by *post hoc* Dunn's tests with Bonferroni adjustment were used for inter-provincial comparisons. Seasonal-Trend Decomposition using Loess (STL) and Seasonal Index calculations were applied to identify seasonal patterns, and Simple Linear Regression to assess the influence of monthly rainfall on dengue seasonality. Additionally, a negative binomial regression analysis was conducted, and spatial autocorrelation was investigated using Moran's *I* analysis.

**Results:** The analysis revealed significant spatiotemporal heterogeneity and distinct cyclical patterns in dengue incidence. Pronounced annual peaks consistently occurred during the rainy season (June-September), with major epidemics observed in 2015, 2019, and 2023. Inter-provincial comparisons revealed statistically significant differences in monthly dengue incidence across the study area ($H$=10.08, $P$=0.039). *Post–hoc* Dunn's tests indicated that UBN and SSK had higher transmission burden compared to YST and MDH. Seasonal Index calculations confirmed July as the predominant overall peak month (indices 1.4-2.5), with minimal dengue activity from January to March. While rainfall significantly influenced seasonality across all provinces. A negative binomial regression analysis indicated that all of the variables included in the model had no statistically significant relationship with dengue incidence. Furthermore, a Moran's *I* analysis revealed a significant clustering effect only in YST ($I$=0.314, $P$=0.037).

**Conclusions:** The finding underscores the critical requirement for adopting a highly focused approach, necessitating a shift toward region-specific interventions to effectively combat dengue and sustain progress toward good health and well-being for all.

**Summary**

**Question:** What were the localized spatiotemporal patterns and feasibility for robust forecasting of dengue incidence in five northeastern Thai provinces over a ten-year period?

**Findings:** This 10-year spatiotemporal analysis (2014-2023) of five provinces revealed a statistically significant difference in monthly incidence distributions. Ubon Ratchathani and Sisaket exhibited the highest burden. Rainfall's predictive power for seasonality varied widely, and significant spatial clustering was observed only in Yasothon.

**Meaning:** These findings underscore the critical need for a shift toward region-specific interventions and advanced, localized predictive modeling for effective public health preparedness.

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## 1. Introduction

Dengue fever, a globally significant mosquito-borne viral disease, causes an estimated 390 million infections annually[1-3]. Primarily transmitted by *Aedes (Ae.) aegypti* and *Ae. albopictus*, dengue is endemic in over 100 countries, with its global burden expanding significantly in recent decades due to urbanization, climate change, increased international travel, and persistent vector control challenges[1,3-7].

Thailand is hyperendemic for dengue, experiencing co-circulation of all four dengue virus serotypes[8,9]. Nationwide, large-scale outbreaks typically recur every 2–5 years[10,11]. Despite ongoing national efforts in integrated vector control and early warning systems[12], dengue remains a formidable public health challenge. For instance, 2023 recorded over 150 000 cases with a national incidence rate of approximately 230 per 100 000 population, marking one of the highest spikes in a decade[13,14]. However, beyond these national trends, rural and border provinces in northeastern Thailand, adjacent to Laos and Cambodia, face unique surveillance and control challenges. These stem from factors like limited health access and complex cross-border population movements, leading to distinct epidemiological patterns and potentially underrecognized outbreaks. The northeastern border provinces of Sisaket (SSK), Ubon Ratchathani (UBN), Yasothon (YST), Amnat Charoen (ACR), and Mukdahan (MDH) present a particularly distinct epidemiological setting for dengue transmission. These areas are characterized by diverse ecological landscapes, significant transboundary population movement, and varying vector ecologies, all influencing outbreak dynamics[15]. Dengue incidence rates in these border regions can fluctuate dramatically due to socio-environmental risk factors like agricultural labor migration, abundant vector breeding sites, and cross-border health-seeking behaviors. Furthermore, proximity to endemic areas in neighboring countries facilitates viral circulation and reintroduction[16,17]. Despite these complexities, long-term spatiotemporal trends in these specific provinces have received limited systematic examination, underscoring their critical importance for public health planning and early warning system development.

While numerous studies have explored dengue epidemiology in Thailand, most focus on short-term outbreak investigations, national trends, or localized urban settings[18,19]. Research addressing long-term spatiotemporal dynamics at the subnational level, particularly in rural and border areas, remains scarce. This gap is concerning, given that local transmission patterns in border provinces often differ significantly from national averages due to unique environmental conditions, vector populations, and human mobility patterns[20-22]. Recognizing this unmet need for granular, long-term spatiotemporal analysis and predictive insights, this study investigates dengue patterns and trends in these under-studied, high-risk northeastern border provinces from 2014 to 2023. Using detailed monthly incidence data, the aims are to identify province-specific temporal trends and cyclical patterns, and to evaluate the feasibility of applying statistical and machine learning models for forecasting. The insights derived are intended to support data-driven public health decision-making, fostering targeted, regionally appropriate dengue prevention programs and more effective early warning systems.

## 2. Methods

### 2.1. Study area

This study focused on dengue epidemiology within five northeastern Thai border provinces, SSK, UBN, YST, ACR, and MDH (Figure 1). These provinces, collectively home to over 5 million people, are situated along the Lao and Cambodian borders, characterized by a distinct monsoonal climate influencing *Aedes* mosquito breeding and dengue transmission cycles[23]. Ecologically, their blend of rural-agricultural and peri-urban landscapes, coupled with widespread domestic water storage, fosters abundant *Ae. aegypti* populations[24]. The region also experiences significant seasonal and cross-border population mobility, contributing to virus importation and spatial spread[25]. From a public health perspective, these areas present unique operational challenges in disease surveillance and control due to varying resource availability and complexities in cross-border coordination. Detailed geographical characteristics, administrative divisions (districts, sub-districts, villages), and population demographics of these provinces are provided in a related study[26].

### 2.2. Data source

Dengue incidence data for this study were acquired from the Office of Disease Prevention and Control Region 10, Ubon Ratchathani (ODPC10), the primary regional authority for epidemiological surveillance and vector-borne disease control in northeastern Thailand. This secondary dataset encompassed monthly aggregated dengue incidence rates for the five specified provinces from January 2014 to December 2023. Incidence rates, reported as clinically diagnosed cases per 100 000 population, were derived from the national dengue surveillance system, incorporating suspected, probable, and confirmed infections based on Thai Ministry of Public Health standard case definitions. Data were collected through routine

passive surveillance at provincial healthcare facilities, anonymized, and aggregated at the provincial level to ensure confidentiality. Further details on the specific data collection protocols and initial data management are available in Loyha *et al.*, 2025[26].

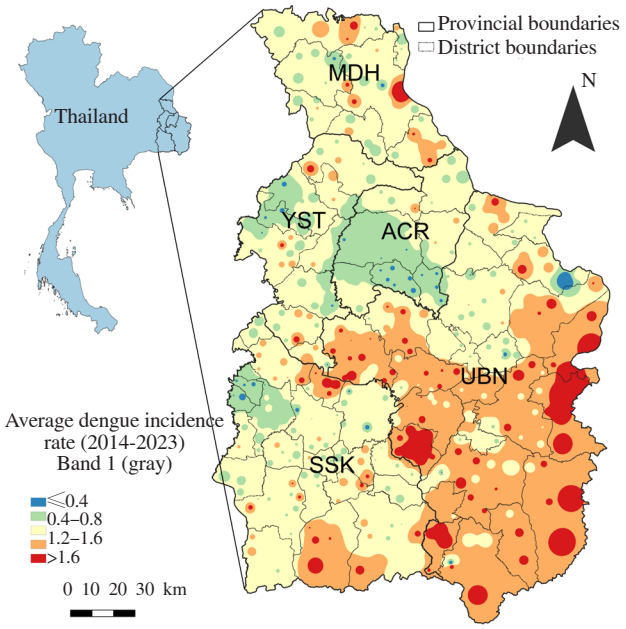


**Figure 1.** Spatial distribution map of the five study provinces in Northeast Thailand. ACR: Amnat Charoen; MDH: Mukdahan; SSK: Sisaket; UBN: Ubon Ratchathani; YST: Yasothon. This figure illustrates the longitudinal 10-year average dengue incidence rates, cases/1 000 population (represented by color gradients).

### *2.3. Data processing and analysis*

The ten-year (2014–2023) monthly dengue incidence dataset underwent initial review for completeness and consistency. Data were then reshaped into a long format to facilitate time series analysis and statistical modeling, with no imputation performed due to data completeness. The primary analytical approach focused on understanding long-term temporal patterns, inter-provincial differences, and evaluating the feasibility of predictive modeling, directly addressing the study's core objectives and identifying research gaps. Time series analysis, employing line plots and three-month moving averages, assessed monthly and annual trends for each province, complemented by descriptive statistics (mean, SD, min, max). Inter-provincial incidence differences were evaluated using Kruskal–Wallis *H* test followed by *post hoc* Dunn's tests with Bonferroni adjustment ($P<0.05$).

Seasonal Patterns and Time Series Decomposition were explored by performing a Seasonal-Trend Decomposition using Loess (STL) analysis to isolate the trend, seasonal, and residual components of the time series, as well as by calculating seasonal indices for each calendar month. For predictive modeling, the study explored the feasibility of Autoregressive Integrated Moving Average (ARIMA) models to forecast future incidence based on historical observations.

A negative binomial regression model was also applied to investigate factors influencing dengue incidence, including the year and provincial indicators (ACR, MDH, SSK, UBN, YST). The influence of climatic variables was assessed using simple linear regression models for monthly rainfall, temperature, and humidity as predictors of the calculated Seasonal Indices. Spatial autocorrelation was investigated using Moran's *I* analysis to assess the spatial distribution of dengue incidence, based on a spatial weight matrix where provinces sharing a border were given a value of 1. All analyses and visualizations were performed utilizing Microsoft Excel and SPSS Version 28.0.

## 3. Results

### *3.1. Negative binomial regression analysis*

The results from the negative binomial regression analysis indicated that all of the variables included in the model, specifically, year and province, had no statistically significant relationship with dengue incidence. Variables, including the year and the provincial indicators (ACR, MDH, SSK, UBN, and YST), had *P*-values well above the significance threshold of 0.05 (Table 1). The year variable showed a non-significant negative coefficient (Estimate=–0.041, $P=0.404$), indicating no reliable long-term decrease in incidence over the study period. Similarly, while the provincial estimates varied, none of the provinces showed a statistically reliable difference in incidence when compared to the reference group. The UBN had the highest positive estimate (16.30), suggesting a higher incidence, but statistically insignificant with *P*-value of 0.326. These findings collectively

**Table 1.** Negative binomial regression analysis of dengue incidence in northeastern Thai border provinces (2014–2023).

| Variable | Estimate | Standard error | *Z*-value | *P*-value | 95% *CI* |
|---|---|---|---|---|---|
| Intercept | 74.55 | 82.91 | 0.899 | 0.369 | –87.96 to 237.05 |
| Year | -0.041 | 0.049 | -0.834 | 0.404 | –0.14 to 0.06 |
| ACR | 13.84 | 16.58 | 0.835 | 0.404 | –18.66 to 46.35 |
| MDH | 14.24 | 16.58 | 0.858 | 0.391 | –18.27 to 46.74 |
| SSK | 15.67 | 16.58 | 0.945 | 0.345 | –16.83 to 48.18 |
| UBN | 16.30 | 16.58 | 0.983 | 0.326 | –16.20 to 48.81 |
| YST | 14.49 | 16.58 | 0.874 | 0.382 | –18.02 to 46.99 |

95% *CI*: 95% confidence interval. ACR: Amnat Charoen; MDH: Mukdahan; SSK: Sisaket; UBN: Ubon Ratchathani; YST: Yasothon.

indicate that this specific model, utilizing aggregated provincial data, was unable to identify a statistically reliable influence of these variables on the observed dengue incidence rates.

### 3.2. Spatial autocorrelation analysis

Moran's *I* analysis was conducted to assess the spatial distribution of dengue incidence, based on a spatial weight matrix where provinces sharing a border were given a value of 1. The ten-year period from 2014 to 2023 indicated that only YST province showed a statistically significant positive spatial autocorrelation (Moran's *I* value=0.314, *P*-value=0.037). This finding suggests a spatial clustering effect for dengue incidence in YST, where provinces with a high number of cases tend to be located near other provinces with high case numbers. Conversely, the Moran's *I* values for the other provinces, SSK, UBN, ACR, and MDH were not statistically significant (*P*-values>0.05). This indicates that no significant spatial autocorrelation was detected for these provinces over the study period, suggesting that their dengue incidence patterns are more heterogeneous and do not exhibit a distinct clustered distribution based on contiguity (Table 2).

### 3.3. Inter–provincial comparison

A Kruskal–Wallis *H* test was conducted to assess differences in monthly dengue incidence across the five northeastern provinces. The analysis revealed a statistically significant spatial heterogeneity in dengue transmission (*H*=10.08, *P*=0.039). This finding indicates that the distribution of monthly incidence rates varied significantly among the provinces over the ten-year study period.

To understand these differences more precisely, *post hoc* Dunn's tests with Bonferroni adjustment were conducted. The results allowed for the classification of provinces into two overlapping groups. UBN and SSK exhibited the highest ranks of dengue burden, specifically, UBN showed significantly higher incidence than YST and MDH, while SSK was significantly higher than YST.

Conversely, YST and MDH represented the group with the lowest statistical ranking of incidence. ACR occupied a middle position, as its incidence distribution did not differ significantly from either the high-burden provinces (UBN, SSK) or the lower-burden provinces (YST, MDH). Notably, while SSK had a higher median, UBN recorded the highest maximum monthly incidence (109.73 per 100 000 population) during the study period, highlighting its role as a high-intensity transmission hub (Table 3).

### 3.4. Seasonal patterns and time series decomposition

A strong seasonal pattern consistently emerged across all provinces, aligning with Thailand's monsoon cycle. Dengue incidence typically begins to rise in May, reaching peak activity from June to August, followed by a gradual decline towards the end of the year. This is clearly reflected in the Seasonal Index (SI) values, which indicate that incidence starts to exceed the annual average in May (SI>1.0) and reaches its highest points from June through September (SI>1.3). July is consistently identified as a predominant peak month for the region (Figure 2).

While the overall seasonal pattern is consistent, a detailed analysis of the seasonal indices by province reveals subtle variations in the timing of peak transmission, for instance, SSK and UBN show highest seasonal indices in August (2.38 and 2.58, respectively), whereas YST peaks in September (2.67). MDH and ACR) both experience their highest indices in July (2.79) and August (2.53), respectively, demonstrating a slight shift in the precise peak month across the region (Figure 2).

To further investigate this underlying seasonality, a Seasonal-Trend Decomposition using Loess (STL) analysis was performed to isolate the temporal components of each province's dengue time series. The

**Table 2.** Moran's *I* analysis of dengue incidence in Northeastern Thai border provinces (2014–2023).

| Province | SSK | UBN | YST | ACR | MDH | Dengue | Moran's I | Expected I | *Z*-score | *P*-value |
|---|---|---|---|---|---|---|---|---|---|---|
| SSK | 0 | 1 | 0 | 0 | 0 | 14 056 | 0.216 | –0.2884 | 1.60 | 0.109 |
| UBN | 1 | 0 | 1 | 1 | 0 | 25 924 | -0.116 | –0.2884 | 0.56 | 0.575 |
| YST | 0 | 1 | 0 | 0 | 0 | 4 540 | 0.314 | –0.2884 | 2.08 | 0.037 |
| ACR | 0 | 1 | 0 | 0 | 1 | 2 313 | -0.077 | –0.2884 | 0.37 | 0.711 |
| MDH | 0 | 0 | 0 | 1 | 0 | 3 253 | -0.279 | –0.2884 | 0.03 | 0.975 |

**Table 3.** Summary of monthly incidence rates and *post hoc* Dunn's test results.

| Province | Median (Q1-Q3) | Min | Max | Kruskal–Wallis Test | Dunn's test with Bonferroni-adjusted *P*-values |
|---|---|---|---|---|---|
| ACR | 2.26 (3.79)[b] | 0 | 38.52 | H=10.08<br>*P*= 0.039 | UBN>YST<br>UBN>MDH<br>SSK>YST |
| MDH | 1.58 (3.79)[b] | 0 | 58.09 | | |
| SSK | 4.52 (7.06)[a] | 0 | 47.68 | | |
| UBN | 3.77 (13.92)[a] | 0 | 109.73 | | |
| YST | 1.67 (5.56)[b] | 0 | 90.95 | | |

Different letters (a,b) indicate significant differences at *P*<0.05 using Dunn's test with Bonferroni-adjustment.

decomposition revealed a strong, fundamental seasonal component that is highly consistent across all five provinces. The seasonal component's values rise from negative values in the dry season to positive values during the monsoon season, peaking consistently in July and August (Supplementary Table 1). This decomposition reinforces that despite the minor variations in peak months observed in the raw SI data, there is a powerful, shared seasonal signal driving dengue transmission across the entire study area. The trend component across all provinces was found to be a near-constant value, suggesting that after accounting for seasonality, the long-term trend in incidence was relatively stable over the study period.

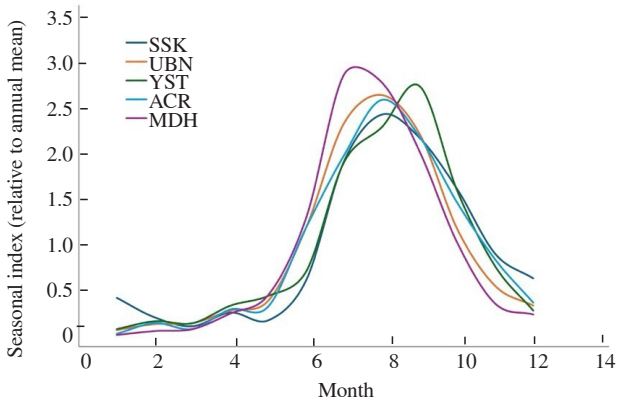


**Figure 2.** Seasonal Index of dengue incidence by province (2014–2023). The graph illustrates the average monthly dengue incidence relative to the annual mean for ACR, MDH, SSK, UBN, and YST. ACR: Amnat Charoen; MDH: Mukdahan; SSK: Sisaket; UBN: Ubon Ratchathani; YST: Yasothon.

### *3.5. Influence of rainfall and climatic factors on seasonal index*

To investigate the impact of climatic factors on dengue seasonality, simple linear regression models were applied to monthly rainfall, temperature, and humidity data (predictors) and the calculated Seasonal Indices (dependent variable) for each province from 2014 to 2023.

The analysis revealed a statistically significant linear relationship between rainfall and the SI in all provinces ($P$<0.05), indicating that simple linear regression was an appropriate model. The standardized coefficients ( β ) confirmed that rainfall significantly influenced the SI, with the strongest influence observed in SSK ( β =0.917). The predictive power of rainfall, as indicated by the Adjusted $R^2$ value, was highest for SSK, explaining 82.4% of the variance in its SI. In contrast, the predictive power was lowest for YST, where rainfall explained only 34.8% of the variance, suggesting other unmeasured factors play a more significant role in that province. The remaining provinces exhibited varying predictive capabilities, namely MDH (59.7%), ACR (46.9%), and UBN (40.2%). This spatial variation in the correlation between rainfall and dengue incidence highlights the heterogeneity of transmission dynamics across the region (Table 4).

In contrast, the influence of temperature on the SI was found to be non-significant in any of the provinces for which data were available (ACR, YST, SSK, UBN). MDH was excluded from the temperature analysis due to the unavailability of consistent meteorological station data covering the entire study period (2014-2023). The $P$-values for all provinces were well above the 0.05 threshold (Table 4), suggesting that monthly temperature, when considered as a single variable, does not have a strong linear relationship with the SI in these provinces.

Similarly, the analysis for humidity showed mixed results. While UBN exhibited a statistically significant relationship between humidity and its SI ($P$<0.05), with humidity explaining 16.5% of the variance, no significant relationship was found for SSK or ACR. This suggests that while humidity may be a contributing factor in some provinces, its influence is not universal across the study area (Table 4).

**Table 4.** Simple linear regression results for rainfall, temperature, and humidity predicting SI by province (2014–2023).

| Regression | Province | β | *t* | *P* | 95% *CI* | | *F* | $R^2$ | Adjusted $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower bound | Upper bound | | | |
| Rainfall and SI | ACR | 0.719 | 3.274 | 0.008 | 0.001 | 0.005 | 10.721 | 0.517 | 0.469 |
| | YST | 0.638 | 2.621 | 0.026 | 0 | 0.004 | 6.870 | 0.407 | 0.348 |
| | MDH | 0.796 | 4.162 | 0.002 | 0.014 | 0.047 | 17.325 | 0.634 | 0.597 |
| | SSK | 0.917 | 7.255 | 0 | 0.003 | 0.006 | 52.635 | 0.840 | 0.824 |
| | UBN | 0.676 | 2.897 | 0.016 | 0.001 | 0.004 | 8.395 | 0.456 | 0.402 |
| Temperature and SI | ACR | 0.051 | 0.295 | 0.769 | –4.269 | 5.722 | 0.087 | 0.003 | –0.027 |
| | YST | 0.060 | 0.351 | 0.728 | –11.325 | 16.050 | 0.123 | 0.004 | –0.026 |
| | SSK | 0.024 | 0.161 | 0.873 | –16.283 | 19.116 | 0.026 | 0.001 | –0.021 |
| | UBN | 0.169 | 1.164 | 0.250 | –13.388 | 50.122 | 1.533 | 0.029 | 0.008 |
| Humidity and SI | UBN | 0.428 | 3.210 | 0.002 | 4.422 | 19.295 | 10.303 | 0.183 | 0.165 |
| | SSK | 0.278 | 1.965 | 0.056 | –0.123 | 10.155 | –3.806 | 0.077 | 0.057 |
| | ACR | –0.002 | –0.013 | 0.990 | –0.093 | 0.092 | 0 | 0 | –0.029 |

SI: Seasonal Index; 95% *CI*: 95% confidence interval.

## 4. Discussion

The analysis of dengue trends in northeastern Thailand reveals patterns consistent with, and providing nuanced detail to, broader global and regional epidemiological understanding. A comprehensive spatiotemporal analysis in this region identified pronounced annual peaks consistently occurring during the rainy season (June-September), with major epidemics observed in 2015, 2019, and 2023. This directly aligns with the widely recognized 2-5 year global periodicity of dengue outbreaks[3,10,26,27], exemplified by Costa Rica's consistent 3-year cycles[28] and Singapore's historical 5- to 6-year epidemic cycle[29]. The identified 4-year cycle (2015-2019) and subsequent 4-year cycle (2019-2023) in these border provinces thus fall within established global periodicities. Such patterns and the overall increase in global dengue incidence[3] reflect an intricate interplay of factors, including population immunity dynamics, the introduction or re-emergence of different dengue virus (DENV) serotypes, and environmental conditions affecting vector populations[7,25,30,31]. This granular, decade-long perspective contributes to filling crucial research gaps by providing specific temporal markers for these border provinces, areas often underrepresented in broad national or regional reports.

Beyond overall cyclical patterns, distinct cyclical and spatial differences were observed among provinces, highlighting pronounced heterogeneity in disease burden. While epidemics broadly impacted Thailand during the study period, UBN and MDH were particularly affected, consistently showing higher incidence and greater volatility. For instance, UBN recorded its highest monthly incidence in a decade in July 2023 (exceeding 70 cases/100 000 population), with MDH also surpassing 50 cases/100 000 during the same period. This high incidence and volatility in UBN and MDH align with established understanding that climatic conditions, including extended rainy seasons and higher humidity, foster more favorable *Aedes* breeding and viral replication[23,32]. Furthermore, extreme weather events, such as recurrent flooding and intense monsoon activity, as observed in general environmental disruptions[33], can enhance *Aedes* breeding by increasing water stagnation and overwhelming sanitation infrastructure[34]. In contrast, ACR and SSK displayed more moderate and consistent outbreak profiles, with their peak years primarily in 2015 and 2016. Yasothon consistently maintained the lowest incidence rates, reporting minimal or no cases during several months between 2020 and 2022. This provincial heterogeneity in incidence and outbreak patterns aligns with other studies within Thailand and Southeast Asia[18,35]. For example, research in southern Thailand has similarly reported significant variations in peak months among neighboring provinces, with some peaking in June and others in August, directly influenced by localized weather patterns[35,36]. This broader micro-epidemiological variability indicates that dengue dynamics are not uniform even within a single country, and is also observed in other Southeast Asian contexts, where factors like urbanization, population density, and environmental conditions contribute to diverse transmission patterns within countries.

SI analysis consistently confirmed the monsoonal effect on dengue dynamics, identifying July as the predominant peak transmission month across all five provinces. This consistent pattern aligns with established relationships between rainfall, humidity, and vector proliferation[23,24,33,37], highlighting a crucial window for preemptive vector control and community engagement. However, examination of the Adjusted $R^2$ values, representing the proportion of variance in the SI explained by rainfall, revealed considerable disparities in predictive capabilities among provinces. Rainfall in SSK demonstrated the highest predictive power, explaining 82.4% of the variance in its SI, indicating a strong and direct influence of rainfall. In contrast, the predictive power of rainfall for the SI in MDH, ACR, UBN, and YST was notably lower (59.7%, 46.9%, 40.2%, and 34.8% respectively). These marked differences underscore the highly localized nature of dengue epidemiology and the varying importance of climatic drivers. Such disparities likely stem from a complex interplay of factors, including local environmental and geographical heterogeneity[32,38,39], variations in urbanization and water management practices[3,40], differential public health interventions and community engagement[41,42], and the influence of other unmeasured climatic and socio-economic factors[38].

A key addition to our findings is the result from the negative binomial regression analysis, which indicated that all of the variables included in the model (year and the provincial indicators for ACR, MDH, SSK, UBN, and YST) had no statistically significant relationship with dengue incidence. This finding is significant as it suggests that a simple, broad-scale model is insufficient to capture the intricate, multi-faceted dynamics of transmission, necessitating more granular data and sophisticated modeling approaches. Furthermore, the spatial autocorrelation analysis using Moran's *I*, based on a spatial weight matrix where provinces sharing a border were given a value of 1, revealed a significant clustering effect only in YST. This finding suggests that disease spread in YST may be driven by factors that promote localized spatial clusters, such as contiguous high-risk areas or unique human movement patterns. Conversely, the lack of significant spatial autocorrelation in the other provinces suggests their transmission dynamics are more heterogeneous and less influenced by simple spatial proximity. Variations in public health response capacity, with larger, better-resourced provinces generally having more robust surveillance and control systems, also contribute to observed disparities. Under-resourced areas may face underreporting due to diagnostic limitations or delayed responses[41,42]. Additionally, significant population mobility, particularly cross-border travel in economic

hubs like UBN and MDH, can amplify transmission through new viral strain importation, posing challenges to containment efforts.

Furthermore, the diversity of circulating DENV serotypes (DENV-1, DENV-2, DENV-3, and DENV-4) profoundly impacts cyclical patterns, outbreak dynamics, and disease severity[43]. Thailand, including the study area in the northeastern border provinces, is a hyperendemic country experiencing co-circulation of all four DENV serotypes[8,9]. This co-circulation, coupled with shifts in the predominant circulating serotype, can lead to secondary infections with a heterologous serotype, a major risk factor for severe dengue due to phenomena like antibody-dependent enhancement[25,44]. The introduction of a new serotype into a susceptible population can trigger large-scale epidemics, significantly altering the expected cyclical pattern and often being associated with increased disease burden and severity[45,46]. Similar dynamics are observed in other hyperendemic areas worldwide, where serotype diversity and shifts in dominance drive the waxing and waning of outbreaks and influence their intensity.

Ultimately, this study contributes novel insights to the national dengue landscape by offering a granular, longitudinal perspective on border regions areas of increasing public health concern due to factors like population mobility, ecological vulnerability, and existing health system challenges. These results reinforce calls for more decentralized, data-informed approaches to vector surveillance and outbreak preparedness, and crucially, lay the groundwork for effective predictive modeling in these high-risk settings.

In conclusion, the findings from this comprehensive, decade-long analysis of dengue incidence in northeastern Thailand underscore the critical need for context-specific public health interventions. The study revealed significant spatiotemporal heterogeneity and consistent cyclical patterns, with major epidemics observed in 2015, 2019, and 2023, aligning with broader global trends in dengue periodicity. Distinct inter-provincial differences were identified, categorizing areas into high and low incidence clusters. A statistically significant influence of climatic factors, like rainfall on local seasonality was demonstrated. However, this predictive power was found to vary considerably between provinces.

The limitations of simple, broad-scale models were highlighted by the finding that the negative binomial regression analysis, which included variables such as year and provincial indicators, did not reveal a statistically significant relationship with dengue incidence. Furthermore, the spatial autocorrelation analysis using Moran's *I* revealed a significant clustering effect in only one province (YST), suggesting that transmission dynamics are highly heterogeneous and less influenced by simple spatial proximity in the other provinces. These insights are crucial for developing targeted early warning systems and resource allocation strategies.

Ultimately, this study contributes novel insights to the national dengue landscape by offering a granular, longitudinal perspective on border regions, which are areas of increasing public health concern. The results reinforce calls for more decentralized, data-informed approaches to vector surveillance and outbreak preparedness. Crucially, they lay the groundwork for effective predictive modeling in these high-risk settings by demonstrating the need to prioritize sub-provincial or community-level analyses that incorporate a broader range of covariates, including entomological data, specific DENV serotype distributions, and detailed socio-environmental determinants. Such granular data and advanced modeling approaches are essential to unraveling the complex micro-epidemiological dynamics driving dengue transmission and, ultimately, to creating more precise forecasting models and highly effective, decentralized public health responses.

## Conflict of interest statement

We, the authors, declare that no competing interests exist in relation to the work reported in this manuscript.

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## Authors' contributions

KL, WN, SH, DS, KH, CK, and PK performed the data collection, data management, and data cleaning. KL, WN, SH, DS, and PK drafted the initial manuscript. WN was responsible for finalizing the data analysis and results writing. SH performed and finalized the spatiotemporal analysis and associated manuscript sections. PK provided overall supervision and finalized the final version of the manuscript for submission.

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