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Spatial Association between Environmental Factors and Dengue Shock Syndrome in Endemic Area of Lao PDR

Mick Soukavong[1], Apiporn T. Suwannatrai[2], Matthew Kelly[3], and Kavin Thinkhamrop[4*]

[1]Department of Natural and Social Sciences, Faculty of Medicine, University of Health Sciences, Lao PDR.
[2]Department of Parasitology, Faculty of Medicine, Khon Kaen University, Khon Kaen, Thailand.
[3]National Centre for Epidemiology and Population Health, College of Health and Medicine, Australian National University, Canberra, Australia.
[4]Health and Epidemiology Geoinformatics Research (HEGER), Faculty of Public Health, Khon Kaen University, Khon Kaen, Thailand

*Corresponding author: kavith@kku.ac.th
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Abstract

Dengue fever remains a pressing health issue in many tropical and subtropical regions, with Lao People's Democratic Republic (Lao PDR) facing recurring outbreaks that significantly impact public health. Dengue shock syndrome (DSS), a life-threatening complication, is of particular concern due to its severe symptoms and potential fatality. This study investigated the spatial patterns and environmental determinants of DSS incidence in southern Lao PDR from 2015 to 2020. Spatial autocorrelation analysis and regression models were employed to examine the relationships between DSS incidence and environmental factors, including altitude, vegetation cover, water content, precipitation, temperature, and nighttime light intensity. A total of 588 DSS cases were reported, with an incidence rate of 6.87 per 100,000 inhabitants. Strong positive spatial autocorrelation (Moran's I = 0.675) indicated significant clustering of DSS cases. High-risk clusters were identified in southwestern Lao PDR, particularly in Champasak Province, while low-risk clusters were observed in the northern areas. Spatial regression models revealed that temperature was positively associated with DSS incidence (coefficient: 3.36, 95%CI: 0.42 – 6.30, $p < 0.05$), while normalized difference vegetation index (NDVI) showed a significant negative association (coefficient: -43.09, 95%CI: -81.55 – 4.63, $p < 0.05$). Areas with lower NDVI values, typically indicating urban environments with less dense vegetation, were associated with higher DSS incidence. The study highlights the complex spatial dynamics of DSS in the region and the significant roles of temperature and vegetation cover in shaping its distribution. These findings can inform targeted interventions, urban planning strategies, and climate change adaptation measures to mitigate the burden of dengue in southern Laos.

Keywords: Dengue shock syndrome; Spatial analysis; Lao PDR; Climate factors; Vector-borne diseases; Environmental determinants

1. Introduction

Dengue fever, a mosquito-borne viral infection, is a significant global health challenge, with annual incidence estimates ranging from 50 to 100 million new cases worldwide. The number of dengue cases reported to the World Health Organization has surged dramatically over the past two decades. In 2000, there were 505,430 reported cases, which increased to over 2.4 million by 2010, and further escalated to 4.2 million in 2019. The year 2024 has seen the highest number of dengue cases ever recorded. By July 23, over 10 million cases have been reported from 176 countries in all WHO regions, with the majority occurring in the Americas. More than 24,000 of these cases were severe, and 6,508 people have died. This total has already exceeded the case count for 2023, which had previously set the record (Cogan, 2020; Lancet, 2024) Among these, approximately 500,000 cases progress to severe dengue, requiring hospitalization and carrying a mortality rate of about 2.5% (Cogan, 2020). The disease's impact is particularly pronounced in Asia, where a substantial portion of the estimated two billion people at risk of infection reside, including populations in the Lao People's Democratic Republic (Lao PDR) (Guo *et al.,* 2017). In Southeast Asian region bore a considerable burden of dengue between 2001 and 2010. During this period, an average of 816,000 dengue-related hospitalizations occurred annually, resulting in around 5,900 deaths (Shepard *et al.,* 2013). Within this regional context, Dengue has since become a major and urgent public health issue in the Lao PDR (Louangpradith *et al.,* 2020). Lao PDR is a landlocked country in Southeast Asia, characterized by diverse geography. The country is divided into three distinct regions: the mountainous north, the central plains along the Mekong River, and the southern lowlands (Bureau Lao Statistics, 2018).

In Lao PDR, dengue is endemic, with recurring outbreaks causing substantial morbidity and mortality (Phommanivong *et al.,* 2016). National surveillance data from 2015 to 2020 have highlighted the persistent burden of dengue in the country (Soukavong *et al.,* 2024). Of particular concern is dengue shock syndrome (DSS), a severe form of dengue infection characterized by plasma leakage, severe bleeding, and organ impairment (World Health Organization, 2009). DSS, as the most critical manifestation of severe dengue, carries a mortality rate reportedly 50 times higher than that of dengue patients without DSS (Anders *et al.,* 2011). A higher incidence of 44,171 cases along with 95 deaths recorded in 2013 (Ministry of Health National center for Laboratory and Epidemiology, 2019). In the southern region of the country alone, there were 4,638 reported cases and 32 deaths (Ministry of Health National center for Laboratory and Epidemiology, 2019).

The transmission dynamics of dengue virus are complex, influenced by various environmental factors that affect both the vector mosquito population and viral replication. Climate variables such as temperature and precipitation have been shown to play crucial roles in dengue transmission (Xu *et al.,* 2020). Additionally, urbanization, population density, and socioeconomic factors contribute to the spatial heterogeneity of dengue incidence (Banu *et al.,* 2011). Recent advancements in geospatial technologies and the availability of open-source geographic information system (GIS) software have provided powerful tools for spatial epidemiological analysis of vector-borne diseases like dengue (Hay *et al.,* 2013). These tools allow for the integration and analysis of multiple environmental factors that are known to influence dengue transmission. For instance, the normalized difference vegetation index (NDVI) and the normalized difference water index (NDWI) derived from satellite imagery have been used to assess vegetation cover and surface water, respectively, which are linked to mosquito breeding habitats (Machault *et al.,* 2014). Mean temperature (TEMP) and precipitation (PREC) data, obtainable from climate databases, directly affect mosquito survival, development, and virus replication rates (Butterworth *et al.,* 2017). Nighttime light intensity (NTL), often used as a proxy for urbanization and human activity, can provide insights into the human-vector interface in dengue transmission (Elvidge *et al.,* 1997). Altitude (ALT), which influences temperature and mosquito habitat suitability, is another crucial factor in dengue epidemiology (Dhimal *et al.,* 2015). The integration of these diverse environmental factors through GIS allows for comprehensive spatial analysis, helping to identify high-risk areas and potential environmental drivers of dengue transmission (Khormi & Kumar, 2012).

In Lao PDR, where resources for dengue control are limited, understanding the spatial association between these environmental factors and DSS is critical for targeted intervention strategies. Previous studies have highlighted the importance of spatial analysis in identifying high-risk areas and potential environmental drivers of dengue transmission (Lowe *et al.,* 2018). However, research specifically focusing on the spatial patterns of DSS in Lao PDR remains scarce. DSS represents the most severe and life-threatening form of dengue infection, with a mortality rate significantly higher than milder forms, it warrants special attention in spatial analyses (Huy *et al.,* 2013). Moreover, the southern region has reported a significant number of cases and deaths, indicating a potentially higher disease burden. Therefore, understanding the spatial distribution of DSS cases can inform critical resource allocation decisions, such as the placement of intensive care units or the distribution of specialized medical supplies needed for DSS treatment.

Previous research has highlighted significant gaps in community knowledge, attitudes, and practices regarding dengue prevention in peri-urban areas of Lao PDR (Mayxay *et al.,* 2013). To address these gaps, we utilized advanced spatial analysis techniques with open-source GIS software to identify environmental and climatic predictors of dengue shock syndrome (DSS) and map high-risk areas throughout Lao PDR. The findings of this research will contribute to evidence-based decision-making for dengue prevention and control efforts in Lao PDR, potentially reducing the burden of this severe form of dengue infection.

2. Methodology

2.1 Study Location

The research was conducted in the southern region of Lao PDR, encompassing four main provinces: Champasak, Salavan, Sekong, and Attapeu. These provinces are located approximately between 13°55’ and 16°30’ North latitude, and 105°30’ and 107°30’ East longitude (Figure 1). This southern region covers a total area of approximately 47,200 square kilometers, representing about 20% of Laos’ total land area (Bureau Lao Statistics, 2018). This area account for 21% (1.5 million) of the country’s population and most are endemic for dengue with year-round transmission. Peak transmission occurs during the rainy season, from May to October (Zafar *et al.,* 2022).

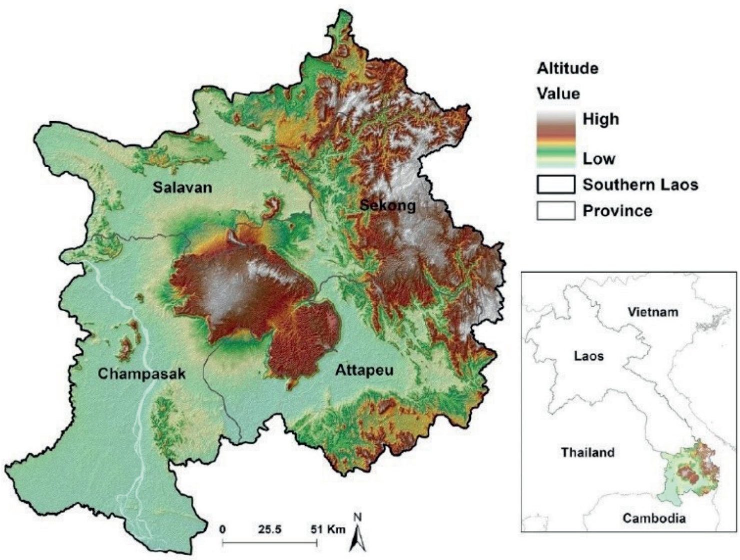

Figure 1. Map of Southern part of Lao PDR and neighboring countries

2.2 Population, Source of Information, and Study Variables

DSS data were obtained from case reports provided by the National Center for Laboratory and Epidemiology (NCLE) in Lao PDR. The data covers monthly dengue cases recorded in 27 districts across southern Lao PDR from January 2015 to December 2020. These cases are categorized according to the spectrum of dengue severity, ranging from dengue fever (DF) to more severe and potentially fatal conditions such as dengue hemorrhagic fever (DHF) and DSS. Since 1998, dengue has been classified as a nationally reportable disease in Lao PDR, under a reporting system where district hospital epidemiologists collect and submit aggregated data daily to the Department of Health. The Department of Health then compiles this information and sends it to the NCLE on a weekly basis (Khampapongpane *et al.,* 2014).

District population data from 2015 to 2020 were estimated by adjusting figures from the national and provincial population projections provided by the Lao Statistics Bureau, which are updated yearly (Ministry of Planning and Investment, 2015). The study obtained administrative boundaries corresponding to the district level in Lao PDR and neighboring countries from the DIVA-GIS website (www.diva-gis.org). The administrative boundary map included 27 district-level areas. The maps were created using ArcGIS Pro version 3.2 software (ESRI, Redlands, CA, USA).

The study analyzed environmental and climatic data for 27 districts from January 2015 to December 2020 focused on six key variables: altitude (ALT): elevation above sea level; normalized difference vegetation index (NDVI): a measure of vegetation density and health; normalized difference water index (NDWI): an indicator of surface water presence; precipitation (PREC): amount of rainfall; temperature (TEMP): average air temperature; nighttime light intensity (NTL): a proxy for urbanization and human activity.

Environmental and climatic data were obtained from various sources at monthly intervals. ALT data were sourced from the WorldClim database (https://www.worldclim.org/). For NDVI, monthly averages were processed using Google Earth Engine (GEE) from LANDSAT/LC08/C01/T1 and COPERNICUS/S2 datasets, with spatial resolutions of 30 and 10 meters, respectively. Monthly NDWI data were extracted from GEE's MODIS/MOD09GA_006_NDWI dataset, which has a resolution of 500 meters. PREC data were provided by the Center for Hydrometeorology and Remote Sensing. For monthly TEMP, GEE's ECMWF/ERA5_LAND/MONTHLY dataset was utilized, offering a resolution of 9 square kilometers. Monthly NTL data were derived from GEE's NOAA/VIIRS/DNB/MONTHLY_V1/VCMSLCFG dataset, with a 500-meter resolution.

2.3 Data Analysis

The average annual DSS incidence per 100,000 residents in each district in southern Lao PDR for the years 2015 to 2020 was calculated by dividing the average number of reported DSS cases over this period by the mean population of the respective districts.

2.3.1 Crude standardized morbidity ratios

To initiate descriptive analysis of DSS incidence, crude standardized morbidity ratios (SMR) were calculated for each district. The SMR was computed using the following approach:

$$Y_i = \frac{O_i}{E_i}$$

Within this framework, Y_i denotes the comprehensive SMR within i^{th} district. The collective count of documented DSS cases within the district is designated as O_i, whereas E_i represents the expected number of DSS cases in the i^{th} district. The expected number of cases was computed by multiplying the southern part DSS incidence rate by the mean population of each district during the study period.

This calculation allows for a standardized comparison of DSS incidence across districts, accounting for differences in population size and providing a relative measure of disease burden. The SMR values offer an initial insight into the spatial distribution of DSS cases, highlighting areas with higher or lower than expected incidence rates.

2.3.2 Spatial autocorrelation

To examine the geographical patterns of DSS incidence, spatial statistical techniques, specifically Global Moran's I and Local Indicators of Spatial Association (LISA) were employed. These analyses were conducted using GeoDa (version 1.14.0) software (Steiniger & Hunter, 2013).

Global Moran's I statistics were employed to assess spatial autocorrelation. The mathematical definition is:

$$I = \frac{N\sum_{ij} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{ij} W_{ij} \sum_i (x_i - \bar{x})^2}$$

In this equation, x_i represents the independent variable, N the number of spatial units (i and j), W_{ij} the spatial weight matrix, and $(x_i - \bar{x})$ and $(x_j - \bar{x})$ the deviations from the mean. This statistic indicates the correlation between x_i and its neighbors, as defined by the W_{ij} (Moran 1950).

However, Global Moran's I have limitations in pinpointing exact correlation locations. To address this, Local Moran's I, developed by Anselin (1995), was utilized as part of local indicators of spatial association (LISA) (Anselin 1995). The formula for Local Moran's I is:

$$I_i = \frac{(x_i - \bar{x})\sum_j W_{ij}(x_j - \bar{x})}{S_i^2}$$

Here, I_i is the Local Moran's index, W_{ij} the spatial weight matrix, and

$S_i^2 = \frac{\sum_j (x_j - \bar{x})^2}{(N-1)}$ is the number of spatial units.

LISA was applied to identify local spatial autocorrelation patterns, producing significance maps ($p < 0.05$) and cluster maps categorizing locations by association type. The choice of spatial-weight matrix is crucial; a distance-based matrix calculated was used by GeoDA software, ensuring non-zero spatial weights nationwide (Getis &Aldstadt, 2004). The resulting cluster maps revealed areas of high DSS incidence surrounded by similar high-incidence areas (High-High or HH clusters, also known as hot spots) and areas of low incidence surrounded by other low-incidence areas (Low-Low or LL clusters, or cold spots). Additionally, outliers were identified: high-incidence areas surrounded by low-incidence ones (HL) and vice versa (LH). Moran's I represents autocorrelation, with HH and LL indicating positive outcomes, while HL and LH represent negative outcomes.

2.3.3 Spatial econometric models

After confirming the presence of spatial autocorrelation, regression models were developed to assess the relationship between various factors and DSS incidence. Initially, Ordinary Least Squares (OLS) regression was employed as a traditional method to compare and validate the spatial models. The OLS equation is as follows:

$$Y_i = \beta_0 + \beta X_i + \varepsilon i$$

where Y represents the dependent variable, β_0 is the y-intercept, β is the coefficient of the independent variable, X is the independent variable, and ε is the error term (Wooldridge *et al.,* 2016).

Following this, the spatial lag model (SLM) and the spatial error model (SEM) were used to address spatial autocorrelation. The SLM incorporates a spatially lagged dependent variable into the equation, represented as follows:

$$Y_i = \beta_0 + \beta X_i + \rho W_{ij} Y_j + \varepsilon i$$

where W is the spatial weight and ρ is the spatial lag coefficient (Anselin, 1998). The SEM, on the other hand, integrates spatial autocorrelation within the error term:

$$Y_i = \beta_0 + \beta X_i + ui; ui = \lambda W_{ij} uj + \varepsilon i$$

In the analysis, λ denotes the spatial error coefficient, while other terms maintain their definitions from previous models. Distance-based weights were employed as spatial weights in the spatial regression model (Pacheco & Tyrrell, 2002). To evaluate the spatial autocorrelation of DSS incidence, Local Moran's I was utilized. When significant spatial dependence was detected, SLM and SEM were applied instead of OLS (Anselin, 1998).

To determine the most suitable model between SLM and SEM, the robust Lagrange Multiplier (LM) test statistic was used (Ullah & Zinde-Walsh, 1984; Anselin, 2001). In instances where both models exhibited statistically significant LM values, the model with the lower value was selected. For final model selection, the Akaike Information Criterion (AIC) was used. The model with the lowest AIC value was considered the best fit (Akaike, 1981). This methodological approach allowed to account for spatial dependencies in data and select the most appropriate model for analyzing the spatial patterns of DSS incidence.

3. Results and Discussion

3.1 Descriptive analysis

During the period from January 2015 to December 2020, a total of 588 DSS cases were reported to the NCLE in the Southern part of Lao PDR. The incidence rate of DSS was calculated at 6.87 per 100,000 inhabitants. The median ALT in Southern Lao PDR was 299.14 meters above sea level (masl), with an interquartile range (IQR) of 204.00 to 650.00 masl. The ALT ranged from a minimum of 136.00 to a maximum of 1158.38 masl. The NDVI showed a median value of 0.35 units (IQR: 0.30 - 0.37), with values spanning from 0.25 to 0.40 units. The NDWI had a median of -0.01 units (IQR: -0.02 - 0.02), ranging from -0.03 to 0.03 units. PREC, measured in millimeters (mm), displayed a median of 147.74 mm (IQR: 141.61 - 154.27 mm), with a minimum of 122.60 mm and a maximum of 174.58 mm. TEMP, measured in degrees Celsius (°C), had a median of 25.10 °C (IQR: 23.36 - 26.00 °C), ranging from 20.43 °C to 27.00 °C. NTL intensity showed a median value of 0.15 units (IQR: 0.13 - 0.18), with a wide range from 0.11 to 1.90 units (Table 1).

3.2 Spatial Distribution

The distribution of DSS incidence exhibited variation among districts, with incidence rates ranging from zero to 19.42 per 100,000 population throughout the study period. This pattern shows a clear concentration of high DSS incidence in the western districts, particularly in Champasak Province consists of Sanasomboon, Pakse, Phonthong, Champasak and Sukhuma districts as the top 5 districts with the highest DSS incidence with a gradual decrease towards the east and north. The easternmost districts show very low incidence or no reported cases (Figure 2). Significant spatial variation in SMR for DSS was observed during the study, with notably higher values exceeding 2.01 concentrated in districts such as Phonthong, Pakse, and Sanasomboun (Figure 3).

3.3 Univariate spatial correlation

The Global Moran's I statistic of 0.675, as shown in (Figure 4a), indicates a strong positive spatial autocorrelation in DSS incidence across the region, suggesting that districts with similar DSS rates tend

Table 1. Distribution of monthly means of climate and environmental variables, Southern Lao PDR, 2015–2020

Variables	Median (IQR)	Min–Max
ALT (masl)	299.14 (204.00 – 650.00)	136.00 – 1158.38
NDVI (Unit)	0.35 (0.30 – 0.37)	0.25 – 0.40
NDWI (Unit)	-0.01 (-0.02 – 0.02)	-0.03 – 0.03
PREC (mm)	147.74 (141.61 – 154.27)	122.60 – 174.58
TEMP (°C)	25.10 (23.36 – 26.00)	20.43 – 27.00
NTL (nW/cm²/sr)	0.15 (0.13 – 0.18)	0.11 – 1.90

ALT altitude, *NDVI* normalized difference vegetation index, NDWI normalized difference water index, *PREC* precipitation, *TEMP* mean temperature, NTL nighttime lights, IQR interquartile range, *masl* meters above sea level, *mm* millimeter.

to be clustered together geographically. The LISA map (Figure 4b) reveals specific spatial patterns, including a significant High-High cluster of high DSS incidence identified in the southwestern part of the region, corresponding to districts in Champasak Province such as Sanasomboon, Bachiangchaleunsouk, Pakse, Phonthong, and Champasack. These districts show significantly higher DSS rates compared to the regional average and are surrounded by other districts with high rates. Conversely, a Low-Low cluster of low DSS incidence is observed in the northern region, likely corresponding to districts in Salavan Province, including Ta Oi and Saravane district. The southwestern cluster shows the highest significance ($p = 0.01$ and $p = 0.001$), while the northern cluster has a weaker but significant clustering ($p = 0.05$) (Figure 4c). This indicates a clear spatial pattern, with a hot spot in southwestern Champasak and a cold spot in northern Salavan.

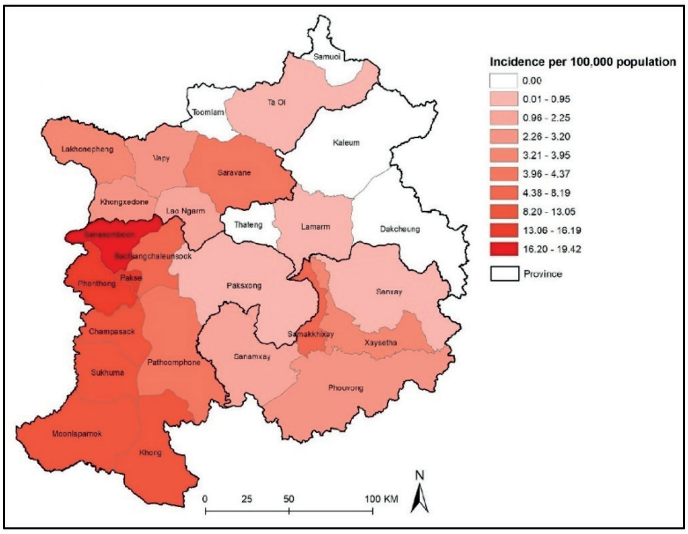

Figure 2. Dengue shock syndrome incidence by districts, Southern part of Lao PDR, year 2015 – 2020

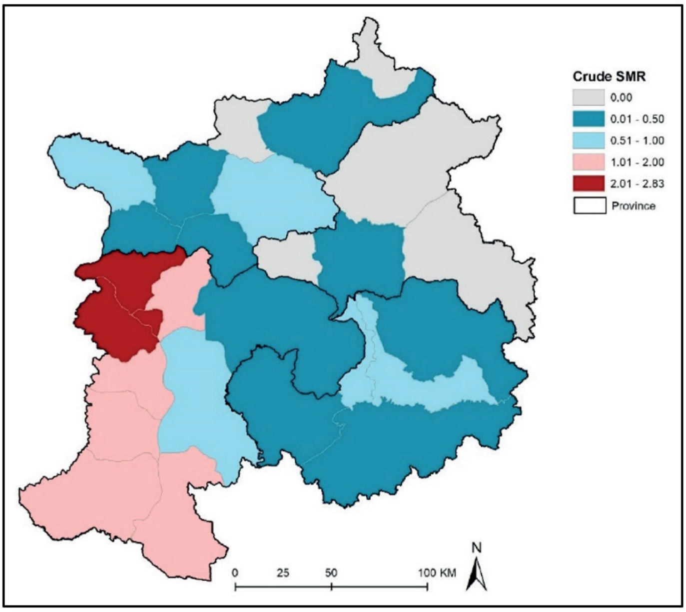

Figure 3. Crude standardized morbidity ratios (SMR) of dengue shock syndrome incidence by districts, Southern part of Lao PDR, year 2015 – 2020

3.4 Bivariate spatial relationships

As portrayed in Figure 5 for each factor, a bivariate analysis using Moran's I and LISA was employed to illuminate the spatial interplay between various influential factors and DSS incidence across southern Laos districts.

3.4.1 Moran's I Analysis

Factors such as TEMP (0.594) and NTL (0.218) exhibited positive spatial autocorrelation with DSS incidence. This suggests a concerning trend wherein regions with higher TEMP and increased urbanization face elevated DSS rates. In contrast, factors like ALT (-0.533), NDWI (-0.436), NDVI (-0.349), and PREC (-0.182) demonstrated negative spatial autocorrelation, suggesting these factors might be protective against high DSS incidence (Table 2). The strong correlation with TEMP implies its substantial influence on DSS risk, while the weaker correlation with PREC suggests its effect might be indirect or mediated by other factors in the Laotian context.

3.4.2 LISA Analysis

On a granular level, regional specificities were unearthed by LISA. Predominantly, the southwestern Lao PDR, particularly districts within Champasak Province such as Sanasomboon, Bachiangchaleunsouk, Pakse, Phonthong, and Champasak, exhibited a concerning synergy of high TEMP, low ALT, and increased urbanization with elevated DSS incidence. Conversely, the upper part of Southern regions, including districts like Ta Oi and parts of Saravane in Salavan Province, demonstrated a different pattern, with higher ALT, lower TEMP, and less urbanization, which were associated with decreased DSS rates (Figure 5).

Vegetation cover (NDVI) and water presence (NDWI) exhibited complex patterns. Some low-high clusters were observed in southwestern districts, indicating areas where low vegetation or water presence coincided with high DSS incidence, contrary to the overall negative correlation. It is suggested by this observation that the influence of these environmental variables on DSS risk may be

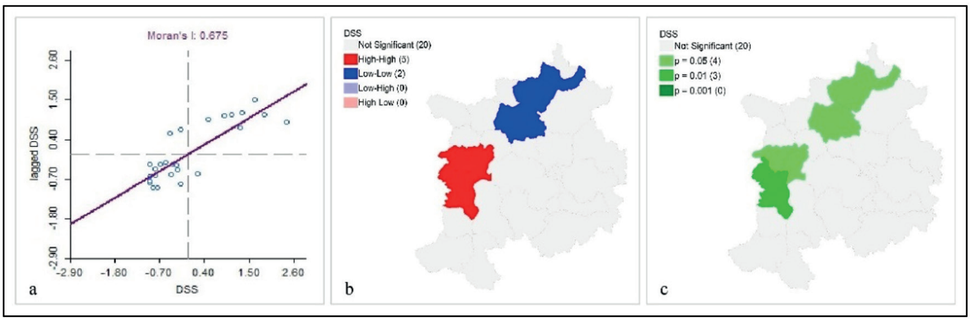

Figure 4. Univariate spatial correlation of dengue shock syndrome (DSS) incidence, (a) Global Moran's I scatter plot (b) DSS incidence clusters (c) LISA p-value

Table 2. Bivariate Moran's I statistics of dengue shock syndrome incidence and satellite-based environmental factors (2015 – 2020)

Dengue Shock Syndrome incidence (2015 – 2020)	Moran's *I* coefficient of variables					
	ALT	NDVI	NDWI	PREC	TEMP	NTL
	-0.533	-0.349	-0.436	-0.182	0.594	0.218

ALT altitude, *NDVI* normalized difference vegetation index, NDWI normalized difference water index, *PREC* precipitation, *TEMP* mean temperature, NTL nighttime lights modulated by local factors in districts like Lakhonepheng, Khongxedone, and parts of Paksong (Figure 5). The southwestern region, particularly Champasak Province, was identified as a high-risk area, characterized by a combination of environmental factors conducive to DSS transmission. In contrast, the northern areas in Salavan Province were found to be relatively protected.

3.5 Spatial Regression Models

Three models OLS, SLM, and SEM were employed in the spatial regression analysis to assess the influence of environmental and climatic factors on DSS incidence in southern Lao PDR. Among the three models, the SLM demonstrated the best fit, as indicated by the lowest AIC and Bayesian Information Criterion (BIC). This finding suggests that consideration of spatial dependencies in DSS incidence enhances the understanding of the disease's distribution (Table 3).

Across all models, two factors consistently emerged as significant predictors of DSS incidence: NDVI and TEMP. The negative coefficients for NDVI (OLS: -68.95, $p < 0.01$; SLM: -43.09, $p < 0.05$; SEM: -62.34, $p < 0.01$) suggested that areas with higher vegetation cover were associated with lower DSS incidence. This relationship remained significant even when spatial effects were considered. The positive coefficients for TEMP (OLS: 5.54, $p < 0.01$; SLM: 3.36, $p < 0.05$; SEM: 5.28, $p < 0.001$) indicated that higher TEMP was associated with increased DSS incidence. This relationship was particularly strong in the SEM model (Table 3).

ALT showed a slight positive association with DSS incidence, reaching statistical significance in the SEM model (0.02, $p < 0.05$). PREC consistently showed a negative association across all models, though not reaching statistical significance. This suggests a trend where higher rainfall might be associated with lower DSS incidence. The NDWI and NTL showed inconsistent and non-significant associations across models, indicating their effects on DSS incidence may be less direct or influenced by other factors. The significant spatial autoregressive parameter (ρ) in the SLM (0.38, $p < 0.01$) indicates strong spatial dependencies in DSS incidence. This suggests that DSS rates in one district are influenced by rates in neighboring districts, emphasizing the importance of considering spatial relationships in understanding DSS distribution (Table 3).

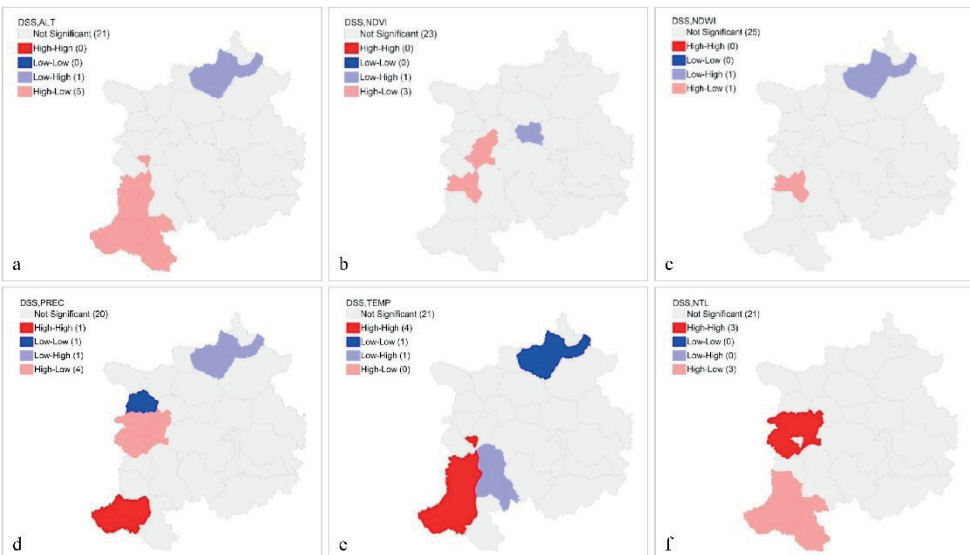

Figure 5. Cluster maps of LISA: Localized associations between influencing factors and dengue shock syndrome (DSS) incidence as (a) altitude, (b) normalized difference vegetation index, (c) normalized difference water index, (d) precipitation, (e) temperature, (f) nighttime lights

Table 3. Spatial regression model that has an impact on dengue shock syndrome incidence

Factors	OLS Coefficient (SE)	Spatial regression analysis	
		SLM Coefficient (SE)	SEM Coefficient (SE)
ALT (masl)	0.02 (0.01)	0.01 (0.01)	0.02 (0.01)*
NDVI (Unit)	-68.95 (24.04)**	-43.09 (19.62)*	-62.34 (21.23)**
NDWI (Unit)	75.29 (81.24)	6.90 (64.32)	55.54 (70.46)
PREC (mm)	-0.13 (0.07)	-0.08 (0.06)	-0.12 (0.06)
TEMP (°C)	5.54 (1.69)**	3.36 (1.50)*	5.28 (1.50)***
NTL (nW/cm²/sr)	-0.19 (2.67)	0.93 (2.10)	0.02 (2.23)
Constant	-98.27 (44.38)*	-59.46 (37.01)	-94.86 (40.00)*
ρ		0.38 (0.15)**	
λ			0.12 (0.20)
F-statistic	9.91		
R-Squared	0.75	0.79	0.75
Log Likelihood	-66.66	-64.80	-66.6
AIC	147.33	145.60	147.2
BIC	156.40	155.96	156.27

* Significance at p-value < 0.05; ** Significance at p-value < 0.01; *** Significance at p-value < 0.001; OLS: Ordinary Least Squares method; SLM: Spatial Lag Model; SEM: Spatial Error Model; SE: Standard Error measure; Constant: Model intercept when predictors = 0; ρ: Rho, spatial autoregressive parameter; λ: Lambda, spatial error coefficient; F-statistic: Variance comparison ratio; R-Squared: Variance proportion explained by predictors; AIC: Akaike's model fit criterion; lower is better; BIC: Bayesian model fit criterion; prefers fewer parameters.

3.6 Discussion

Significant spatial patterns and environmental determinants of DSS incidence in southern Laos were revealed in this study. The strong positive spatial autocorrelation indicates that DSS cases are not randomly distributed but tend to cluster geographically. This finding aligns with previous studies that have demonstrated spatial clustering of dengue cases in various endemic regions (Phanitchat *et al.,* 2019; Xu *et al.,* 2019; Zheng *et al.,* 2019; Soukavong *et al.,* 2024) .

The identification of a high-risk cluster in southwestern Lao PDR, particularly in Champasak Province, provides valuable information for targeted intervention strategies. This hotspot is characterized by higher temperatures, lower altitudes, and increased urbanization, factors that have been associated with elevated DSS risk in other studies (Choi *et al.,* 2016; Li *et al.,* 2019). Champasak, one of the most populated provinces in Lao PDR, has undergone extensive development, including agricultural intensification and dam construction, leading to population resettlement (Doum *et al.,* 2020). High-density built-up areas and elevated development levels correlate with increased dengue vulnerability (Tsheten *et al.,* 2020). Population density is a crucial factor in dengue transmission rates. Changes in circulating dengue virus serotypes may have increased secondary infections, a risk factor for severe cases like DSS (Kanakaratne *et al.,* 2009; World Health Organization, 2009; Rathore *et al.,* 2020; Yuan *et al.,* 2022). Additionally, Champasak's borders with Cambodia and Thailand facilitate potential cross-border transmission of dengue through increased human movement associated with travel and trade activities (Srithongtham *et al.,* 2024) .

High NDVI values typically indicate sparsely populated areas where the conditions for human-mosquito contact, necessary for DSS transmission, are less likely to occur. Conversely, higher DSS incidence is often observed in urban and peri-urban areas with greater population density (Araujo *et al.,* 2015). These areas tend to have lower NDVI values due to urbanization, changes in land use, and the replacement of natural vegetation with built environments. Such urbanized environments are conducive to the proliferation of Aedes mosquitoes, the primary vectors of the dengue virus (Tsheten *et al.,* 2020).

Temperature emerged as a crucial factor positively associated with DSS incidence. This relationship underscores the potential impact of climate change on future dengue transmission patterns. Higher temperatures can accelerate mosquito development, increase biting rates, and shorten the extrinsic incubation period of the virus, all of which contribute to increased transmission risk (Choi *et al.,* 2016; Li *et al.,* 2019; Li *et al.,* 2020). The identification of a high-risk cluster in southwestern Laos, particularly in Champasak Province, characterized by higher temperatures, provides valuable information for targeted intervention strategies and climate change adaptation planning.

The significance of spatial dependencies, as indicated by the spatial autoregressive parameter in the SLM emphasizes the importance of considering neighborhood effects in dengue risk assessment and control strategies (Hussain-Alkhateeb *et al.,* 2021). This spatial dimension is often overlooked in traditional epidemiological studies but is crucial for understanding disease dynamics at a regional level.

A key strength of this study is its comprehensive spatial analysis approach, combining global and local spatial statistics with spatial regression models. This multi-faceted methodology provides a robust framework for understanding the complex interplay between environmental factors and DSS incidence. However, the study has several limitations. First, the ecological nature of the analysis means that inferences cannot be drawn at the individual level. Second, the use of aggregated data at the district level may mask finer-scale variations in DSS incidence and environmental factors. Third, the study does not account for socio-economic factors or healthcare access, which could influence both DSS incidence and reporting. Future research should aim to incorporate finer-scale data, including entomological indices and human mobility patterns, to further elucidate the drivers of DSS transmission in southern Laos. Additionally, longitudinal studies are needed to assess the temporal dynamics of these spatial patterns and their implications for long-term dengue control strategies. Moreover, this study did not consider the potential influence of dengue vaccination programs, which may confound the relationship between environmental determinants and the incidence of DSS.

4. Conclusion

In conclusion, this study provides valuable insights into the spatial patterns and environmental determinants of DSS in southern Laos. The findings highlight the complex interplay between climatic factors, vegetation cover and urbanization in shaping DSS risk. Temperature was positively associated with DSS incidence, underscoring the potential impact of climate change on future dengue transmission patterns. Areas with lower NDVI value, typically urban environments, showed higher DSS incidence emphasizing the role of urbanization in dengue risk. Significant spatial clustering of DSS cases was observed, with high-risk areas concentrated in southwestern part of the region. These insights can inform targeted interventions, urban planning strategies, and climate change adaptation measures to mitigate the burden of dengue in the region.

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Ethics declarations

This study was approved by Khon Kaen University Ethics Committee for Human Research, Thailand (HE662296) and University of Health Sciences Research Ethics Committee, Lao PDR (643/REC).

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