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Spatial association between socio-economic health service factors and sepsis mortality in Thailand

Juree Sansuk, Wongsa Laohasiriwong, Kittipong Sornlorm

Faculty of Public Health, Khon Kaen University, Khon Kaen, Thailand

Abstract

Sepsis is a significant global health issue causing organ failure and high mortality. The number of sepsis cases has recently increased in Thailand making it crucial to comprehend the factors behind these infections. This study focuses on exploring the spatial autocorrelation between socio-economic factors and health service factors on the one hand and sepsis mortality on the other. We applied global Moran's *I*, local indicators of spatial association (LISA) and spatial regression to examine the relationship between these variables. Based on univariate Moran's *I* scatter plots, sepsis mortality in all 77 provinces in Thailand were shown to exhibit a positive spatial autocorrelation that reached a significant value (0.311). The hotspots/ high-high (HH) clusters of sepsis mortality were mostly located in the central region of the country, while the coldspots/low-low (LL) clusters were observed in the north-eastern region. Bivariate Moran's *I* indicated a spatial autocorrelation between various factors and sepsis mortality, while the LISA analysis revealed 7 HH clusters and 5 LL clusters associated with population density. Additionally, there were 6 HH and 4 LL clusters in areas with the lowest average temperature, 4 HH and 2 LL clusters in areas with the highest average temperature, 8 HH and 5 LL clusters associated with night-time light and 6 HH and 5 LL clusters associated with pharmacy density. The spatial regression models conducted in this study determined that the spatial error model (SEM) provided the best fit, while the parameter estimation results revealed that several factors, including population density, average lowest and highest temperature, night-time light and pharmacy density, were positively correlated with sepsis mortality. The coefficient of determination (R^2) indicated that the SEM model explained 56.4% of the variation in sepsis mortality. Furthermore, based on the Akaike Information Index (AIC), the SEM model slightly outperformed the spatial lag model (SLM) with an AIC value of 518.1 compared to 520.

Correspondence: Kittipong Sornlorm, Faculty of Public Health, Khon Kaen University, Khon Kaen, Thailand.
Tel.: +6643424820 - Fax: +6643424821
E-mail: kittsorn@kku.ac.th

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Introduction

Sepsis is a severe infection that can cause systemic inflammation and organ dysfunction leading to complications, such as low blood pressure, respiratory failure and renal failure due to malfunctions of the heart, lungs or the kidneys, respectively (Singer *et al.*, 2016). It is a major contributor to global mortality rates; elderly are especially vulnerable to sepsis due to reduced immunity and increased risk of infection as well as age-related deterioration of organ systems (Palacios-Pedrero *et al.*, 2021). In 2018, the worldwide incidence of sepsis had increased to approximately 30 million people per year, with a death rate of 1 of 6 patients (Rudd *et al.*, 2020). The incidence rate is 77 cases per 100,000 population in Australia and New Zealand and 240 cases per 100,000 population in the United States (Lagu *et al.*, 2012), while the mortality rate from septic shock can be vary between 30.8 and 62.5% (Makic & Bridges, 2018).

In Thailand, roughly 63% of cases involving sepsis were attributed to infections contracted during hospital stays. The factors independently associated with 28-day mortality in sepsis included the receipt of an immunosuppressive agent (Tancharoen *et al.*, 2022). According to the Ministry of Public Health (MoPH), the mortality rate from septic shock in those infected during 2018, 2019 and 2020 was 34.8%, 32.4% and 32.5%, respectively (MoPH, 2021). The cause of bloodstream infections of this kind is most common among people with respiratory tract infections, followed by those with urinary and gastrointestinal tract infections (Revelas, 2012). Connection with various harmful variables has been shown to contribute to this situation, e.g., respiratory diseases due to farmland exposure to harmful chemicals and poor ventilation in urban areas (Shah *et al.*, 2019). In addition, urban areas that are densely populated and have poor ventilation are more likely to cause this kind of health problems. (Yin *et al.*, 2021), notably related to cigarette smoke and other air pollution with particulate matter of 2.5 µm size ($PM_{2.5}$) (Honda *et al.*, 2022). These reported sepsis associations are only related to geographical areas, and there is still insufficient research in Thailand on the geo-epidemiological effect of socio-economic and public health service factors, particularly with respect to the mortality rate of sepsis. Among the tools available are night-time light (NTL) that can be used for analysing urbanization (Zheng *et al.*, 2023), while geographical information systems (GIS) data analysis can be used to study quantitative characteristics of the sepsis mortality rates in various geographical areas. This study aimed to apply such tools to investigate these relationships and provide useful information for the development of the public health service system.

Material and Methods

Study area

Thailand is a Southeast Asian country with a land area of 513,120 km^2 and a population of about 71.6 million people. It consists of 32 provinces with part of their border in contact with a neighbouring country, 22 without such borders and the 23 coastal provinces, including the island province of Phuket. Thailand shares borders with Myanmar and Laos in the North; Laos and Cambodia in the East; Malaysia in the South; and Myanmar together with the Andaman Sea in the West. The country's terrain comprises mountains, hills, plains and coastlines including 400 islands, most of which are located in the Andaman Sea. The area is divided into four regions: the Central, North, Northeast, and South and stretches generally from latitude 20°28'N to 5°36'S and longitude 105°38'E to 97°22'W. There a three climatic seasons: a rainy one from mid-May to mid-October followed by winter from to mid-February and then summer to mid-May.

Time of study

The analysis presented here was based on data in 2021 and carried out in 2021 and 2022.

Data source

The study utilized secondary data from the Health Data Centre (HDC) (http://healthkpi.moph.go.th/kpi2/kpi/index/?id=1608&kpi_year=2564) to analyse the incidence of sepsis per 100 population across all 77 provinces in the country. To identify sepsis cases, HDC employs the diagnosis codes R65.1 and R57.2, following the guideline of the International Statistical Classification of Diseases and Related Health Problems, 10th revision (ICD-10) (https://apps.who.int/iris/handle/10665/246208). In 2021, the mortality rate for sepsis patients in Thailand was 33.7% according to data from the HDC database. Furthermore, the trend from 2019-2020 indicated an increase in the mortality rate of sepsis patients in the population, rising from 32.4% to 32.5%. This increase exceeded the target value (26%) set by the MoPH (2021).

We investigated the potential influence on sepsis mortality by five variables: population density, pharmacy density, NTL and the lowest and the highest average temperatures. These variables were obtained from the National Statistical Office (http://statbbi.nso.go.th/staticreport/page/sector/th/01.aspx) except the NTL index that was derived from the visible infrared imaging radiometer suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership (SNPP) project of the U.S. National Oceanic and Atmospheric Administration (NOAA). The data were via the Google Earth Engine (http://earthengine.google.com).

QGIS (https://qgis.org) was used to aggregate exploratory spatial data. Identification of statistically significant information with regard to the spatial distribution of sepsis mortality, and its associations with other socio-economic factors, was carried out by autocorrelation and spatial regression analyses as described by Anselin & Le Gallo (2006) and Steiniger & Hunter (2013) using GeoDa, version 1.14.0 (https://geoda.software.informer.com/1.6/). The GeoDa program was used to analyse spatial autocorrelation and determine the spatial regression of socio-economic, health service factors and sepsis mortality in Thailand.

Distance served as a criterion for the weight matrix, and the spatial correlations were analysed. One of the most common approaches for calculating the degree of geographical correlation is Moran's *I* (Anselin, 2022; Griffith, 1983). The Moran scatter plot comprises the spatially lagged variable on the *x* and *y* coordinates of the original independent variables. Moran's *I* ranges between −1 and 1, where the latter indicates a highly positive spatial autocorrelation and the former an extremely negative one. Values around 0 indicate absence of spatial autocorrelation**.** This study was performed with 999 permutation simulations at the significance level of $p<0.05$.

Statistics

Autocorrelation

We used Global Moran's *I* statistics, which is mathematically defined as:

$$I = \frac{N \sum_{ij} W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{ij} W_{ij} \sum_i (x_i - \bar{x})^2} \quad \text{(Eq. 1)}$$

where x_i is the independent variable; *N* the number of spatial units represented by *i* and *j*; W_{ij} the spatial weight matrix; $(x_i - \bar{x})$ the deviation of x_i from its mean; and $(x_j - \bar{x})$ the deviation of x_j from its mean.

The value computed using this equation indicates the correlation between x_i and its neighbours, which is geographically specified by the spatial weight matrix (W_{ij}). The limitation of Global Moran's *I* statistic is that it cannot identify the exact location of the correlation. Accordingly, Anselin (1995) developed a Local Moran's *I* which extends the mathematical fundamentals of Moran's *I* under the name of local indicators of spatial association (LISA). Its mathematical equation is as follows:

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

where I_i is 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.

We used LISA to determine the local spatial autocorrelation patterns of the variables depicting locations with outcomes at the p<0.05 level of significance (called LISA significance maps) and classified these locations according to association type (called LISA cluster maps). The selection of the spatial-weight matrix is one of the key factors contributing to the outcome of LISA computation; thus, its specification was carefully formulated in the present study for all provinces. Since the spatial weight matrix using the adjacent boundaries as criterion did not apply nationwide, we used a distance-based spatial weight matrix that was automatically calculated by GeoDA software. Mathematically speaking, this value is the minimum distance ensuring a non-zero spatial weight matrix. Cluster maps were produced to show the presence and localization of areas with particularly high or low presence of sepsis mortality. Briefly, areas with high levels of sepsis mortality surrounded by other areas with high levels are called High-High (HH) clusters or hotspots, while areas with low such levels surrounded by other areas with low levels are called Low-Low (LL) clusters or cold spots. In addition, there are outliers, *i.e.* high level areas surrounded by low level ones (HL) or low level areas surrounded by high level ones (LH). Moran's *I* is a presentation of autocorrelation, where both HH and LL are positive outcomes, while HL and LH are negative.

Regression analysis

Spatial regression models were used to analyse the associations among socio-demographic factors and sepsis mortality. The three main specifications of spatial regression models were i) the traditional ordinary least squares (OLS) approach; ii) the spatial lag model (SLM); and iii) the spatial error model (SEM). The limitation with OLS regression is due to the fact that it assumes that the autocorrelation between dependent and explanatory variables is uniform in space, which is often viewed as an outright violation of the principle of independence of observations in classical regression. SLM and SEM, on the other hand, capture the spatial dependence in regression analysis where, in the former, the dependent variable relates to the dependent variable in the neighbouring space, whereas spatial influence arises only through error terms in the latter (Viton, 2010). Here, we used the maximum likelihood function to estimate the spatial regression models (Elhorst, 2010). The following equation represents the mathematical form of SLM.

$$Yi = \beta 0 + \beta Xi + \rho WijYj + \varepsilon i \qquad \text{(Eq. 3)}$$

where Y is the dependent variable; X the independent variable; β the coefficient of the independent variable; W the spatial weight; and ρ the spatial lag coefficient.

Alternatively, the spatial influence can be propagated through disturbance caused. The next equation denotes the mathematical specification of SEM.

$$Y_i = \beta_0 + \beta_{Xi} + ui; ui = \lambda Wijuj + \varepsilon i \qquad \text{(Eq. 4)}$$

where λ is the spatial error coefficient and other terms are the same as above. In the spatial regression model, distance-based weights were selected as spatial weights. (Pacheco & Tyrrell, 2002). The spatial autocorrelation of Sepsis mortality was detected by Local Moran's *I*. When a significant spatial dependence was identified, SLM and SEM were performed but not OLS. The (robust) Lagrange multiplier (LM) test statistic (Ullah & Zinde-Walsh, 1984) was used for determining which of the two models (*i.e.* SLM or SEM) would be suitable (Anselin, 2001). Insinuations where both models had statistically significant LM values, the model with the lower value would be selected. The Akaike information criterion (AIC) was used to find the model with of the best fit, *i.e.* the lowest AIC value (Akaike, 1981).

Results

Global spatial patterns

Moran's *I* indicated a significant statistical association patterns between population density and sepsis mortality ($p<0.05$). There was a spatial correlation between the distribution pattern of population density in the same direction as the sepsis mortality pattern. The average mortality rate from sepsis in Thailand was 33.7%, with variations observed among different provinces. Nonthaburi Province had the highest mortality rate at 64.3%, while Mae Hong Son Province had the lowest at 14.3% (Figure 1). There were HH clusters in Nonthaburi, Bangkok, Nakhon Pathom, Pathum Thani, Samut Sakhon, Ratchaburi Samut, Songkhram Nakhon and Samut Prakan, with significant low-rate clusters at the $p=0.05$ level were noted in some provinces in the north-eastern region. The univariate Moran's *I* scatter for sepsis mortality in 2021 showed a slight positive spatial autocorrelation, with a Moran's *I* value of 0.311 for Thailand as a whole, while it varied with respect to the different variables investigated as shown in Table 1. Figure 2 depict the provincial distribution of the cluster tendency.

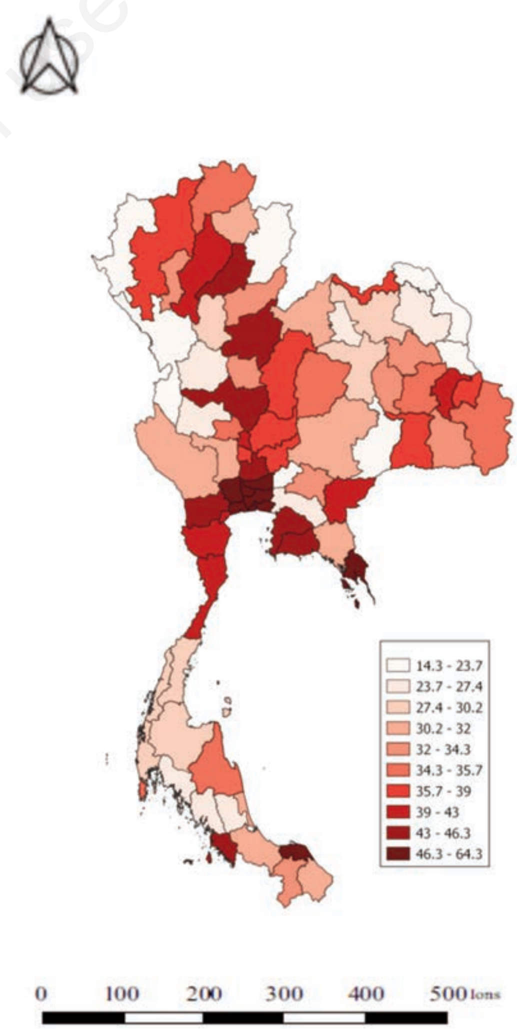

Figure 1. Distribution of sepsis mortality in Thailand 2021.

Analysis by local indicators of spatial association (LISA)

The GeoDa program was used for the analysis of spatial autocorrelation of the set of variables under study in relation to sepsis mortality in Thailand. The results are shown in Tables 2-7 and Figures 3-7. We noted a significant correlation between population density, NTL, density of pharmacies and the lowest/highest average temperatures on the one hand and sepsis mortality on the other.

Correlation with population density

LISA indicated areas with a population density and high prevalence of sepsis mortality with high values in the surrounding seven provinces (hotspots/HH clusters) in Samut Songkhram, Samut Sakhon, Bangkok Nonthaburi, Nakhon, Pathom, Pathum Thani and Ayutthaya. In contrast, coldspots/LL clusters clusters appeared in Nong Khai, Sakon Nakhon, Nakhon Phanom, Kalasin and Nakhon Si Thammarat provinces. The results are shown in Table 2 and Figure 3.

Correlation with nighttime light (NTL)

LISA indicated areas with a NTL and high prevalence of sepsis mortality with high values in the surrounding 8 provinces. HH clusters were found in Ratchaburi Samut Songkhram Samut Sakhon Bangkok, Nonthaburi, Nakhon Pathom, Ayutthaya and Pathumthani In contrast, LISA analysis showed clusters of a province with a low of NTL and sepsis mortality with low values of the surrounding 5 provinces coldspot clusters or (LL clusters). In Nong Khai, Sakon Nakhon, Nakhon Phanom, Kalasin and Nakhon Si Thammarat provinces. The results are shown in in Table 3 and Figure 4.

Correlation with the density of pharmacies

LISA indicated areas with a density of pharmacies and high prevalence of sepsis mortality with high values in the surrounding 6 provinces hotspot clusters or in Samut Sakhon, Bangkok, Pathum Thani, Nonthaburi, Ayutthaya and Nakhon Pathom, while there was LL clusters in Nakhon Si Thammarat, Nong Khai, Nakhon Phanom, Kalasin and Sakon Nakhon provinces. The result are shown in Table 4 and Figure 5

Temperature correlations

LISA indicated areas with low average temperatures and high prevalence of sepsis mortality (HH clusters) in Samut Sakhon, Bangkok, Pathum Thani, Nonthaburi, Ratchaburi and Samut Songkhram, LL clusters in Nong Khai, Nakhon Phanom, Kalasin and Sakon Nakhon provinces. In contrast, with respect to high temperatures, LISA indicated HH clusters in Nakhon Pathom, Ayutthaya, Bangkok and Pathum Thani, while LL clusters appeared in Nakhon Si Thammarat and Sakon Nakhon province. The result as shown in Tables 5 and 6 and Figures 6 and 7.

Spatial regression analysis

The spatial modelling results are summarized in Table 7. The results of the OLS regression SLM and SEM model estimated population density, the average lowest and highest temperature, NTL, pharmacy density were likely to be associated with sepsis mortality. The OLS and SLM models explained approximately 56.3% of sepsis mortality (R^2=0.563). In addition, the last SEM showed that population density, the average lowest and highest temperatures, NTL, pharmacy density were significant predictors and explained approximately 56.4% of sepsis mortality (R^2 = 0.564) underlining that SEM was the best regression model in this case. The parameter estimation showed that the population density, the average lowest and highest temperature, NTL, pharmacy density were positively autocorrelated with the sepsis mortality. The R^2 indicated that SEM accounted for 56.3% of the variation in sepsis mortality. In the AIC test, SEM slightly outperformed the SLM with AIC 518.087 versus 520. This is a clear indication that SEM was preferable in explaining the geographical distribution of the sepsis mortality in Thailand.

Discussion

Our spatial analysis provides statistical quantification of the mortality rate of sepsis patients in Thailand, revealing that the highest mortality rates are concentrated in the central, western, and southern regions of the country. These findings have important implications for healthcare resource allocation and targeted interventions to reduce sepsis-related mortality.

In terms of socioeconomic factors affecting bloodstream infection, it is worth noting that the incidence of infection and mortality varies greatly from region to region. According to Rudd *et al.* (2020), countries with low or moderate socio-economic develop-

Table 1. Geographical distribution of sepsis mortality.

Local indicators of spatial association (LISA)			
High-high (HH)	High-low (HL)	Low-low (LL)	Low-high (LH)
Ratchaburi*	Nong Khai*	Sakon Nakhon**	None
Samut Songkhram*	Nakhon Si Thammarat*	NakhonPhanom**	
Nakhon Pathom***		Kalasin*	
Samut Sakhon**			
Ayutthaya**			
Nonthaburi**			
Pathum Thani*			
Bangkok***			
NakhonPhanom**			
Kalasin*			

*Correlation significant at the 0.05 level; **correlation significant at the 0.01 level; ***correlation significant at the 0.001 level.

ment, such as sub-Saharan Africa, Oceania, South Asia, East Asia, and Southeast Asia have the highest incidence of infection and mortality rates. These findings underscore the importance of targeted interventions to improve healthcare access and infrastructure in these regions and to address social determinants of health that contribute to sepsis outcomes (Rudd *et al*., 2020).

NTL) has emerged as a useful tool for forecasting economic growth, assessing industry and people's living conditions, and monitoring immigration changes in urban societies, reflecting the overall growth of the economy, and predicting the well-being of people. Currently, the average NTL intensity is being studied in various public works.

Light pollution, in various forms and through multiple pathways, can significantly impact the nature of host-pathogen interactions. The physiological effects of NTL can cause biorhythm disruption, leading to metabolic and immune dysfunction, as highlighted by Kernbach *et al.* (2018). As such, it is crucial to consider the potential impacts of NTL exposure on health out-

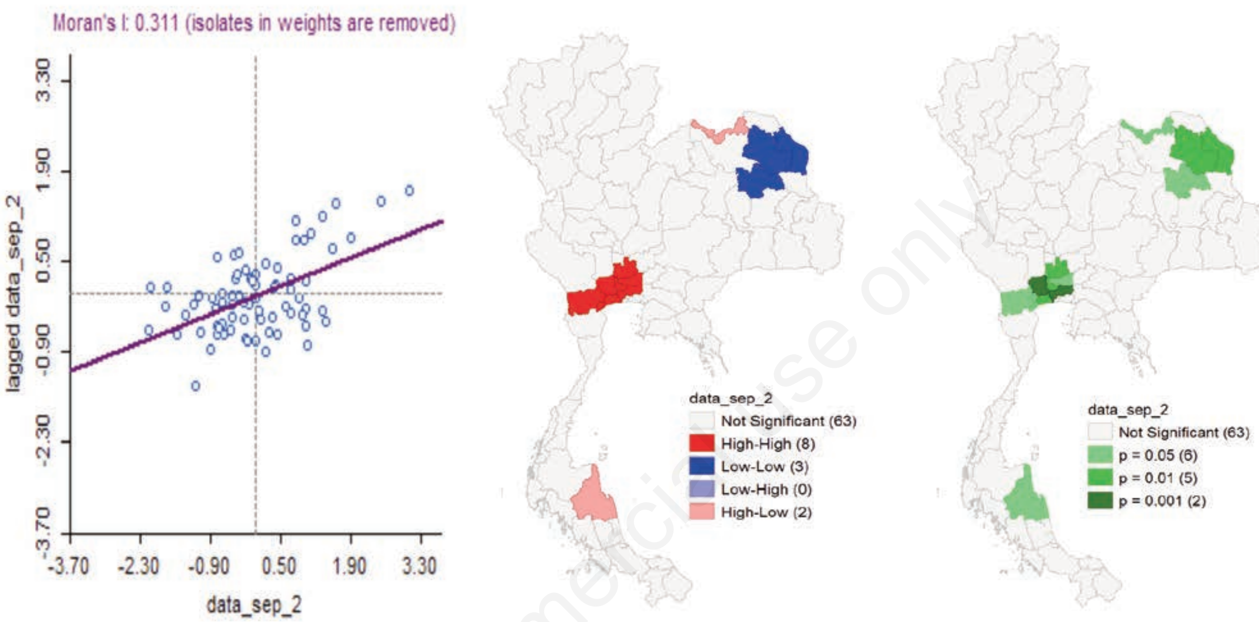

Figure 2. LISA and Moran's *I* scatter plot of sepsis mortality in Thailand 2021.

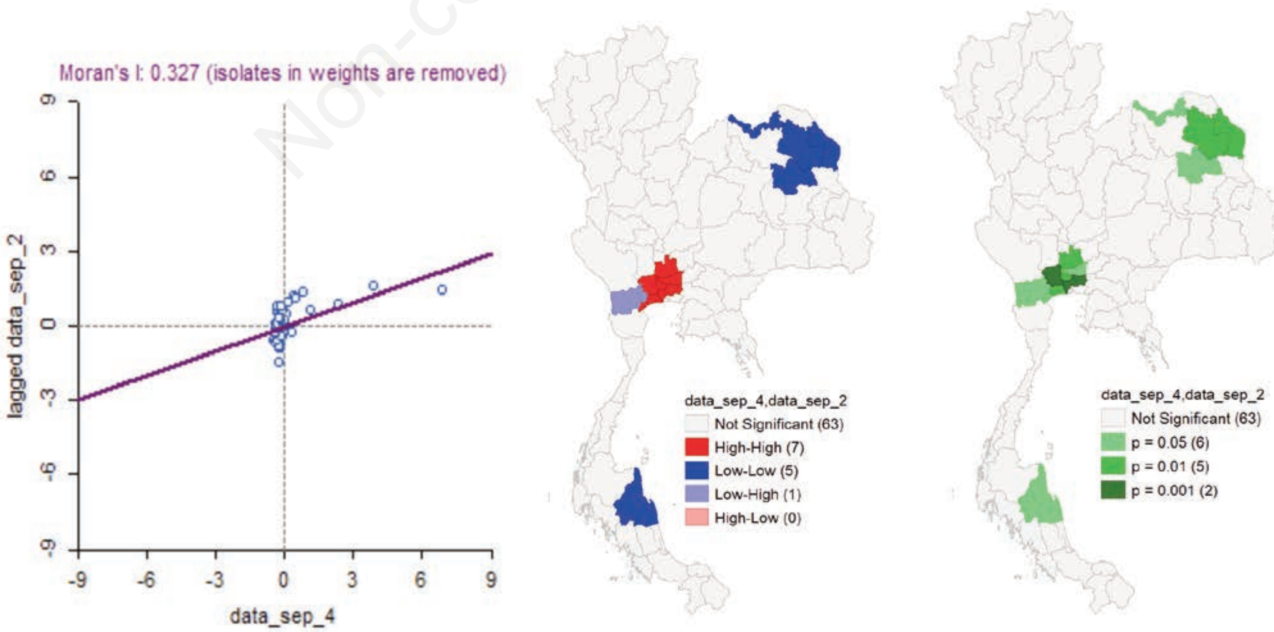

Figure 3. LISA and Moran's *I* scatter plot matrix of population density and sepsis Mortality.

comes and to develop strategies to mitigate any negative effects. Specifically, we found that counties with the highest NTL intensity (ranging from 1.78 to 59.61 nW/cm^2/sr) had a 15% higher COVID-19 mortality rate compared to counties with the lowest NTL intensity (ranging from 0.14 to 0.37 nW/cm^2/sr). These results are generally in line with those reported in the United States by (Zhang *et al.*, 2022), but our results deviate from their finding of NTL having a stronger correlation with the COVID-19 incidence rate than its mortality rate, since we did not find a significant association for this association.

Table 2. Geographical distribution of population density and sepsis mortality.

Local indicators of spatial association (LISA) High-high (HH)	High-low (HL)	Low-low (LL)	Low-high (LH)
Samut Songkhram*	None	Nong Khai*	Ratchaburi*
Samut Sakhon**		Sakon Nakhon**	
Bangkok***		Nakhon Phanom**	
Nonthaburi**		Kalasin*	
Nakhon Pathom***		Nakhon Si Thammarat*	
Pathum Thani*			
Ayuttha**			

*Correlation significant at the 0.05 level; **correlation significant at the 0.01 level; ***correlation significant at the 0.001 level.

Table 3. Geographical distribution of night-time light and sepsis mortality.

Local indicators of spatial association (LISA) High-high (HH)	High-low (HL)	Low-low (LL)	Low-high (LH)
Ratchaburi*	None	Nong Khai*	None
Samut Songkhram**		Sakon Nakhon**	
Samut Sakhon**		Nakhon Phanom**	
Bangkok***		Kalasin*	
Nonthaburi**		Nakhon Si Thammarat*	
Nakhon Pathom***			
Ayutthaya**			
Pathum Thani*			

*Correlation significant at the 0.05 level; **correlation significant at the 0.01 level; ***correlation significant at the 0.001 level.

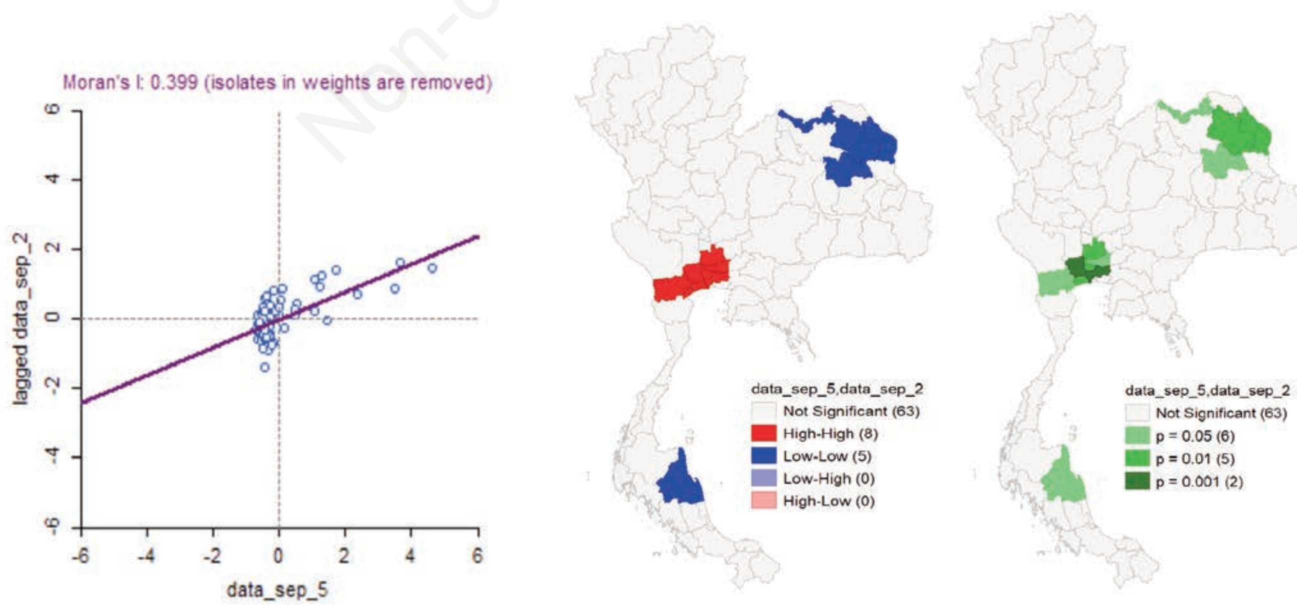

Figure 4. LISA and Moran's I scatter plot matrix of night-time light (NTL) and sepsis mortality.

Both the highest and the lowest temperatures correlated with mortality due to sepses at the 0.05 significance level. The role of temperature in this association is unclear, but it has been suggested that hypothermia as well as hyperthermia can be associated with increased amounts of lactic acid in the blood, which is an indicator of tissue hypoxia, a disorder that can lead to lactic acidosis, a serious and sometimes life-threatening condition (Murtuza *et al.*, 2015). Age, community-acquired sepsis, lower BMI and lower outside temperatures are known to be associated with hypothermia, while bacteraemia and higher serum procalcitonin correlate with

Table 4. Geographical distribution of density of pharmacies and sepsis mortality.

Local indicators of spatial association (LISA) High-high (HH)	High-low (HL)	Low-low (LL)	Low-high (LH)
Samut Sakhon**		Nakhon Si Thammarat*	Ratchaburi*
Bangkok***		Nong Khai*	Samut Songkhram*
Pathum Thani*		Nakhon Phanom**	
Nonthaburi**		Kalasin*	
Ayutthaya**		Sakon Nakhon**	
Nakhon Pathom***			

*Correlation significant at the 0.05 level; **correlation significant at the 0.01 level; ***correlation significant at the 0.001 level.

Table 5. Geographical distribution of lowest average temperature and sepsis mortality.

Local indicators of spatial association (LISA) High-high (HH)	High-low (HL)	Low-low (LL)	Low-high (LH)
Samut Sakhon**	Nakhon Si Thammarat*	Nong Khai*	Nakhon Pathom***
Bangkok***		Nakhon Phanom**	Ayutthaya**
Pathum Thani*		Kalasin*	
Nonthaburi**		Sakon Nakhon**	
Ratchaburi*			
Samut Songkhram*			

*Correlation significant at the 0.05 level; **correlation significant at the 0.01 level; ***correlation significant at the 0.001 level.

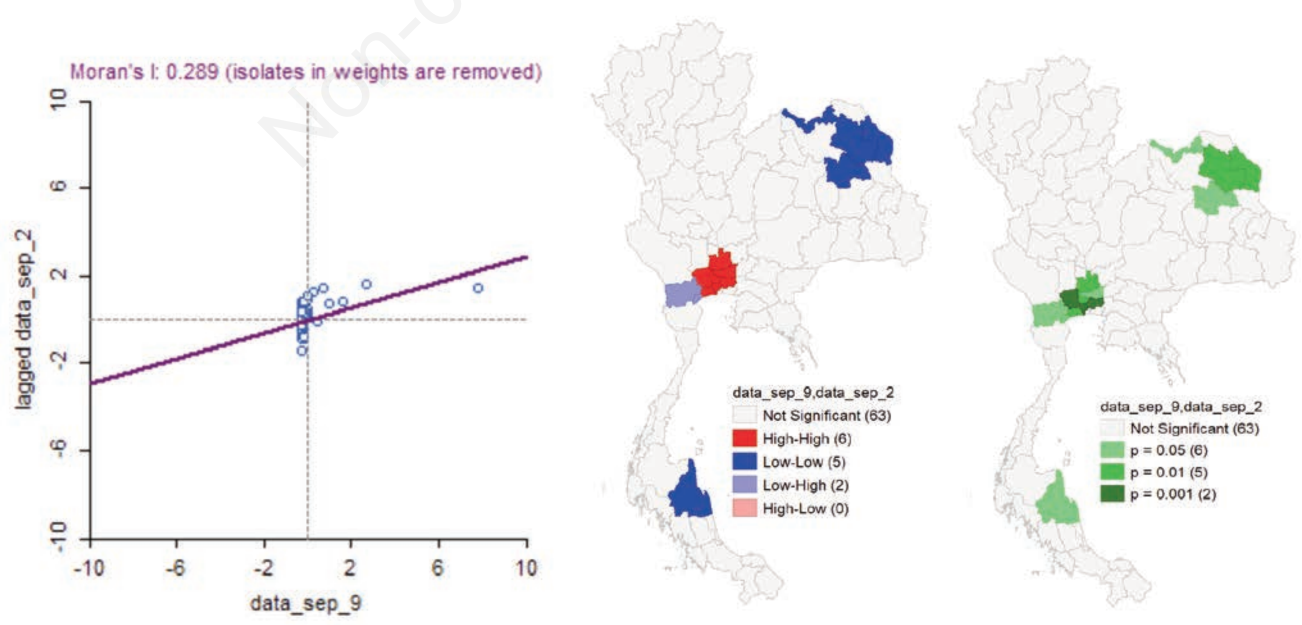

Figure 5. LISA and Moran's *I* scatter plot matrix of Density of pharmacies and sepsis mortality.

high fever (Thomas-Rüddel *et al.*, 2021). Respiratory infections are the most common cause of septicaemia, accounting for 54.2% of all cases (Martin, 2012). and it has been suggested that high-density populations in urbanization develop respiratory diseases due to exposure to airborne toxins. Indeed, respiratory tract infections have been shown to be significantly (p=0.011) associated with congestion and poor ventilation (Ratna & Mahalul, 2022). However, while urbanization and population density can contribute to respiratory health problems and sepsis, there are many other factors that can influence these outcomes, such as air pollution levels, access to healthcare, and individual health behaviour (Charoenpong, 2020). Therefore, further research is needed to better understand the complex relationships between urbanization, population density, respiratory health, and sepsis mortality. Importantly, the relationship between the environment and population density is consistent with the association between population density and respiratory infection rates in China, as well as with the severity of COVID-19 outbreaks and higher morbidity rates (R^2 =

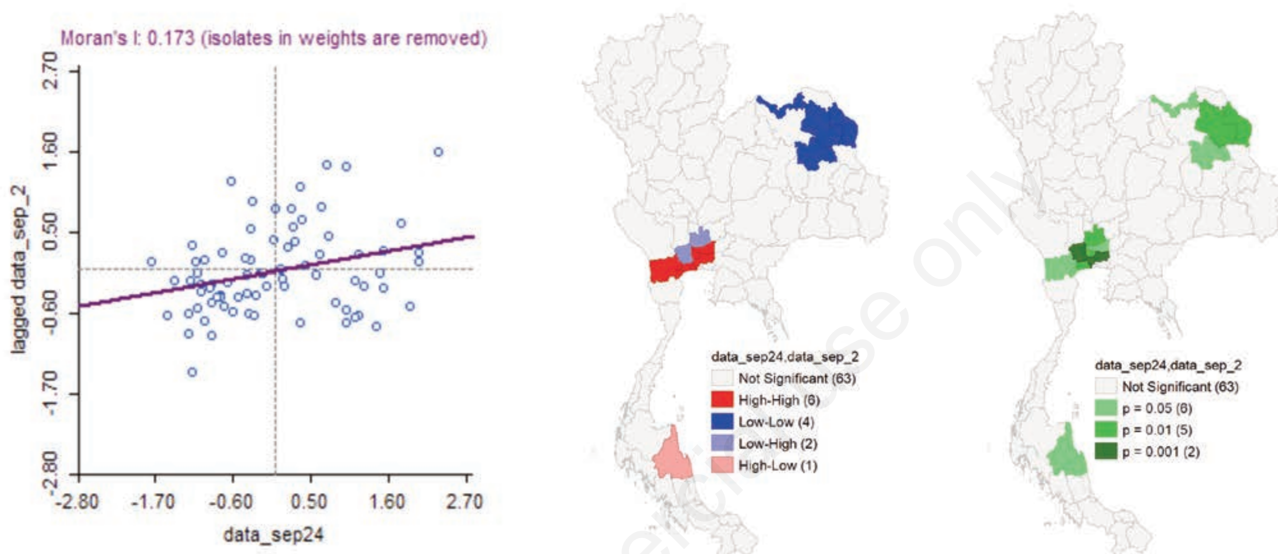

Figure 6. LISA and Moran's *I* scatter plot matrix of the lowest average temperature and sepsis mortality.

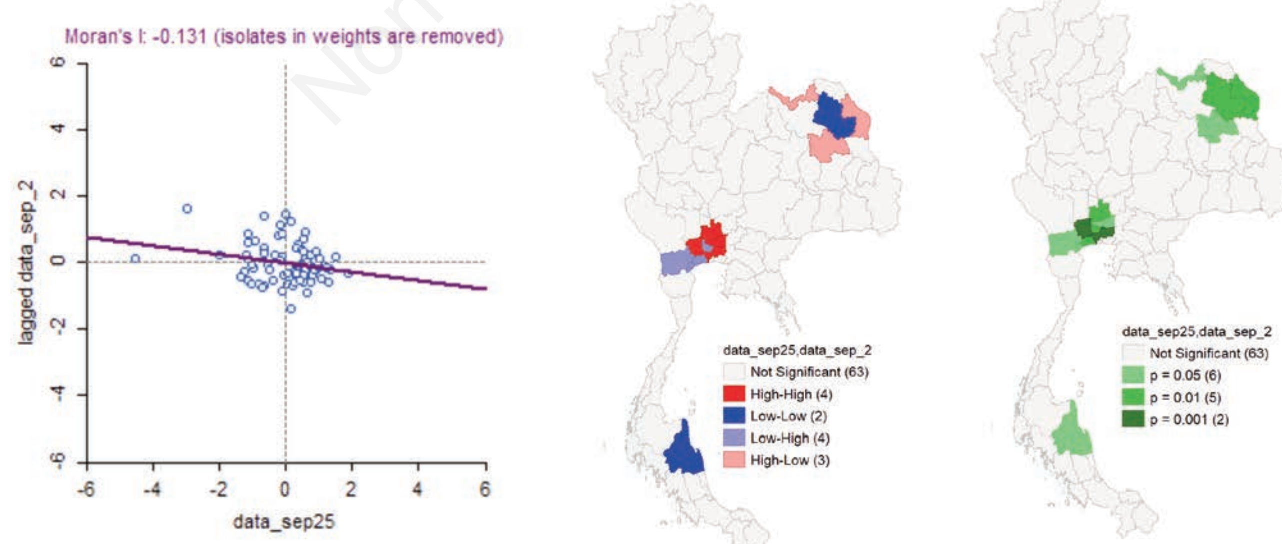

Figure 7. LISA and Moran's *I* scatter plot matrix of the highest average temperature and sepsis mortality.

0.62) (Yin *et al.*, 2021). This finding aligns with similar studies conducted in 51 states across the United States. In fact, the morbidity rate of COVID-19 was higher in populations residing in high-density areas compared to those living in less densely populated areas, with an R^2 of 0.55 (Thomas *et al.*, 2020). Spatial analytical studies conducted in the city of Sandesh, Iran found a positive correlation between infection rate and population density per area, with densely populated areas and their neighbourhoods being significantly affected at a significance level of 0.01 (Irandoost *et al.*, 2023). We found an association (p=0.05) between sepsis mortality and high population density. This information, together with the results given above, suggests that in areas with high population densities can be used to define the spatial extent of the development of sepsis mortality.

During the COVID-19 pandemic, access to health services was limited, leading to self-medication and a decline (approximately 8%) in hospital admissions disproportionately affecting vulnerable populations, such as those with chronic or congenital diseases, low-income individuals, elderly, single mothers and children. This may have long-term implications for the whole health spectrum (Institute for Population and Social Research, 2022). There were several, significant associations between drug use and sepsis, *e.g.,* the use of antidepressants and sepsis (p=0.016); the use of drug combinations (p=0.020); while substance abusers with positive urine test results were 80.8% more likely to develop sepsis (p=0.001) indicating that the individuals who depended on these kind of drugs were more likely to develop sepsis compared to the healthy, general population (Annie *et al.*, 2018).

The quality of healthcare services is influenced by medical personnel, particularly doctors and professional nurses, as demonstrated by a cross-sectional analysis to examining the correlation between the number of nurses and sepsis among patients with septicaemia in the United States (Dierkes *et al.*, 2022). These authors' results show that an increased proportion of patients was associated with 9% increased mortality at day 30 and 10% at day 60 after admission, a 12% higher rate of being moved to the intensive care unit (ICU) and a 10% increased risk of longer hospital stay (p<0.001; Oami *et al.*, 2023) on the other hand, demonstrated that ICU admission was potentially associated with decreasing in-hospital mortality among sepsis patients Likewise, in a study involving 702,140 patients for a multivariable regression model of the relationship between the number of registered nurse hours per

Table 6. Geographical distribution of Number of Highest average temperature and sepsis mortality.

Local indicators of spatial association (LISA) High-high (HH)	High-low (HL)	Low-low (LL)	Low-high (LH)
Nakhon Pathom***	Nong Khai*	Nakhon Si Thammarat*	Nonthaburi**
Ayutthaya**	Nakhon Phanom**	Sakon Nakhon**	Ratchaburi*
Bangkok***	Kalasin*		Samut Sakhon**
Pathum Thani*			Samut Songkhram*

*Correlation significant at the 0.05 level; **correlation significant at the 0.01 level; ***correlation significant at the 0.001 level.

Table 7. Regression analysis between socio-economic, health service factors and sepsis mortality in Thailand, 2021.

Independent variable	OLS coefficient (SE)	Spatial regression analysis SLM coefficient (SE)	SEM coefficient (SE)
Population density	0.021 (0.009)*	0.020 (0.009)*	0.021 (0.008) *
Night-time light (NTL)	0.379 (0.177)*	0.378 (0.163)*	0.380 0.163*
Density of pharmacies	-0.266 (0.099)**	-0.248 (0.106)**	-0.266 (0.092)**
Lowest average temperature	0.647 (0.270)*	0.644 (0.250)*	0.647 (0.250)**
Highest average temperature	1.131 (0.506)*	1.110 (0.469)*	1.131 (0.467)*
Constant	-685.861 -328.367	-68.348 30.352	-68.618 -30.361
ρ		0.038	
λ			-0.003
R^2	0.563	0.563	0.564
Log likelihood	-248.043	-248	-248.043
Akaike information criterion (AIC)	518.087	520	518.087
Bayes information criterion (BIC)	543.725	547.969	543.725

*Correlation significant at the 0.05 level; **correlation significant at the 0.01 level; ***correlation significant at the 0.001 level; OLS, ordinary least squares; SLM, spatial lag model; SEM, spatial error model; SE is standard error; Constant, the regression model intercept (the expected mean value of Y when all X=0); ρ, spatial autoregressive parameter; λ, spatial error coefficient; R2, coefficient of determination.

patient day (HPPD) and the mortality risk of patients with bloodstream infections, Cimiotti *et al.* (2022) found that each additional registered nurse HPPD was associated with a 3% decrease in the odds of 60-day mortality.

Conclusions

The research presented here reveals that there are positive and statistically significant associations in the Thai population between several socio-economic factors and public health services on one hand and sepsis-related mortality on the other. The strongest associations were observed in urban areas. Overall, these findings emphasize the importance of addressing social determinants of health and improving access to healthcare services, particularly with regard to vulnerable populations. Further research is needed to fully understand the mechanisms underlying these associations and to develop targeted interventions to reduce sepsis-related mortality in Thailand. The public sector should promote the determination plan and guidelines to prevent sepsis mortality using an integrated working procedure supporting the participation of the community and all sectors to create a 'health-literate' society through policymaking mechanisms with tools to prevent population risk. Furthermore, the government should promote a healthy environment, especially in urban areas. Besides, it would be important to create legislation pertaining to drug usage, whether it pertains to unauthorized substances or medicinal applications that empowers governments to institute guidelines aimed at safeguarding individuals from the potential risks linked to drug ingestion. Moreover, applications of spatial analysis using open data and open-source software packages in public health planning should also be promoted and extended to other diseases.

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