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Geospatial determinants of diabetes risk in Thailand: socioeconomic and health service factors

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Abstract

Diabetes prevalence is increasing in Thailand, creating growing demands on the health system. Understanding the spatial distribution of diabetes risk and its association with socioeconomic and healthcare system factors among the diabetes risk population is critical for designing targeted prevention and intervention strategies. We examined the distribution of diabetes risk groups across provinces in Thailand with reference to the spatial association between economic, social and public health service factors based on data from the Ministry of Public Health's Health Data Center (HDC) for the year 2021. The dataset included 22,491,934 individuals across the 76 provinces as well as social, economic and public health services. The methods included Local Indicators of Spatial Association (LISA), Ordinary Least Squares (OLS), Spatial Lag Model (SLM) and spatial error model (SEM). Explanatory variables included average night-time light intensity, average monthly income, hospital-to-population ratio and proportion of the population with health insurance. Major clusters of High-High (HH) diabetes risk were identified by LISA mainly located in the North of Thailand. In all models, the direction and significance of the associations were consistent ($p<0.001$ for all variables investigated and $p<0.01$). $R2=0.47$. The SLM gave the best fit, capturing spatial spill-over effects. Higher night-time light intensity (coefficient = -85.70, $p<0.05$) and higher monthly income (coefficient = -0.079, $p<0.001$) were negatively associated with diabetes risk. These inverse relationships implied that greater urbanization and higher socio-economic standing may protect against diabetes risk, possibly through improved access to health infrastructure, improved health education and preventive services. Conversely, the higher hospital-to-population ratios (coefficient = 572.28, $p<0.001$) and the larger proportions of Civil Servant Medical Benefits Scheme (CSMBS) coverage (coefficient = 226.46, $p<0.001$) the higher diabetes risk. These counterintuitive findings likely reflect reverse causation, in which provinces with higher disease burden or poor health attract more resources of health care and have increased insurance coverage, a pattern consistent with healthcare service distribution responding to existing health needs rather than preventing occurrence of disease.

Key words: diabetes risk; spatial clustering; socioeconomic determinants; health services; geospatial analysis; Thailand.

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Introduction

Diabetes mellitus is a major and increasingly urgent public health challenge in Thailand. According to the National Health Examination Survey 2020, 9.5% of Thai adults tested positive for diabetes, however with a high probability of a significant number of undiagnosed patients (Rajatanavin *et al.*, 2022). During the past 20 years, diabetes has become far more common, with rapid urbanization, population aging and changes in lifestyle patterns (such as less physical activity, food alterations, etc.) acting as driving forces. Those developing the disease are now adding to the pressure on Thailand's healthcare system; this in turn means that more precise strategies for prevention are urgently needed.

Geographic Information Systems (GIS) and spatial statistical techniques permit researchers to detect disease clusters, measure spatial auto-correlation and model how geographical location influences health outcomes, which has been demonstrated by Sansuk *et al.* (2023). Occurrence of diabetes follows mainly two types of risk factors: behaviour and clinical risk factors. Few previous studies have employed geospatial analytical methods to explore large-scale risk of diabetes and dependent care infrastructure in relation to the economic conditions in Thailand. Most previous research is based on traditional regression models assuming independent observations, thus ignoring spatial dependence with regard to environmental conditions, policies and population mobility. By eschewing widely accepted paradigms in favour of more unconventional approaches related to health economics it may be possible to exploit some inappropriate assumptions or errors. Further, while it is true that indicators of economic well-being (such as income levels and urbanization, which can be approximated by using night-time light intensity as a proxy) are also likely to affect both exposure to metabolic risk and the capacity to prevent, as well as manage, the disease (Xu *et al.*, 2013). The spatial connections of such indicators with diabetes in Thailand remain unclear due to two main reasons: the variable impact of the prevailing health system and the differential access to prevention services and treatment. The context also changes in time and space because both are factors that shape social phenomena. The spatial distribution of health care resources – including hospital availability and health insurance coverage – mirrors both the underlying health needs of populations and the socioeconomic pattern (WHO, 2013). However, no study has yet studied how health system factors are related to the general socioeconomic pattern in order to see if they contribute to the differences in diabetes risk across Thailand.

Importantly, not everyone faces the same diabetes risk in Thailand. Emerging evidence shows that geographic, economic and health system variables all contribute to wide disparities in disease patterns across different regions or provinces (National Statistical Office, 2023). It is urgent that we understand these differences because only by doing so can we develop intervention tools specific to local circumstances and allocate resources so they work optimally for each area. Spatial epidemiology is a powerful framework for hazard assessment. This approach tried to identify the type of non-random geographic patterns of disease occurrence, disclose clusters where risk level is high and measure how disease distribution relates to its environmental, social and health care determinants (Oliveau & Guilmoto 2022).

Spatially-informed findings from this analysis can ensure that public health resources are used more effectively by pointing to particular high-risk provinces which require priority intervention. They also give rise to place-based diabetes prevention programmers, with local environments in mind, and can be used for further development of these regional strategies while accounting for spill-over effects between contiguous areas. In showing how useful it is to bring spatial tools into diabetes surveillance and control; this research attempts to lay a foundation for how one might tackle Thailand's rapidly growing chronic disease burden more effectively in future. It would be highly useful for Thailand's policy for public health research to investigate which of the given factors are important and how this information might affect the country's current situation.

Materials and Methods

Study design

A cross-sectional ecological approach was used to explore relationships between economic, social (public health service) and the distribution of diabetes risk in Thailand.

Without considering previously accepted and specific social phenomena linked to diabetes within defined geographic areas, this study used Local Indicators of Spatial Association (LISA) to find certain clusters of high and low diabetes risks, which would show where triage interventions could be most beneficial. By using three types of spatial regression approaches: Ordinary Least Squares (OLS), the Spatial Lag Model (SLM) and the Spatial Error Model (SEM), we investigated spatial autocorrelation and spill-over effects between nearby provinces, *i.e.* more precisely measuring how factors as socioeconomic background and health care quality could influence the diabetes risk distribution. Meanwhile, we also studied various dimensions of development and health care availability, including objective assessments of economic activity through different variables and the impact of health insurance and hospital/population ratios. This multidimensional approach was chosen to visualize the way these factors interact spatially to produce areas of high or low diabetes risk, conclusions which cannot be drawn from individual-level studies or traditional statistical analyses.

Study area

The study covered all 76 provinces of Thailand. The diverse social, economic and healthcare infrastructure of the country makes it an ideal subject for geographical analyses examining health outcomes, such as diabetes danger/problem zones. The province-level scale also enables regional comparison of demographics and disease risk distribution patterns.

Study population

The research subjects were Thai citizens aged 35 years or older. Altogether 22,491,934 people were included in the list covering the 76 provinces. The inclusion criteria were: Thai citizen over 35 years of age considered at risk based fasting capillary blood glucose of 100 to 125 mg/dL. The exclusion criteria included persons who did not fit the diagnosis of diabetes risk and those with incomplete data (not within the HDC database).

Study variables

The dependent variable (fasting capillary blood glucose levels between 100 and 125 mg/dL) consisted of data for 202 obtained from the Ministry of Public Health's Health Data Center (HDC). The economic variables included average monthly household income and the average Night-Time Light Index (NTLI), which was used as a correlate for economic activity. Social indicators consisted of the proportion of people registered in government health insurance schemes. Public health service factors included the ratio of hospitals to population and access to screening services. Information on socio-economics and health service systems comes from the National Statistical Office and the Ministry of Digital Economy and Society. Spatial data, such as the boundaries of provinces and geographical coordinates, were harmonized to allow for spatial analysis. The secondary data for 2021 from HDC were used for spatial and statistical analyses at the province-level scale.

Data analysis

A cross-sectional ecological study design was applied to describe diabetes risk prevalence from province to province. Quantum GIS (QGIS) spatial data visualization was used, with GeoDa as the spatial computational environment. Univariate spatial analysis by Global Moran's I was employed to examine the overall spatial autocorrelation of the provincial diabetes risk prevalence. LISA was then applied to identify High-High (HH), Low-Low (LL), High-Low (HL) and Low-High (LH) clusters of diabetes prevalence.

In the bivariate spatial analysis, Moran's I and LISA were used for diabetes risk prevalence for each spatial relationship to investigate which specific risk factor coincided in spatial terms with high prevalence. Weight matrices were constructed using queen contiguity criteria to describe the neighbouring provinces. Three regression models were compared: OLS as a baseline spatial model, SLM for the capture of spatial spill-over effects and SEM for the spatial autocorrelation in the residuals. Lagrange multiplier tests (LM-lag and LM-error) and their robust versions were employed to select the most appropriate spatial model specification. The performance of the model was assessed using log-likelihood values as well as Rayfield's Moran's I statistics for the residuals to control spatial autocorrelation adequately. The models also included control variables such as the number of healthcare facilities per capita and the percentage of healthcare utilization to address possible ascertainment bias attributable to variations in screening rates for diabetes and access to health services across provinces. This was done to cover discrepancies in the detection capacity of illnesses, which may result in an over-estimation of prevalence rates in provinces that have better health care infrastructure. Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), widely used statistical method for model evaluation, were used for estimating the goodness of fit.

Results

In 2021 the diabetes risk population in Thailand was 3,212.96 per 100,000 in general. However, these numbers vary greatly according to geographical location. Phatthalung Province registered the highest rate of any province (7,889.80 per 100,000 population) and Samut Prakan Province the lowest at only 568 per 100,000 population. In the highest quintile (with diabetes ratings between 4,8% and 7,9%), we found eight provinces: Phatthalung, Uttaradit, Mae Hong Son, Phang Nga, Roi Et, Nan, Trat and Sukhothai (Figure 1).

Univariate analysis

The diabetes risk distribution had significant positive spatial autocorrelation (Moran's I = 0.234, p<0.05). The LISA analysis showed HH clusters in Nan, Phrae, Phitsanulok and Satun provinces. These four provinces showed a high level of inherited diabetes risk coupled with neighbouring towns that were also at

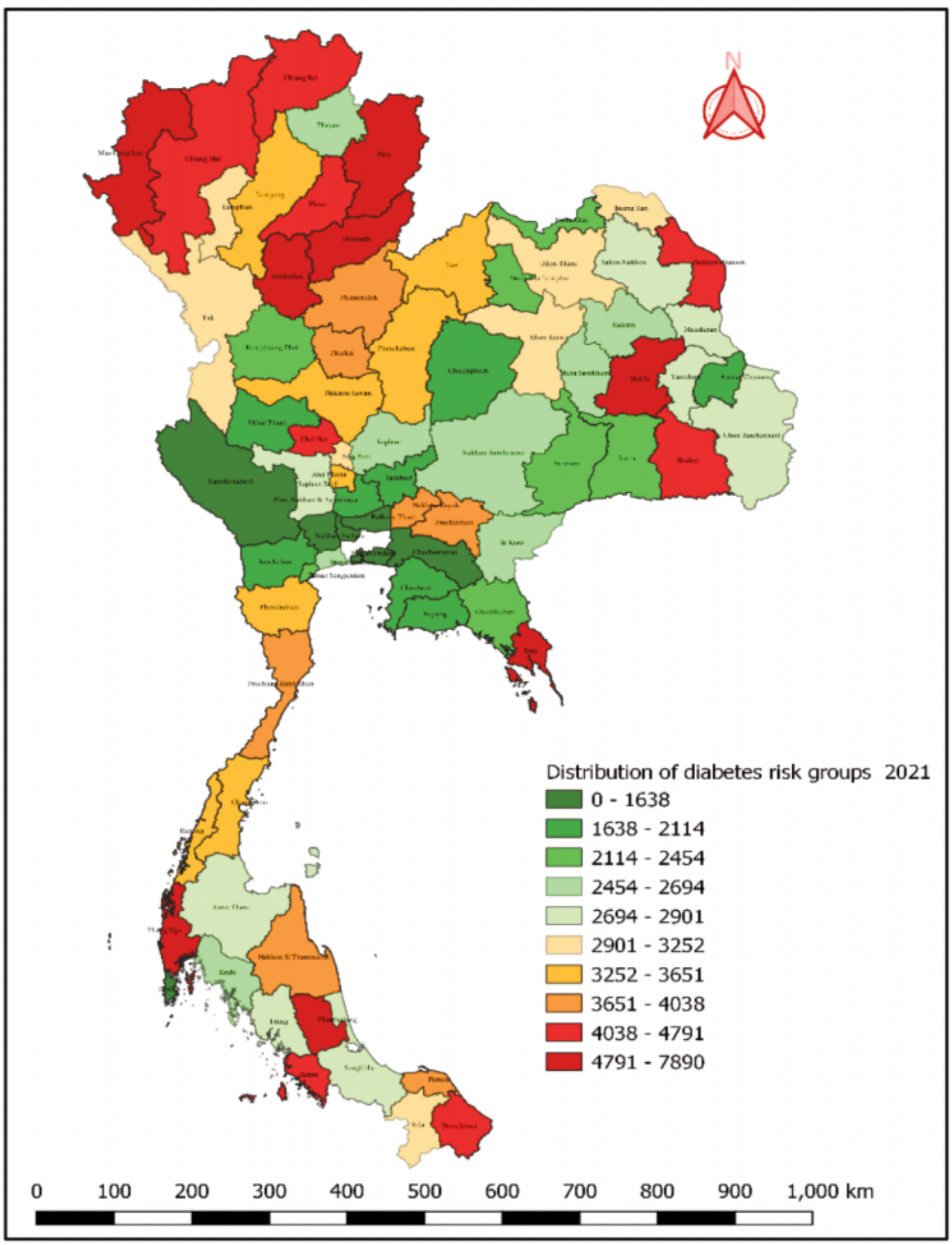


Figure 1. Distribution of diabetes risk (per 100,000 population) by province in 2021.

more than average risk, indicating regional concentration in northern Thailand. LL clustering was seen in a band of 9 central metropolis provinces: Rayong, Chonburi, Samut Songkhram, Samut Sakhon, Samut Prakan and Nakhon. A uniformly low diabetes risk, forming what can be called a protective area, was noted in Pathom, Nonthaburi, Pathum, Thani, Phra, Nakhon and Si Ayutthaya kept. Three provinces: Songkhla, Trang and Phayao had LH clusters and were at low risk (Table 1, Figure 2).

Bivariate analysis of NTLI and diabetes risk group distribution

Night light brightness apparently decreases with increasing urbanization (p<0.05). That is, in areas where artificial light is bright and numerous, diabetes risk diminished. Had such places alone been examined as case studies rather than simply samples or vignettes, the deviation between our data and this model would have been even more pronounced. In the metropolitan belt of provinces, a HL pattern appeared (high urbanization, low diabetes risk), while in the northern provinces (Nan, Phrae, Phayao, Phitsanulok, Songkhla, Satun and Trang) the pattern was LH (low urbanization, high diabetes risk). This reversal shows that the protective effects of urbanization could outweigh the metabolic hazard in Thailand, which might be a vicious cycle (Table 2, Figure 3).

The average monthly income in Thailand (24,462 Bath - around 788 USD) was found to have the strongest negative spatial autocorrelation with the Moran's I score (-0.288, p <0.05). High-

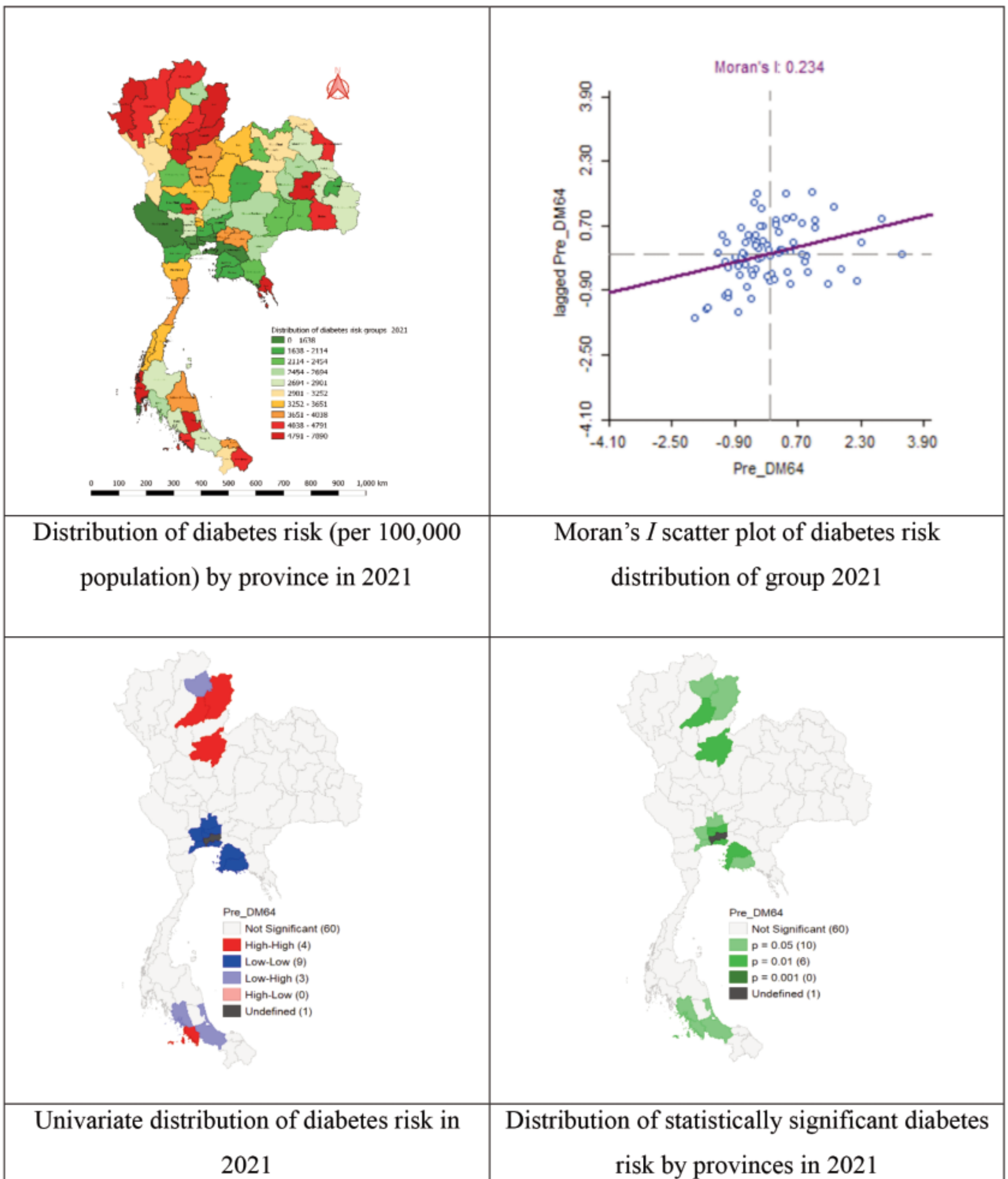


Figure 2. Spatial analysis results of diabetes risk groups between provinces in 2021 using Moran's I and Local Indicators of Spatial Association (LISA).

Low spatial clustering was observed in nine provinces with high income but low diabetes risk: Rayong, Chonburi, Samut Songkhram, Samut Sakhon, Samut Prakan, Nakhon Pathom, Nonthaburi, Pathum Thani and Ayutthaya. In contrast, Low-High spatial associations were found in seven northern and southern provinces with low income but high diabetes risk: Nan, Phrae, Phayao, Phitsanulok, Songkhla, Satun and Trang. These patterns indicate that provinces with lower income tend to cluster spatially with higher diabetes risk, while higher-income provinces show lower diabetes risk, reflecting socioeconomic disparities in disease burden across regions (Table 3, Figure 4). «Hospitals/population showed little positive spatial autocorrelation (Moran's $I = 0.095$, $p<0.05$) indicated limited spatial clustering. Three adjacent northern provinces had health service concentrations (in terms of high-burden areas) that were distributed in a HH pattern. It might indicate that health resources had been effectively allocated in response to the needs: i) Phrae province; ii) Nan; and iii) Phayao. Seven provinces formed LL clusters, suggesting that according to population more people have less availability of health care (Table 4, Figure 5).

CSMBS Coverage Positive spatial autocorrelation (Moran's $I = 0.098$, $p <0.05$) showed HH clustering in seven provinces (Phrae, Nan, Phayao, Phitsanulok, Songkhla, Satun, Trang) – overlapping substantially with high-level diabetes risk areas. This co-location may reflect higher public sector employment in these regions or greater healthcare utilization among at-risk populations (Table 5, Figure 6).

Independent variables in the three models were found to have significant influence on the dependent variable at levels of significance of $\alpha = 0.05$, 0.01 and 0.001, with consistent signs and signif-

Table 1. Spatial distribution of diabetes risk groups in Thailand 2021.

Moran's *I* 0.234	Local indicators of spatial association (LISA)			
	High-High	Low-Low	Low-High	High-Low
Province	Nan*	Rayong*	Songkhla*	
	Phrae*	Chonburi**	Trang*	
	Phitsanulok**	Samut Songkhram*	Phayao**	
	Satun*	Samut Sakhon*		
	Nan*	Samut Prakan**		
		Nakhon Pathom*		
		Nonthaburi**		
		Pathum Thani**		
		Ayutthaya*		

*p=0.05; **p=0.01; ***p=0.001*

Table 2. Night-time light index and distribution of diabetes risk groups in Thailand in 2021.

Moran's *I* 0.234	Local indicators of spatial association (LISA)			
	High-High	Low-Low	Low-High	High-Low
Province			Phayao*	Rayong*
			Phrae**	Chonburi**
			Nan*	Samut Songkhram*
			Phitsanulok**	Samut Sakhon*
			Songkhla*	Samut Prakan**
			Satun*	Nakhon Pathom*
			Trang*	Nonthaburi**
				Pathum Thani**
				Ayutthaya*

*p=0.05; **p=0.01; ***p=0.001*

Table 3. Average monthly income and distribution of diabetes risk groups in Thailand 2021.

Moran's *I* 0.288	Local indicators of spatial association (LISA)			
	High-High	Low-Low	Low-High	High-Low
Province:			Phayao*	Rayong*
			Phrae**	Chonburi**
			Nan*	Samut Songkhram*
			Phitsanulok**	Samut Sakhon*
			Songkhla*	Samut Prakan**
			Satun*	Nakhon Pathom*
			Trang*	Nonthaburi**
				Pathum Thani**
				Ayutthaya*

*p=0.05; **p=0.01*

icance testing levels. This reflects robust variable effects on diabetes risk distribution. In model goodness-of-fit assessment, the three models' R^2-values were all 0.47, meaning that they accounted for 47% of variance in geographic distribution of the diabetes risk. However, Model Fit Criteria distinguished between them. Although R^2 values are all the same (across all three models), the spatial characteristics of the models are better reflected through spatial-econometric parameters and likelihood-based criteria. The SLM outperformed the others on the basis of its greater log likelihood value, lower AIC and BIC. This reveals that the SLM model continued to be superior to both OLS and SEM models in spatial model fit indices. From comprehensive comparisons of models and theoretical analysis on spatial dependent Variable effect, one sees that SLM was the only one with good performance in explaining the diabetes risk distribution of provinces which were adjacent to one another. The SLM successfully caught the spatial autoregressive effects. When there is some change in diabetes risk in one province, the levels in adjacent provinces are influenced. For example, if one

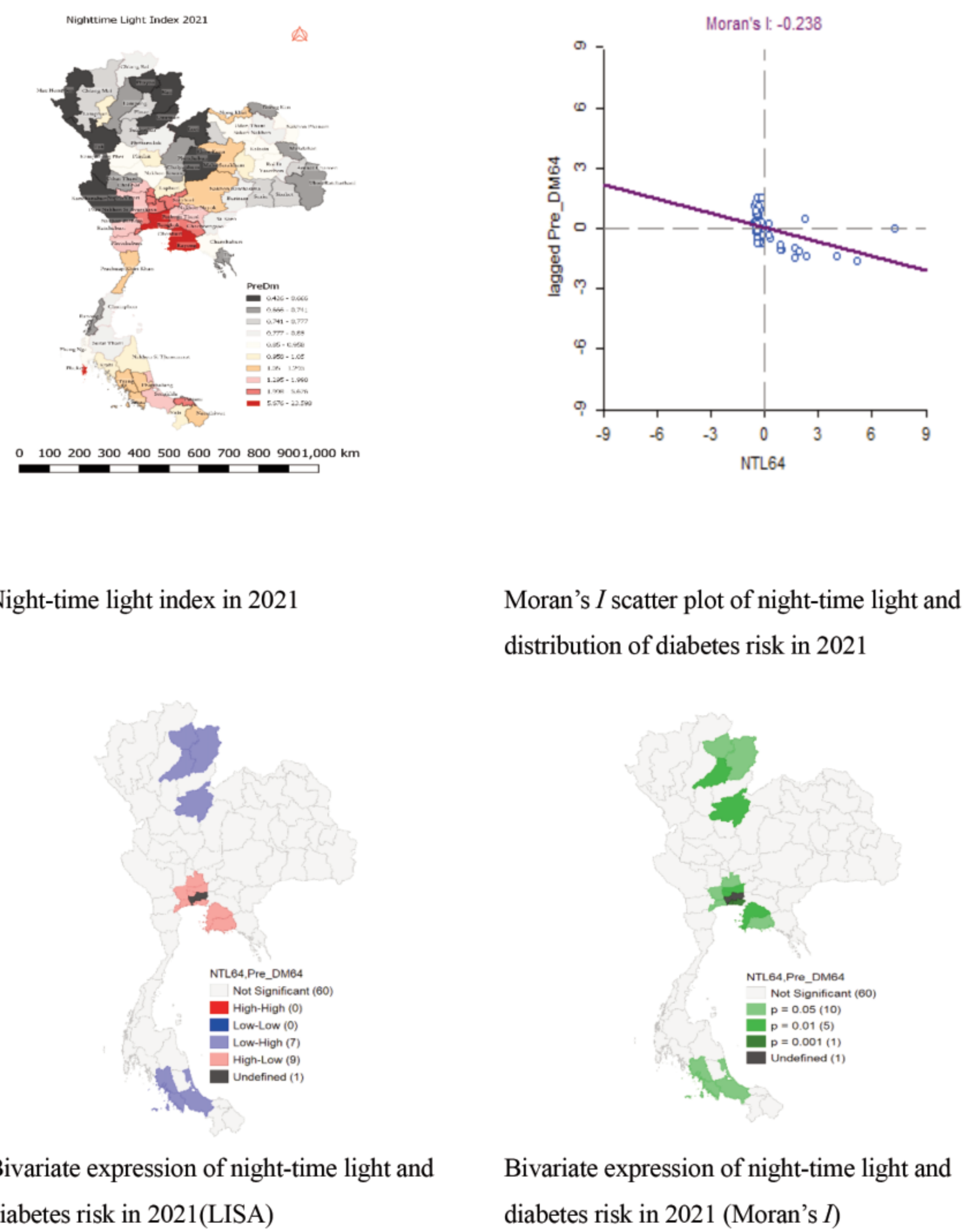


Figure 3. Bivariate analysis of the average night light and the distribution of diabetes risk groups in Thailand in 2021 using the Moran's *I* spatial analysis method and Local Indicators of Spatial Association (LISA).

province goes up in diabetes prevalence, its surrounding regions will often show similar trends. Results of the simulated example simulations demonstrated that the SLM model parameters outperformed those from traditional multiple regressions. This shows that diabetes risk distribution in all of Thailand is the result not only common regional characteristics but also of spill-over effects from adjacent provinces. SLM model indicates that there are significant relationships across a variety of indicators (Table 6).

Table 4. Proportion of hospitals per 100,000 population and distribution of diabetes risk groups in Thailand in 2021.

Moran's *I* 0.095	Local indicators of spatial association (LISA)			
	High-High	Low-Low	Low-High	High-Low
Province:	Phrae**	Rayong*	Phitsanulok**	Samut Prakan***
	Nan*	Chonburi**	Songkhla*	Ayutthaya*
	Phayao*	Samut Sakhon*	Satun*	
		Samut Songkhram*	Trang*	
		Nakhon Pathom*		
		Nonthaburi**		
		Pathum Thani**		

*p=0.05; **p=0.01; ***p=0.001

Table 5. Proportion of health insurance rights according to the Civil Servant Medical Benefits Scheme (CSMBS) and the distribution of diabetes risk groups in Thailand 2021.

Moran's *I* 0.098	Local indicators of spatial association (LISA)			
	High-High	Low-Low	Low-High	High-Low
Province:	Phrae** Nan* Phayao* Phitsanulok** Songkla* Satun* Trang*	Rayong* Chonburi** Samut Sakhon* Samut Prakan** Pathum Thani** Samut Songkhram* Nakhon Pathom*	Nonthaburi** Phra Nakhon Si Ayutthaya*	

*p=0.05; **p=0.01; ***p=0.001

Table 6. Results of spatial regression analysis modelling affecting the distribution of diabetes risk groups in Thailand using spatial regression analysis.

Spatial factor	Spatial regression analysis model		
	OLS (SE)	SLM (SE)	SEM (SE)
Average night-time light	-88.31* 42.98 (SE)	-85.70* 41.73 (SE)	-88.11* 41.59 (SE)
Average monthly income	-0.08*** 0.03 (SE)	-0.079*** 0.028 (SE)	-0.08*** 0.02 (SE)
Hospital per population ratio	568.56** 241.38 (SE)	572.28*** 233.39 (SE)	569.72** 233.71 (SE)
CSMBS	232.54*** 71.65 (SE)	226.46*** 69.66 (SE)	232.22*** 69.38 (SE)
CONSTANT	2546.72 813.28 (SE)	2356.41 886.93 (SE)	2548.07 788.09 (SE)
P	-	0.05	-
	-	-	0.00
R	0.47	0.47	0.47
Log likelihood	-643.79	-643.69	-643.79
AIC	1297.6	1299.38	1297.59
BIC	1309.31	1309.31	1313.44

*OLS, Ordinary Least Squares; SLM, Spatial Lag Model: SEM, Spatial Error Model; SE, Standard Error; CSMBS, Civil Servant Medical Benefits Scheme; Constant, intercept of the regression model; P, spatial autoregressive parameter of SLM; λ, spatial error parameter of SEM; R, R-squared value indicating goodness of fit; *p<0.05; **p<0.01; ***p<0.001". AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; *p=0.05; **p=0.01; ***p=0.001.*

Discussion

A significant geographical correlation was demonstrated in this study for diabetic risks in Thailand, with the risk accentuated in the North. These major, unbalanced conditions coincide with the finding that across regions in Asia even for such small disparities of such a condition as shown by Limwattananon *et al.* (2022), who also believe that such a disease is the result of various sociological changes within an area. Samut Prakan, at the centre of policy-making, had the lowest rate for diabetes risk. It can be argued that this is due to the province's industrial factories bring in fresh labour, a workforce whose mean age is generally in the lower range. Nonetheless, the negative relationship between diabetes risk and intensity of night-time light requires careful interpretation. While broader urbanization may facilitate access to health-promoting infrastructure on a wider scale, greater health literacy, or a more diversified food environment (Wang *et al.*, 2023), this relationship should not be interpreted simplistically by saying that urbanization is inherently «protective» against diabetes. The observed pattern might reflect other confounder factors as well such as age structure (as seen in Samut Prakan's younger labour force), income level or healthcare access patterns rather than only urbanization per se. In addition, urbanization also brings recognized metabolic risks from sedentary lifestyles and processed-food consumption; therefore, it seems probable that the protective relationship seen in this ecological analysis is largely an artefact of economic superiority concentrated in urban areas rather than typical urban living.

In a similar way, increasing per capita monthly income was inversely associated with risk of developing diabetes. The capacity for people of different economic levels to keep up with good health is evident from the worldwide example of poverty: this is poverty that prevents people from having medical treatments in time, eating properly and living normally; or from participating in the mass health survey on all kinds of ailments and preventive care

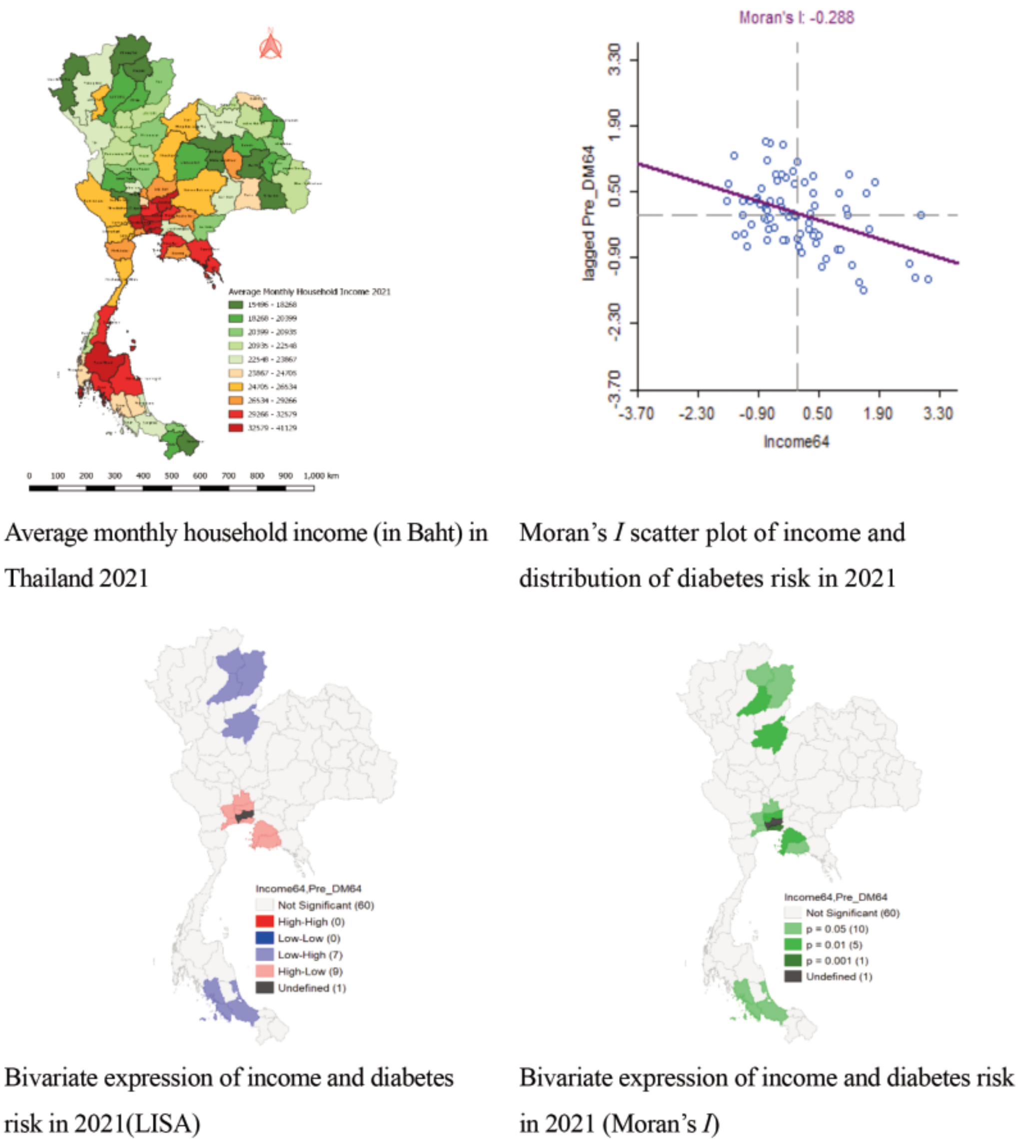
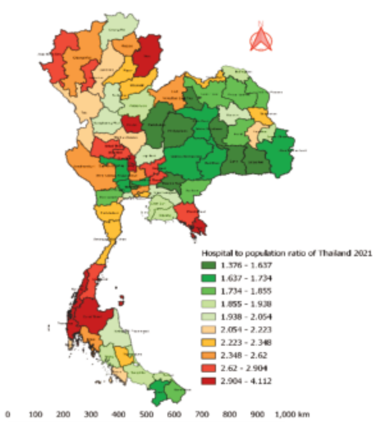
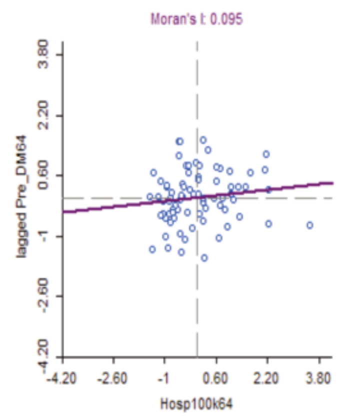


Figure 4. Bivariate analysis of average monthly income and the distribution of diabetes risk groups in Thailand in 2021 using the Moran's *I* spatial analysis method and Local Indicators of Spatial Association (LISA).

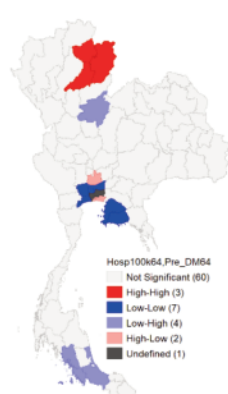
(International Diabetes Federation, 2023). This finding indicates the need to address economic inequalities in long-term disease strategy. Its ecological nature also places some limits on using it to establish cause-and-effect links, for this relationship could very well be affected by oncoming roads or other unmeasured confounding factors; or act as a result of reverse causation. While diabetes rates were positively correlated with numbers of hospitals per capita, as well as the proportion of insured civil servants, this is likely just reflective of these places associating wealth with lower burdens where the disease is heavier, therefore there are more health resources and better insurance coverage among state workers. One is reminded of the health service paradox, in which resources do not precede disease rates but distantly follow them. (Rocco *et al*., 2022) Consequently, these findings should be interpreted as patterns of healthcare system response rather than risk factors in themselves. Longitudinal studies are therefore required to clarify causal relationships. SLM-generated estimates were most satisfactory, suggesting that the risk of one province is influenced by what happens in other provinces. This comes from the understanding that regional policies, reciprocal shifts in population, and common environmental hazards are something apart from administrative units (Xu *et al*., 2022). Policy-wise, this kind of evidence suggests the necessity for geographically specific diabetes strategies tailored to provincial differences. In high-risk northern provinces such as Nan, Phrae, Phitsanulok, and Phayao – with lower incomes, rural populations and an aging demographic – spatially sensitive interventions can be to bring mobile health screening units to remote sub-districts on a quarterly basis, with point of care testing; to train community health volunteer networks in diabetes prevention using existing village structures; or even arrange for agricultural worker health programs addressing occupational risk; village-level food security initiatives such as community vegetable gardens. Telemedicine could also make rural health centres with diabetes specialists in regional hospitals. Greater Bangkok



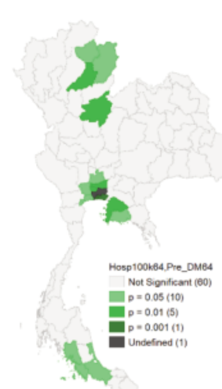
Hospital to population ratio of Thailand 2021



Moran's *I* scatter plot of hospital presence and distribution of diabetes risk in 2021



Bivariate expression of hospital presence and diabetes risk in 2021(LISA)



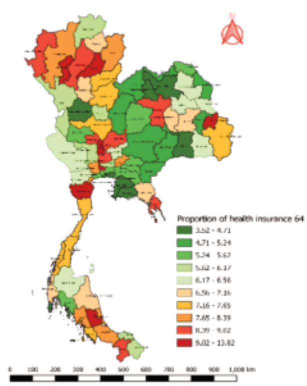
Bivariate expression of hospital presence and distribution of diabetes risk in 2021 (Moran's *I*)

Figure 5. Bivariate analysis of the ratio of hospitals to population and the distribution of diabetes risk groups in Thailand in 2021 using the Moran's *I* spatial analysis method and Local Indicators of Spatial Association (LISA).

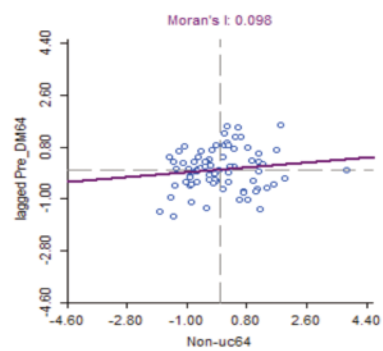
lunches for low-risk urban clusters in the Greater Bangkok area (Samut Prakan, Nonthaburi, and Pathum Thani), present disease rates appear low. However, preventive efforts should be directed towards wellness programmes targeting young adults as they set up their working lives and the city environment's role in spreading diabetes. Health promotion activities in the urban scene should be stepped up to address lifestyle habits that have been broken by industrialization; these may well hold broader implications for ill health. Regarding equalization a regional perspective, cross-cutting policies should target areas of identified social gradient. These include health equity funds providing subsidies for screening and medication to those with lower incomes; equal access to all diabetic prevention programs irrespective of insurance status, whether under CSMBS or the Universal Coverage Scheme, so as not to continue disparities between different social groups.

Limitations

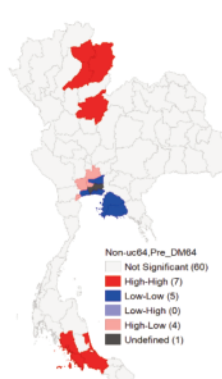
It is necessary to bear in mind that this only data from the entire province, between-provincial differences in disease incidence or due to differences in environmental factors may be overshadowed by the ecological fallacy. Meanwhile, a cross-sectional design means that cause and effect cannot be distinguished. Future research should consider adding time as well as space dimensions to the analysis and replace province-level administrative units with smaller ones so as to gain improved knowledge about diabetes-related spatial epidemiology.



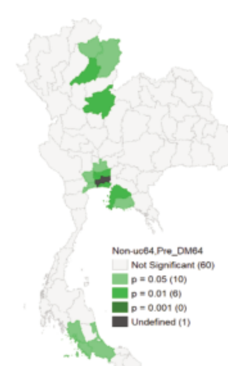
Proportion of Civil Servant Medical Benefits Scheme (CSMBS) by province in 2021



Moran's *I* scatter plot of Civil Servant Medical Benefits Scheme (CSMBS) presence and the distribution of diabetes risk in 2021



Bivariate expression of Civil Servant Medical Benefits Scheme (CSMBS) and diabetes risk in 2021(LISA)



Bivariate expression of Civil Servant Medical Benefits Scheme (CSMBS) and the distribution of diabetes risk in 2021 (Moran's *I*)

Figure 6. Bivariate analysis of the proportion of health insurance rights according to the health service system (civil servant rights) and the distribution of diabetes risk groups in Thailand in 2021 using the Moran's *I* spatial analysis method and Local Indicators of Spatial Association (LISA).

Conclusion

Diabetes risk in Thailand shows significant spatial clustering influenced by intertwined socioeconomic and health service factors. Incorporating spatial analytics into public health planning could enhance resource allocation and enable geographically targeted strategies to reduce diabetes burden or allow for tailor-made, site-specific strategies aimed at reducing Thailand's national diabetes burden.

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