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Spatial association of socio-demographic, environmental factors and prevalence of diabetes mellitus in middle-aged and elderly people in Thailand

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Abstract

The burden of diabetes mellitus (DM), one of the major non-communicable diseases (NCDs), has been significantly rising globally. In the Asia-Pacific region, Thailand ranks within the top ten of diabetic patient populations and the disease has increased from 2.3% in 1991 to 8.0% in 2015. This study applied local indicators of spatial association (LISA) and spatial regression to examine the local associations in Thailand with night-time light, spatial density of alcohol/convenience stores, concentration of elderly population and prevalence of DM among middle-aged and elderly people. Univariate LISA identified the statistically significant cluster of DM prevalence in the upper north-eastern region. For multivariate spatial analysis, the obtained R^2 values of the spatial lag model (SLM) and spatial error model (SEM) were 0.310 and 0.316, respectively. These two models indicated a statistical significant association of several sociodemographic and environmental characteristics with the DM prevalence: food shops (SLM coefficient = 9.625, $p<0.001$; SEM coefficient = 9.695, $p<0.001$), alcohol stores (SLM coefficient = 1.936, $p<0.05$; SEM coefficient = 1.894, $p<0.05$), population density of elderly people (SLM coefficient = 0.156, $p<0.05$; SEM coefficient = 0.188, $p<0.05$) and night-time light density (SLM coefficient = -0.437, $p<0.001$; SEM coefficient = -0.437, $p<0.001$). These findings are useful for policymakers and public health professionals in formulating measures aimed at reducing DM burden in the country.

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Introduction

According to the World Health Organization (WHO) and other institutions related to public health, diabetes mellitus (DM) is a serious public health problem (WHO, 2016; Williams *et al.,* 2020). About 70% of DM patients reside in low- and middle-income countries (Esterson *et al.,* 2014). The burden of DM is expected to increase faster in Asia (Rhee, 2015) and the prevalence of adult type-2 diabetes in Thailand rose from 2.3% in 1991 to 8.0% in 2015 (Papier *et al.*, 2017). DM affects the quality of life as it leads to significant morbidity and premature fatality (Atlas, 2015; Bukhman *et al.*, 2015; Khan *et al.*, 2020). Rapid economic development and urbanisation have led to a rising DM burden globally (Williams *et al.*, 2020). Unhealthy diets and sedentary lifestyles, resulting in overweight, obesity and rising plasma glucose levels have been identified as factors that significantly modify risk. Persons with a higher body mass index (BMI) and those having reached older age are more likely to have type-2 diabetes (Bahijri *et al.*, 2016; Bommer *et al.*, 2017; Avilés-Santa *et al.*, 2020). As a consequence, the global impact and cost of DM are expected to grow significantly (Bommer *et al.*, 2017; Bommer *et al.*, 2018). Already today, the cost of care per capita for this disease is at least 3.2 times higher than the average healthcare expenditure, and 9.4 times in case of complications (Khan *et al.*, 2020).

Many environmental factors, especially the socioeconomic ones, influence DM development. Examples include access to healthy food (Salois, 2012), population density (Hipp and Chalise, 2015) and night-time light (NTL) that can substitute for other variables, such as urbanisation, density and economic growth. The connection between remotely sensed NTL imagery provides a straightforward method to analyze the relationship between urbanisation and human activities. Due to the exclusive capability of the US Defense Meteorological Satellite Program - Operational Linescan System (DMSP - OLS) to detect low levels of visible and near-infrared night-time radiance signals, the composed stable NTL data have been used for mapping urban areas, estimating the spatial expand trends of cities and measuring socioeconomic activities (Fan *et al.*, 2014; Montoya-Betancur *et al.*, 2020).

Geographic information systems (GIS) and spatial analysis are increasingly applied for investigating spatial patterns of diseases. In particular, the use of the local indicators of spatial association

(LISA) according to Anselin (1995) has demonstrated its usefulness in epidemiological studies, including DM (Hipp and Chalise, 2015). Geospatial analysis has shown that non-communicable diseases (NCDs) are prevalent in the elderly, particularly in those living in urban areas with access to high alcohol and tobacco consumption (Shil *et al.,* 2018; Tuoane-Nkhasi and van Feden, 2017). Although several studies have examined prevalence and other factors associated with DM, spatial analysis has rarely been used to investigate the presence of potential DM clusters in Thailand.

Satellite-generated remote-sensing data are useful for the collection of information, such as NTL, urbanisation and public accessibility, but is limited with regard to socioeconomic variables, e.g., economic status and behavioural risk factors in identified geographical areas. Environmental risk factors constitute an important cause of disease burden and their impact on NCDs, specifically air pollution, a unhealthy life (diet and lifestyle) and work environment, have been publicised (Pou *et al*., 2017; Flies *et al*., 2019). Factors, such as presence of alcohol/convenience stores and a high concentration of elderly population can be used as proxies for health and behaviour that influence DM prevalence (Kahr *et al.*, 2016; Papier *et al.*, 2016; Pérez-Ferrer *et al.*, 2020; Williams *et al.*, 2020).

The objective of this study was to quantitatively examine the potential association between NTL, distribution of alcohol/convenience stores and the concentration of the elderly population on the one hand and the prevalence of DM in middle-aged and elderly people of Thailand on the other. The findings should provide informed evidence for policymakers, academics, researchers and related environmental sectors at local and national levels for interventions with regard to prevention and control in areas at risk for type-2 diabetes.

Materials and Methods

Study area

This study focused on Thailand, an upper-middle-income country located in the centre of the Indochinese Peninsula, Southeast Asia. Thailand shares borders with Myanmar, Laos, Cambodia and Malaysia covering 514,000 km^2, with a population of almost 70 million. The country is divided into 77 provinces, including metropolitan Bangkok, the capital city.

Data sources

Secondary data from various publicly available sources were used for the analysis. The dependent factor was DM prevalence. These data were collected in 2019 by the Health Data Centre (HDC), Thailand's Ministry of Public Health. The dependent variable was defined as a person diagnosed as diabetic, who has continuously been receiving treatment but still had plasma glucose levels of 126 mg/dL or higher after overnight fasting. A total of 4,235,113 participants who were 40 years old or above and met these inclusion criteria were included in this study.

The independent variables were the provincial density of alcohol/convenience stores from the Thai Center of Alcohol Studies (https://cas.or.th/?page_id=6305). The provincial concentration of elderly populations (people who were 60 years old or above) was acquired from the National Statistical Office of Thailand. The location of food shops (convenience stores and facilities with access to fast food, café and bars) was obtained from OpenStreetMap (https://www.openstreetmap.org) and the density per km^2 was calculated using Quantum GIS (QGIS), version 3.16.2. The NTL data for Thailand were extracted from the US Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP - VIIRS) satellite, available via the Google Earth Engine (https://earthengine.google.com).

Local spatial-pattern detection methods

QGIS (https://qgis.org) was used to aggregate exploratory spatial data. Spatial autocorrelation and spatial regression analyses were conducted using GeoDa (https://geoda.software.informer.com/1.6/), version 1.6.6, identifying the statistically significant DM spatial distribution and its associations with other socio-demographic factors. Stata (Stata Corp, College Station, TX, USA), version 16.0 was used to calculate the DM prevalence for each province.

Statistical approach

The GeoDa program was used to analyse spatial autocorrelation and determine the spatial regression of geographical factors, economy, demographics and prevalence of DM in Thailand. Distance served as a criterion for the weight matrix, and the spatial correlations were analysed. (Cliff and Ord, 1981; Anselin *et al.*, 2010). The Moran scatter plot comprises the spatially lagged variable on the x and y coordinates of the original independent variables with the spatial correlation expressed by Moran's *I* statistic (Cliff and Ord, 1981; Anselin *et al*., 2010). The value of +1 indicates a strong positive spatial autocorrelation, implying clusters of similar values. Conversely, 0 means random spatial ordering, while −1 identifies strong negative spatial autocorrelation (Anselin *et al*., 2010). Global Moran's *I* statistic (Moran, 1950) is a frequently used method to compute the degree of spatial correlation. It measures spatial autocorrelation based on feature presence and values simultaneously as follows:

$$\text{Moran's } I = \frac{N \sum_{ij} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{ij} W_{ij} \sum_i (X_i - \bar{X})^2} \quad (1)$$

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 $(X_j - \bar{X})$ and the deviation of X_j from its mean.

The value computed using this equation indicates the correlation between X_i and its neighbours 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, Local Moran *I* was developed by Anselin (1995) who extended the mathematical fundamental of Moran's *I* under the name of LISA. Its mathematical equation is as follows:

$$LocalMoran\text{'s } I_i = \frac{(X_i - \bar{X}) \sum_j W_{ij}(X_j - \bar{X})}{S_i^2} \quad (2)$$

where $S_i^2 = \frac{\sum_j (X_j - \bar{X})^2}{(N-1)}$; W_{ij} the spatial weight matrix; and N the number of spatial units.

We used LISA to determine the local spatial autocorrelation patterns of the variables depicting locations with significant (p<0.05) outcomes (LISA significance maps) and classified these locations according to association type (LISA cluster maps) as done by Montoya-Betancur *et al.* (2020). 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 the 32 full-border provinces and 23 coastal ones, including the island province, Phuket. Since the spatial weight matrix using the adjacent boundaries as criterion did not apply nationwide, we used a distance-based spatial weight matrix with a radius of 111.25 km 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 localisation of areas with particularly high or low presence of DM. Briefly, areas with high levels surrounded by other areas with high levels are DM clusters [called High-High (HH) or hotspots], while areas with low levels surrounded by other areas with low levels are clusters characterised by few DM cases or none [called Low-Low (LL) or coldspots]. 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 basically a presentation of autocorrelation, where both HH and LL are positive outcomes, while HL and LH are negative that the two former areas are similar and the two latter are different from each other with respect to the subject studied.

Spatial regression models were used to analyse the associations among socio-demographic factors and DM prevalence. 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 facts that it assumes that the relationship between dependent and explanatory variables is uniform in space and that it does not consider spatial autocorrelation, 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: in SLMs, the dependent variable depends on the dependent variable in the neighbouring space, whereas in SEMs, spatial influence arises only through error terms (Viton, 2010). Herein, we used the maximum likelihood to estimate the spatial regression models (Elhorst, 2010). The following equation represents the mathematical form of SLM.

$$Y_i = \beta_0 + \beta X_i + \rho W_{ij} Y_j + \varepsilon_i \tag{3}$$

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

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

$$Y_i = \beta_0 + \beta X_i + u_i; u_i = \lambda W_{ij} u_j + \varepsilon_i \tag{4}$$

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 and Tyrrell, 2002).The spatial autocorrelation of DM prevalence 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 was used for determining which of the two models (*i.e.* SLM or SEM) would be suitable (Anselin, 2001). In situations where both models had statistically significant LM values, the model with the lower value was selected. The Akaike information criterion (AIC) was used to find the model with of the best fit, *i.e.* the lowest AIC value (Akaike, 1974).

The approach used is described in the schematic workflow chart given in Figure 1.

Results

The overall DM prevalence was 8.67 per 100,000 inhabitants. The highest prevalence was found in Bangkok (15.37 per 100,000), with the lowest in Samut Prakarn with 2.73 per 100,000. The quantile distribution indicated the highest deciles (11.44–15.37 per 1,000 inhabitants in eight provinces (Bangkok, Nong Bua Lamphu, Nakhon Phanom, Phichit, Sa Kaeo, Ubon Ratchathani, Sukhothai and Kalasin) as seen in Figure 2.

Spatial distribution of the independent variables

The spatial distribution per km^2 of the four independent variables varied in the different provinces. The first was alcohol/convenience store distribution, with the highest deciles (2.47–26.24) found in 11 provinces (Rayong, Phra Nakhon Si Ayutthaya, Nakhon Phanom, Samut Songkhram, Chon Buri, Pathum Thani, Samut Sakhon, Nonthaburi, Phuket, Samut Prakan and Bangkok) as seen in Figure 3. The second variable was the density of food shops, cafés and bars. The quantile distribution indicated the high-

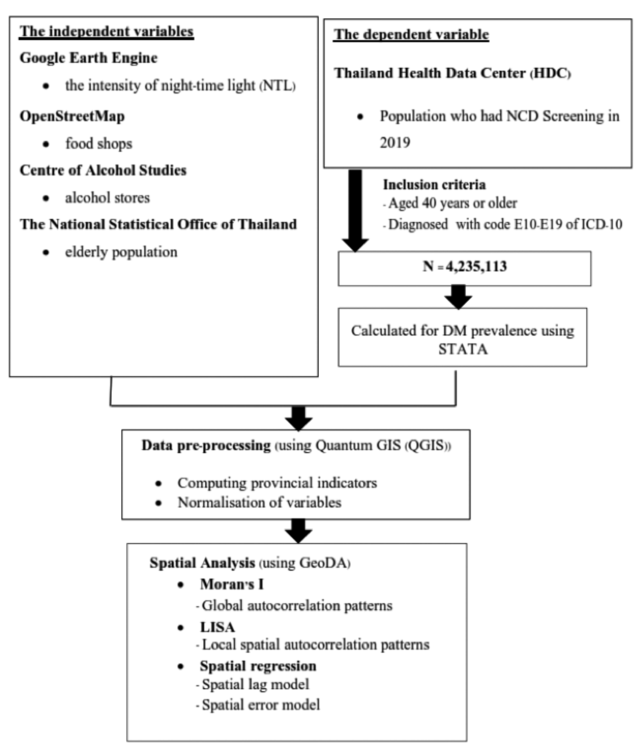

Figure 1. Workflow chart.

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est (0.021–1.156) in 16 provinces (Chiang Rai, Prachuap Khiri Khan, Nakhon Pathom, Surat Thani, Trat, Samut Sakhon, Chiang Mai, Samut Songkhram, Krabi, Rayong, Pathum Thani, Samut Prakan, Chon Buri, Nonthaburi, Phuket and Bangkok) as seen in Figure 4.

The third independent variable was the concentration of the elderly. The quantile distribution identified the highest (20.19–23.09) in nine provinces (Phayao, Lampang, Lamphun, Phrae, Uttaradit, Phichit, Sing Buri, Ang Thong and Samut Songkhram) as seen in Figure 5. The final variable was the mean density of the NTL. The decile distribution presented the highest (3.008–23.279) in 12 provinces (Chon Buri, Rayong, Bangkok, Samut Prakan, Samut Sakhon, Samut Songkhram, Phra Nakhon Si Ayutthaya, Nakhon Pathom, Nonthaburi, Pathum Thani and Phuket) as seen in Figure 6.

LISA results

Univariate Moran's I scatter of DM prevalence showed a positive spatial autocorrelation. Moran's I value was 0.163 at $p<0.05$ (Table 1). As shown in Appendix online, Figures 1-3, LISA indi-

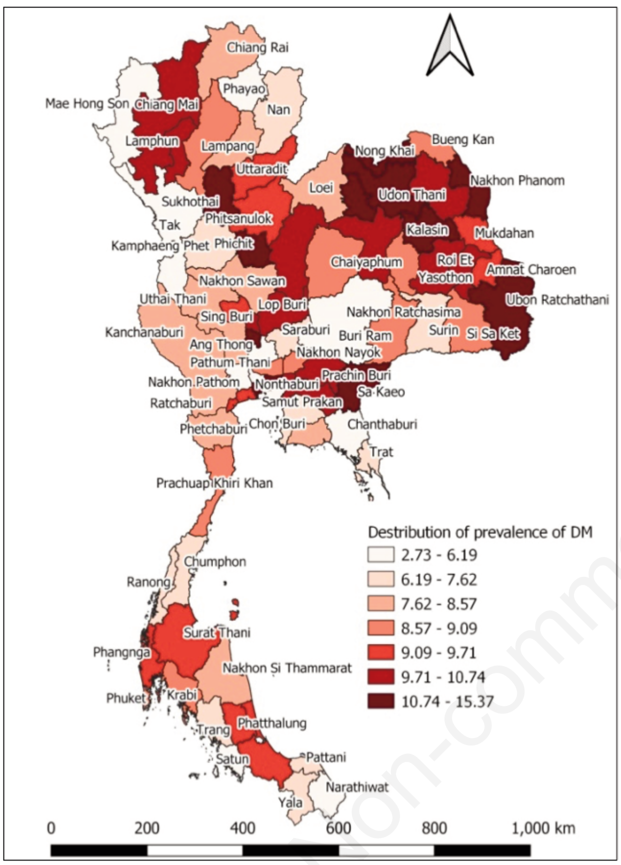

Figure 2. Spatial distribution of DM prevalence among the provinces in Thailand.

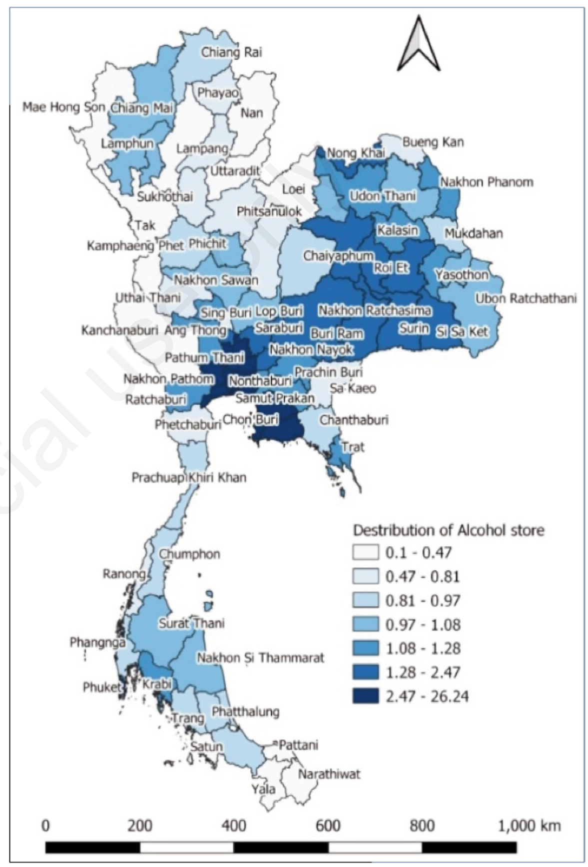

Figure 3. Spatial distribution of alcohol/convenience stores among the provinces in Thailand.

Table 1. Spatial diabetes prevalence clusters.

Factors	Moran's I	LISA High-High (7 Provinces)	LISA High-Low (1 Province)	LISA Low-Low (2 Provinces)	LISA Low-High (1 Province)
Diabetes prevalence	0.163	Nhongkai* MahaSarakham** UdonThani* SakonNakhon* Kalasin** Mukdahan** BuengKan**	Songkha*	Trat* Yala*	Loei*

* Correlation at p = 0.05 **Correlation at p = 0.01 ***Correlation at p = 0.001.

cated that the hotspots (*i.e.* the High-High clusters of DM prevalence) were primarily located in the upper north-eastern region of Thailand, including Nong Khai, Maha Sarakham, Udon Thani, Sakon Nakhon, Kalasin, Mukdahan and Bueng Kan. On the other hand, the coldspot (*i.e.* the Low–Low DM clusters) were scattered, with one located in the eastern region (Trat) and the other in the South (Yala).

Spatial autocorrelation analysis indicated the geographical clustering pattern of alcohol/convenience stores. Table 2 shows that the clusters of these stores were significant at $p<0.05$.

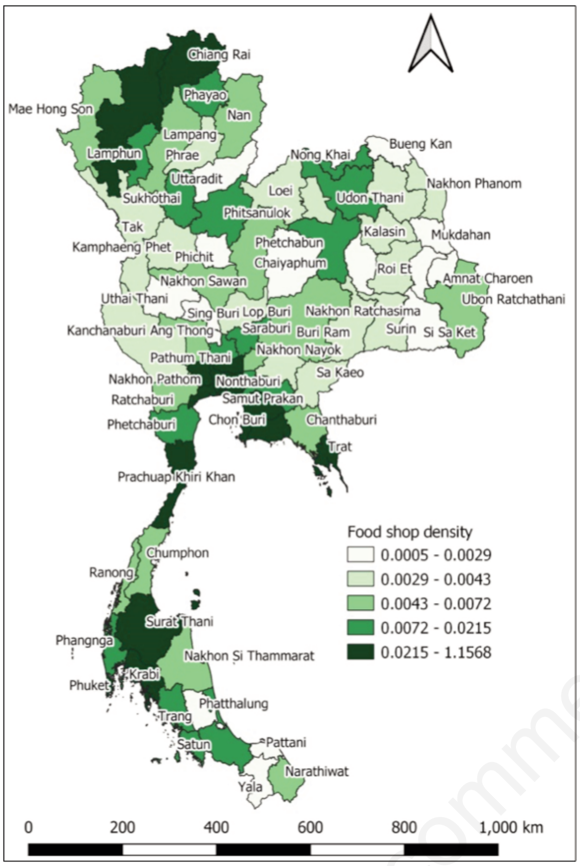

Figure 4. Spatial distribution of food shops among the provinces in Thailand.

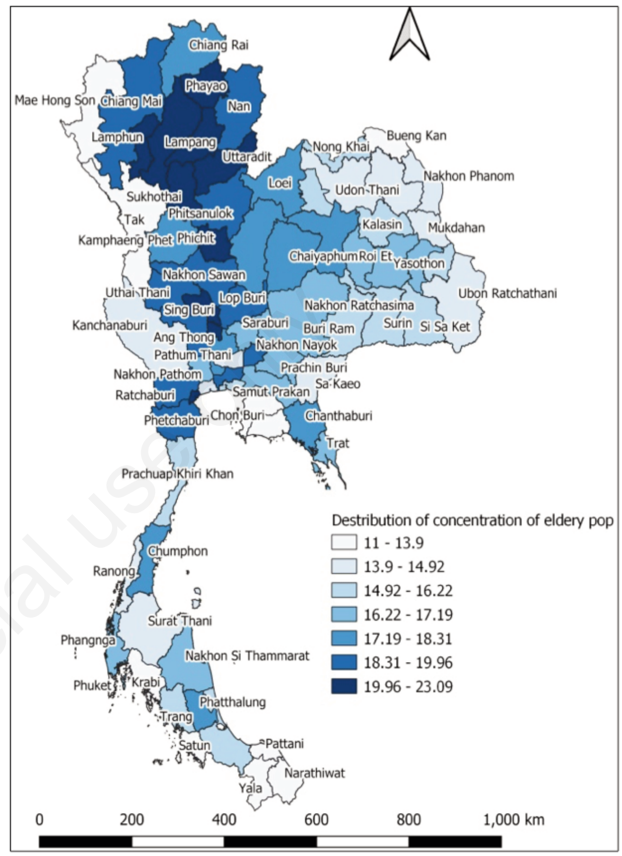

Figure 5. Spatial distribution of concentration of elderly among the provinces in Thailand.

Table 2. Spatial clusters of alcohol/convenience stores.

Factors	Moran's *I*	LISA			
		High-High (6 Provinces)	High-Low (None)	Low-Low (15 Provinces)	Low-High (7 Provinces)
Alcohol/ convenience store	0.113	Samut Prakan* SamutSakhon* Samut Songkhram* Nakhon Pathom* Phra Nakhon Si Ayutthaya* Ang Thong*	none	Songkhla*** Satun* Yala** Pattani*** Narathiwat* Chiang Mai* Lamphun* Lampang* Phayao* Nan* Phitsanulok* Phrae** Uttaradit*** Sukhothai** KamphaengPhet*	Ratchaburi*** Suphan Buri*** Saraburi** Sing Buri** Prachin Buri*** Chachoengsao*** Nakhon Nayok**

* Correlation at p = 0.05 **Correlation at p = 0.01 ***Correlation at p = 0.001.

Univariate Moran's *I* scatter for the density of alcohol/convenience stores showed a positive spatial autocorrelation, with a value of 0.113. However, as illustrated in Appendix online, Figures 4-6, LISA indicated six hotspots in Samut Prakan, Samut Sakhon, Samut Songkhram, Nakhon Pathom, Phra Nakhon Si Ayutthaya and Ang Thong. This result also identified 15 coldspots located in Songkhla, Satun, Yala, Pattani, Narathiwat, Chiang Mai, Lamphun, Lampang, Phayao, Nan, Phitsanulok, Phrae, Uttaradit, Sukhothai and Kamphaeng Phet.

Table 3 shows the cluster pattern of the convenience stores, fast food outlets, cafés and bars). Univariate Moran's *I* statistics for the distribution of these facilities showed a positive spatial autocorrelation. Moran's *I* value of 0.214 was statistically significant ($p<0.05$), thus indicating clustering. Furthermore, as depicted in Appendix online, Figures 7-9, LISA showed five hotspots in Samut-Prakan, Saraburi, Samut Songkhram and Phangnga provinces. Meanwhile, ten coldspots were found in Yasothon, Amnat-Charoen, Mukdahan, Nakhon-Sawan, Nakhon-Pathom, Uthaihani, Ubon Ratchathani, Surin, Roi-Et and Sakon-Nakhon.

Table 4 shows the clusters of the average NTL concentrations. Univariate Moran's *I* of the NTL density showed a positive spatial autocorrelation. The value of 0.504 was statistically significant ($p<0.05$) revealing spatial concentration in many areas. As shown in Appendix online, Figures 10-12, LISA indicated 18 hotspots in Ang Thong, Chon Buri, Chachoengsao, Nakhon Pathom,Nakhon Nayok, Nontha Buri, Phetcha Buri, Pathum Thani, Prachin Buri, Phra Nakhon Si Ayutthaya, Ratcha Buri, Sing Buri, Sara Buri, Samut Songkhram, Samut Sakhon, Samut Prakan, Suphan Buri and Bangkok, which are all situated in central Thailand. Conversely, 18 coldspots were found in Amnat Charoen, Nakhon Pathom, Nong Khai, Lampang, Phitsanulok, Phrae, Uttaradit, Loei, Nong Bua Lamphu, Mukdahan, Ubon Ratchathani, Sisaket, Surin, Sukhothai, Sakon Nakhon, Yasothon, Roi Et and Kalasin. Most of these NTL coldspot provinces were located in the North and also in north-eastern regions.

Table 5 shows the density clusters of the elderly populations. Univariate Moran's *I* showed a moderately positive spatial autocorrelation of elderly population density with a value of 0.449 at $p<0.05$. Confirming the clustering pattern as illustrated in Appendix online, Figures 13-15, LISA showed 20 hotspots in Phayao, Nan, Phrae, Lampang, Lamphun, Uttaradit, Sukhothai, Phichit, Nakhon Sawan, Uthai Thani, Lopburi, Phranakhon Si Ayutthaya, Suphan Buri, Nakhon Pathom, Ang Thong, Bangkok, Sing Buri, Nontha Buri and Chainat. Coldspots were located in Nhongkai, Songkha, Pattani, Yala, Narathiwat and Phangnga.

Spatial regression results

Results of OLS regression were estimated with only four significant factors: concentrations of alcohol/convenience stores, food shops, NTL and elderly inhabitants. The OLS model explained approximately 26.3% of the DM prevalence ($R^2 = 0.263$).

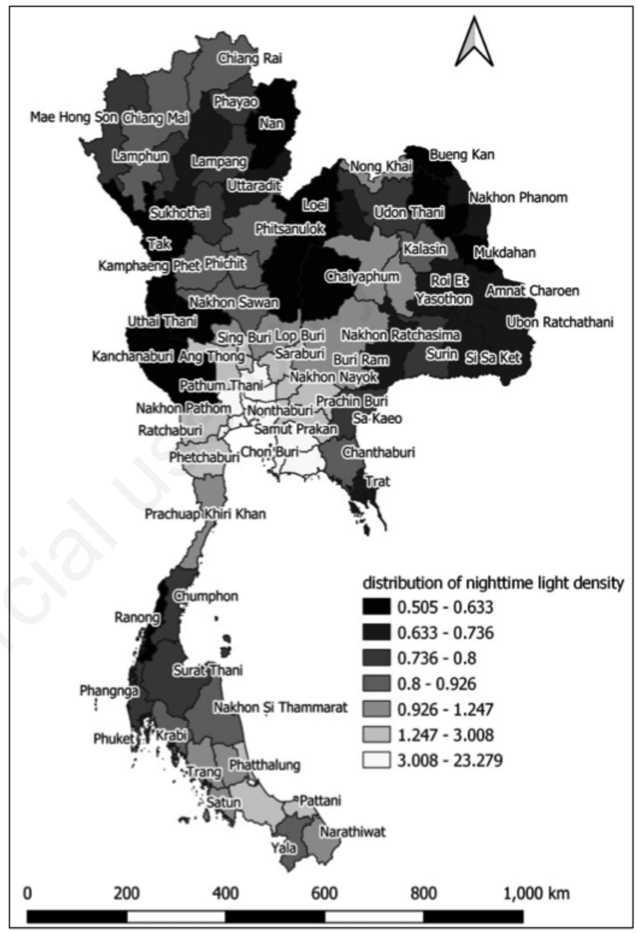

Figure 6. Spatial distribution of NTL density among the provinces in Thailand.

Table 3. Spatial clusters of convenience stores, fast food outlets, cafés and bars.

Factors	Moran's *I*	LISA			
		High-High (4 Provinces)	High-Low (3 Provinces)	Low-Low (10 Provinces)	Low-High (7 Provinces)
Food shops	0.214	Samut Prakan* Saraburi* Samut Songkhram** Phangnga*	Nong Khai* Udon Thani* Khon Kaen*	Yasothon* Amnat Charoen* Mukdahan* Nakhon Sawan* Nakhon Pathom** Uthai Thani* Ubon Ratchathani** Surin* Roi Et** Sakon Nakhon*	Ang Thong* Sing Buri* Suphan Buri* Ratcha Buri*** Chachoengsao*** Prachin Buri** Nakhon Nayok*

* Correlation at p = 0.05 **Correlation at p = 0.01 ***Correlation at p = 0.001.

The SLM model estimated all factors as statistically significant at the p=0.05 level, explaining approximately 31.0% ($R^2 = 0.310$) of the variables. The SEM showed that the presence of all factors (alcohol/convenience stores, food shops, NTL, and density of elderly people) was significant and explained approximately 31.6% of the DM prevalence ($R^2 = 0.316$).

SEM was found to be the best regression model because parameter estimation showed significant explanatory factors for DM prevalence. Concentration of elderly people, alcohol/convenience stores and other food shops were factors positively associated with DM prevalence, whereas NTL was a negatively correlated one. The R^2 value indicated that SEM accounted for 31.6% of the variation in DM prevalence. In the AIC test, SEM slightly outperformed SLM (325.259 versus 327.557, respectively).

Table 4. Spatial clusters of NTL density.

Factors	Moran's *I*	LISA High-High (18 Provinces)	LISA High-Low (None)	LISA Low-Low (18 Provinces)	LISA Low-High (None)
Night time light	0.504	Ang Thong*** Bangkok*** Chon Buri** Chachoengsao*** Nakhon Pathom*** Nakhon Nayok*** Nontha Buri*** Phetcha Buri*** Pathum Thani*** Prachin Buri*** PhraNakhon Si Ayutthaya*** Ratcha Buri*** Sing Buri*** Sara Buri*** Samut Songkhram*** Samut Sakhon* Samut Prakan* Suphan Buri*		Amnat Charoen** Nakhon Pathom* NongKhai* Lampang* Phitsanulok* Phrae* Uttaradit*** Loei* Nong Bua Lam Phu** Mukdahan** Ubon Ratchathani** Si Sa Ket* Surin* Sukhothai* Sakon Nakhon* Yasothon* Roi Et* Kalasin*	

* Correlation at p = 0.05 **Correlation at p = 0.01 ***Correlation at p = 0.001.

Table 5. Spatial clusters of elderly population density.

Factors	Moran's *I*	LISA High-High (20 Provinces)	LISA High-Low (1 province)	LISA Low-Low (6 Provinces)	LISA Low-High (4 Provinces)
Density of elderly inhabitants	0.449	Phayao** Nan*** Phrae*** Lampang** Lamphun** Uttaradit*** Sukhothai** Phichit* NakhonSawan** UthaiThani** Lopburi** Phranakhon Si Ayutthaya* SuphanBuri** NakhonPathom** AngThong* Bangkok** Sing Buri* Nonthaburi ** Chainat*	Pathalung*	Nhongkai* Songkha*** Pattani*** Yala** Narathiwat* Phangnga**	Kanchanaburi* SamutSakhon* Pathum Thani* Saraburi*

* Correlation at p = 0.05 **Correlation at p = 0.01 ***Correlation at p = 0.001.

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Therefore, SEM showed better performance in explaining the geographical distribution of DM prevalence in our study of the middle-aged and elderly people in Thailand (Table 6).

Discussion

In this study, a variation in DM prevalence was observed among middle-aged and elderly people in Thailand. The LISA result indicated six hotspots of high DM prevalence, primarily located in the upper north-eastern region. This concentration of DM was associated with the clusters of low NTL density, *i.e.* cold spots of 18 provinces located in the north-eastern region. Our findings further suggest that socio-demographic and environmental factors are positively correlated with DM prevalence, including a higher than normal density of elderly people and presence of alcohol/convenience stores and food shops. Conversely, NTL was a negative factor. Indeed, previously published literature argues that the NTL data might represent the socioeconomic context, lifestyle, health care facilities and a healthy diet (Laohasiriwong *et al*., 2018). Moreover, these previous studies also report that the north-eastern region had the highest prevalence of type-2 DM.

NTL can predict a correlation with the prevalence of type-2 DM. As conventionally acknowledged, NTL is a good proxy for economic activity. Thus, NTL data are useful in quantitatively characterising socioeconomic, such as urbanisation and an active life, but also a good lifestyle including a healthy diet (Perez-Sindin *et al*., 2021). Moreover, an association between DM prevalence and the most developed municipalities was found and explained by various factors. In particular, poverty has been shown to have an association with the prevalence of DM (Hipp and Chalise, 2015). However, some of our results contradict WHO's note that urbanisation is associated with an incidence of increased chronic disease owing to differences in lifestyles (WHO, 2012). The density of the elderly population could predict a correlation with the prevalence of type-2 DM. Age is one of the critical risk factors in developing pre-diabetes and type-2 DM. The prevalence of diabetes increases at older ages along with impairment of homeostasis and metabolism. As reported in many studies, the prevalence of insulin secretion and insulin resistance are the most common cause of hyperglycaemia (Chia *et al.*, 2018; Forjuoh *et al*., 2011; Mordarska and Godziejewska-Zawada, 2017).

Notably, the consumption of alcohol was found to be associated with the number of DM in most areas. Our findings suggest that environmental factors are significantly correlated with DM prevalence. One of the most important findings of our study was the density of alcohol/convenience stores in areas with high DM presence. Indeed, excessive consumption of alcohol and tobacco are the most significant risk factors for NCDs (Bathna *et al.*, 2019) and geospatial analysis of the impact of NCDs in Indian agro-climatic and political regions shows that alcohol and tobacco consumption is exceptionally high in regions with a high NCD burdens (Shil *et al.*, 2018).

Diabetes incidence and prevalence are higher in people who live in or move to areas with a high density of convenience stores and fast food outlets (Christine *et al*., 2015; Gebreab *et al*., 2017; Mezuk *et al*., 2016). In accordance, our results indicate that there is an association between the density of cafés and convenience stores selling fast food and alcohol beverages on the one hand and DM prevalence on the other. The possible reasons are the influences of food choice, food accessibility, and eating habits. These processes present technological and transport innovations that may increase consumption and promote sedentary lifestyles and behaviour (Oggioni *et al*., 2014).

Table 6. OLS and spatial regression results.

Independent variable	OLS	Spatial regression model	
		SLM	SEM
NTL	-0.467*** (0.129)	-0.437*** (0.121)	-0.437*** (0.129)
Concentration of elderly people	0.155* (0.075)	0.156* (0.071)	0.188* (0.081)
Alcohol store	2.178* (0.926)	1.936* (0.866)	1.894* (0.948)
Presence of food shops (convenience stores with fast food, cafés and bars)	9.821*** (2.374)	9.625*** (2.214)	9.695*** (2.256)
Constant	8.029*** (1.684)	5.341*** (1.945)	7.491*** (1.783)
ρ		0.275* (0.131)	
λ			0.306* (0.140)
F-stat	5.077		
R^2	0.263	0.310	0.316
Log Likelihood	-158.662	-156.779	-156.629
AIC	329.323	327.557	325.259
BIC	343.386	343.964	339.321

* A significant level of 0.05. **A significant level of 0.01. ***A significant level of 0.001. The dependent variable is the logarithm of DM prevalence, and standard errors are in parentheses. OLS = ordinary least squares; SEM = spatial error model; SLM = spatial lag model; and NTL = night-time light.

While many previous studies identified risk factors associated with diabetes, our study showed spatial autocorrelation of DM prevalence and socio-demographic as well as environmental factors. Therefore, it could assist policymakers in targeting populations at risk of DM in relation to administrative and policy implementation. However, our study also has some limitations and requires future extensions. Firstly, environmental factors such as data identifying the location of alcohol store might not be updated. Hence, the real-time open database such as OpenStreetMap can extensively provide geospatial data with finer spatiotemporal details. Secondly, new techniques such as machine learning can be applied to increase the accuracy of prediction and causality investigation. Thirdly, the web-based application can be developed and publicly accessible through a cloud-based platform such as Google Earth Engine, providing a timely dataset for future research.

Conclusions

Socio-demographic and environmental factors were associated with high DM prevalence. The main finding, indicated by the spatial regression result, emphasises the impacts of greater availability of shopping centres, supermarkets, cafés, fast food restaurants, alcohol consumption, and elderly density on DM prevalence.

The main findings of this study could be useful for policymakers, medical practitioners, and researchers to reduce DM burden in Thailand owing to regional differences in DM burden. Specifically, the obtained analytical results could help policymakers prioritise programs aimed at reducing DM prevalence relevant to the geographic and socio-demographic context of the region, especially the upper north-eastern region, where DM prevalence is remarkably high. Thus, efforts should be devoted to strengthening health education and public-policy measures to counteract excessive drinking, such as increasing the excise tax on alcohol, limiting alcohol advertising and promoting healthy behaviour (especially diet and physical activity). Furthermore, applications of spatial analysis using open data and open-source software packages in public-health planning should be promoted and extended to other diseases.

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