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Spatial Association Between Environmental Factors, Physical Geographic Factors and Chronic Obstructive Pulmonary Disease (COPD) in Thailand

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Abstract

This study aimed to identify the prevalence and factors associated with tobacco outlet density on the prevalence of chronic obstructive pulmonary disease (COPD) in Thailand. Using data from the Health Data Center (HDC) of the Ministry of Public Health from 2016 to 2020, this study included 185,891 eligible participants. Data on tobacco outlet density, elderly population density, average nighttime light, and average $PM_{2.5}$ concentration were analyzed for spatial associations using Moran's I, Local Indicators of Spatial Autocorrelation (LISA), and spatial regression analysis. The prevalence of chronic obstructive pulmonary disease (COPD) per 100,000 population was highest in Nan province at 900.30, and lowest in Pathum Thani province at 121.27. When categorized into deciles, the provinces in the highest prevalence group (622.17 – 900.30) included Chiang Rai, Chiang Mai, Tak, Nan, Phayao, Phatthalung, Phichit, and Lampang, as detailed. The results showed a positive spatial autocorrelation of COPD prevalence using Univariate Moran's I (Moran's I = 0.313). LISA analysis revealed high-risk clusters (hot spots or High-High) of COPD prevalence in the northern region. Bivariate Moran's I analysis identified: Cold-spot or low-low clusters (LL) for both tobacco outlet density and COPD prevalence in 7 provincial clusters. LL clusters for average nighttime light and COPD prevalence in 6 provincial clusters. High-High (HH) clusters for elderly population density and COPD prevalence in 4 provincial clusters, and LL clusters in 6 provincial clusters. HH clusters for $PM_{2.5}$ concentration and COPD prevalence in 3 provincial clusters, and LL clusters in 8 provincial clusters. Comparison of spatial regression models, with and without spatial considerations, revealed that the Spatial Lag Model (SLM) was the most appropriate. The SLM explained 36.10% of the variance in COPD prevalence ($R^2 = 0.361$) and identified the following statistically significant spatial factors: Tobacco outlet density (coefficient = 0.223, $p < 0.05$), Average nighttime light (coefficient = -20.870, $p < 0.01$), Elderly population density (coefficient = 16.914, $p < 0.01$).

Keywords: Chronic Obstructive Pulmonary Disease (COPD); Tobacco outlet density; Nighttime light; Elderly population density; $PM_{2.5}$ concentration

1. Introduction

Chronic Obstructive Pulmonary Disease (COPD) is a group of common, chronic obstructive lung diseases and is a leading cause of death worldwide. It results from chronic irritation of the lungs caused by dust and noxious gases, primarily cigarette smoke, leading to an abnormal inflammatory response both in the lungs and other bodily systems (Calazans, *et al.,* 2023).

COPD is a significant cause of morbidity and mortality globally. Currently, it ranks as the 5th leading cause of death. In 2000; 2,750,000 deaths were attributed to COPD, a 1.3-fold increase over the preceding 15 years. Mortality rates from COPD are increasing by approximately 30% every decade, signifying that one person dies from COPD every 15 seconds, or about 250 people every hour worldwide. Projections indicate that COPD will become the 3rd leading cause of death by 2030. Statistics from the World Health Organization (WHO) show that there are approximately 210 million people currently living with COPD, accounting for 10% of the adult population (Ninkron, *et al,* 2024).

In Thailand, approximately 1.5 million people suffer from COPD (Division of Tuberculosis, Department of Disease Control, Ministry of Public Health, 2023). The Bureau of Strategy and Planning, Office of the Permanent Secretary, Ministry of Public Health, reported COPD prevalence rates from 2016 to 2019 as 391.47, 386.26, 388.95, and 386.17 per 100,000 population, respectively. These figures highlight the increasing morbidity and mortality rates of COPD, making it a major public health concern both nationally and globally (Bureau of Policy and Strategy (BPS), 2023)

Tobacco Control Research and Knowledge Management Center TRC. (2022). It can be concluded that every smoker is at risk of developing COPD, with the time of onset dependent on the amount and duration of smoking (Aggarwal AN, 2022). Reducing the global incidence of COPD necessitates mitigating key risk factors, particularly smoking and access to tobacco products (WHO, 2022). Surveys on tobacco sales in Thailand, revealing access to points of sale, indicate that cigarette sales figures between 2014 and 2019, according to the Annual Report on Tobacco Control in Thailand, show that domestic cigarette consumption (Market Size) consistently exceeds the combined figures for domestic sales and exports. This suggests a relatively stable, potentially slight decrease (for non-domestically produced cigarettes) of approximately 10 billion cigarettes annually. Analyzing the trends in domestic cigarette consumption and sales reveals a decline in consumption from around 40 billion cigarettes in 2014 to approximately 32 billion cigarettes in 2019. This indicates a marginal reduction in cigarette consumption over a 5-year period. Similarly, domestic sales volume decreased by more than half, from 30,319 million cigarettes in 2014 to 18,508 million cigarettes in 2018 (Tobacco Control Research and Knowledge Management Center. Report on the situation of tobacco consumption in Thailand, 2022).

Therefore, the density of tobacco outlets is a crucial factor, as it represents an economic, social, and environmental influence that contributes to the risk of developing COPD. Unhealthy lifestyle choices and increased accessibility to convenience stores or tobacco outlets create an environment conducive to exposure to risk factors that accelerate the development of COPD (Lee, *et al.,* 2022).

Moreover, modeling the impact of changes in tobacco outlet density on COPD prevalence may reveal variations in disease patterns across different regions. The average density of tobacco outlets or accessibility to these outlets serves as a controlling factor for COPD prevalence. Trends in changing tobacco outlet density can be used to predict the incidence of the disease resulting from these changes.

This study aimed to analyze the spatial relationship between COPD prevalence and changes in tobacco outlet density, and to investigate the patterns of COPD prevalence under the influence of these changes in Thailand from 2018 to 2022. The findings can inform the development of preventive measures, including planning and controlling access to risk factors associated with tobacco outlets in the future, thereby effectively reducing the prevalence of COPD.

2. Methodology

2.1 Study area

This study focuses on Thailand, a middle-income country located in the heart of Southeast Asia, bordering the Andaman Sea and the Gulf of Thailand. Thailand shares borders with Lao PDR and Cambodia to the east, Myanmar to the north and west, and Malaysia to the south, encompassing a total land area of 513,120 square kilometers. With a population of nearly 70 million people, the country is administratively divided into 76 provinces, excluding the capital city, Bangkok. It exhibits unique characteristics that differentiate it from other provinces, including high data density and complexity, distinct spatial features as a metropolitan area, and uneven distribution of certain data types.

2.2 Data sources

This study utilized secondary data from the Health Data Center (HDC) of the Ministry of Public Health of Thailand. The study population comprised individuals aged 15 years and older diagnosed with COPD across all 76 provinces of Thailand. The final sample, extracted from the HDC database for the fiscal year 2022, consisted of 185,891 individuals meeting the predefined inclusion criteria. Data were organized into standardized formats according to the Ministry of Public Health's health data standards framework (43 files). Variables for this study were selected based on a review of relevant concepts, theories, and prior research, utilizing the "CHRONIC" standard file, which encompasses data on all individuals aged 15 years and older residing within the designated catchment areas or seeking services, including data on chronic diseases, date of diagnosis, and initial diagnosing healthcare facility.

The independent variable, tobacco outlet density, was obtained from OpenStreetMap (https://www.openstreetmap.org). Nighttime light (NTL) data for Thailand were extracted from the US Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) satellite imagery, accessed via Google Earth Engine (https://earthengine.google.com). Provincial-level data on the proportion of the elderly population (aged 60 years and above) were acquired from the National Statistical Office of Thailand. $PM_{2.5}$ data, available in preprocessed MS Excel format for the year 2022, were processed to derive average values per square kilometer for each province.

2.3 Local spatial-pattern detection methods

QGIS 3.16 Hannover (https://qgis.org) was employed for the compilation and visualization of geospatial data. Spatial autocorrelation and regression analyses were performed using GeoDa (https://geoda.software.informer.com/1.6/) version 1.6.6, to identify statistically significant spatial clusters of COPD and their associations with other sociodemographic factors. Stata (Stata Corp, College Station, TX, USA) version 16.0 was utilized to calculate COPD prevalence rates for each province.

2.4 Statistical approach

Data analysis was conducted using STATA, Quantum GIS, and GeoDa software. Descriptive statistics, including percentages, means, maximum and minimum values, standard deviations, medians, and incidence rates per 100,000 population, were calculated for COPD patients, tobacco outlet density, and the proportion of the elderly population.

GeoDa was employed to perform spatial autocorrelation analysis and determine the spatial regression of geographic, economic, demographic, and COPD prevalence rates in Thailand. Distance served as the criterion for the weight matrix, and spatial relationships were analyzed following the methodologies outlined (Cliff and Ord,1981; Anselin, 2022). Moran scatterplots were generated with spatially lagged variables on the y-axis and the original independent variables on the x-axis. Spatial relationships were quantified using Moran's I statistic (Cliff and Ord, 1981; Anselin, 2022), where a value of +1 indicates strong positive spatial autocorrelation (clustering of similar values), 0 represents random spatial arrangement, and -1 indicates strong negative spatial autocorrelation; clustering of dissimilar values (Anselin, 2022). Global Moran's I, a commonly used method to quantify the degree of spatial autocorrelation, was calculated to measure the spatial autocorrelation based on the co-occurrence of attribute values.

Spatial analysis was performed to investigate spatial autocorrelation and identify neighboring relationships. Contiguity-based spatial weights, defining neighboring relationships based on shared borders, were determined for all 76 provinces in Thailand. Cluster analysis was conducted using weight matrices. Spatial correlation analysis, specifically Bivariate Moran's I, was employed to analyze clustering patterns and outliers, where independent variables exhibited a random or non-specific distribution within sub-regions.

Local Indicators of Spatial Association (LISA) analysis was used to identify statistically significant local clusters, indicating areas where neighboring regions had similar values for independent variables.

Spatial regression analysis was performed to develop predictive models of the spatial relationship between tobacco outlet density and COPD incidence. Two models, the Spatial Lag Model (SLM) and the Spatial Error Model (SEM), were compared based on their R-squared, AIC and BIC. The approach used is described in the schematic workflow chart given in Figure 1.

Spatial regression models were used in analyzing the associations among factors and prevalence of COPD. The three main specifications of spatial regression models are (1) traditional OLS regression, (2) spatial lag model (SLM), and (3) spatial error model (SEM). SLM is mathematically defined, as shown in Equation is as follows;

$$y_i = \rho W_{ij} y_j + X_i \beta + u_i$$

Alternatively, using the SEM specification, the spillover effect can be integrated into regression. This framework, in particular, permits the spatial influence of a location j to affect the area i via the disturbance cross-boundary relation. SEM is mathematically defined, as shown in Equation is as follows;

$$y_i = X_i \beta + u_i; \quad u_i = \lambda W_{ij} u_j + \varepsilon_i$$

The conventional form of the regression equation, defining the combination of independent variable X_i and disturbance u_i jointly determining the dependent variable y_i. Specifies a spillover influence originating from u_j and affecting u_i through the spillover coefficient λ and the spatial weight matrix W_{ij}. The statistical significance of λ verifies the existence of spatial influence identified in SEM form by using statistical inference. The error term is ε_i, which is independent and identically distributed (Anselin, 2022).

The OLS regression has significant limitations in that it frequently assumes that the relationship between dependent and explanatory variables is uniform in space and does not account for spatial autocorrelation, which is frequently regarded as an outright violation of the classical regression model's principle of observation independence. Given that an OLS regression fails to detect the spillover effect, the usual specification is adjusted to include the impacts of neighboring areas, resulting in the SLM and SEM formulations. SLM presupposes a direct

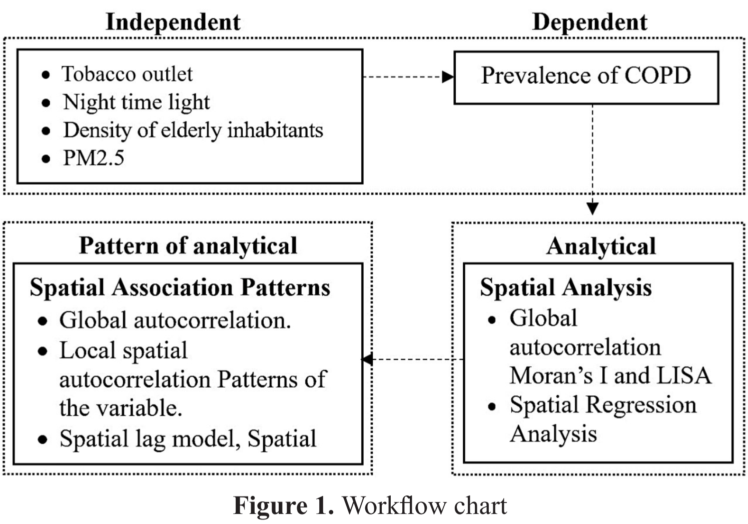


Figure 1. Workflow chart

spatial influence between a specific location and its surroundings and is based on a spatially lagged dependent variable. Meanwhile, by allowing the influence of neighboring areas to pass through the disturbance term, SEM integrates indirect spatial dependency into the regression model. (Fotheringham, *et al.,* 2023) The Akaike Information Criterion (AIC) value was also utilized to compare the model to the spatial regression model as a model selection decision indicator. It denotes a model with a high degree of goodness of fit. Models with small AIC values indicate a good fit.

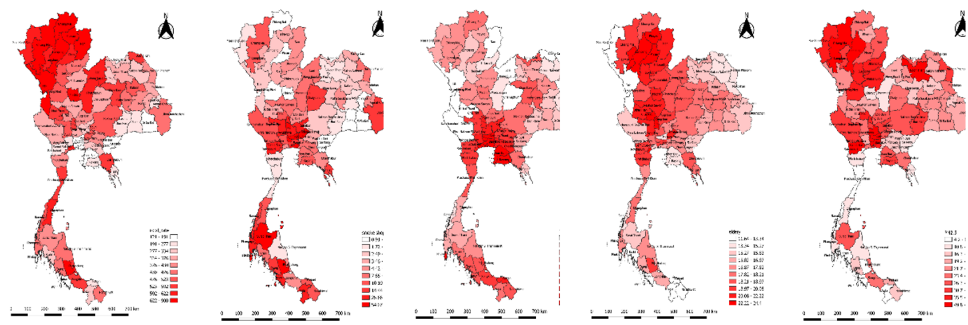
3. Results and Discussion

The highest prevalence of chronic obstructive pulmonary disease (COPD) per 100,000 population was observed in Nan province (900.30 per 100,000 people), while the lowest prevalence was found in Pathum Thani province (121.27 per 100,000 people). When categorized by deciles, provinces in the highest prevalence group (622.17 - 900.30) included Chiang Rai, Chiang Mai, Tak, Nan, Phayao, Phatthalung, Phichit, and Lampang, as illustrated in Figure 2(A).

3.1 Spatial distribution of the independent variables

The spatial distribution per square kilometer of the four independent variables varied across provinces. Firstly, for tobacco outlet density, the highest decile (54.07 - 1,139.53) was observed in eight provinces: Ang Thong, Nakhon Nayok, Nonthaburi, Pathum Thani, Phatthalung, Phuket, Samut Prakan, and Surat Thani, as illustrated in Figure 2(B). Secondly, regarding average nighttime light, the highest decile (5.191 - 23.279) was found in eight provinces: Bangkok, Samut Prakan, Nonthaburi, Pathum Thani, Phuket, Samut Sakhon, Chonburi, and Rayong, as depicted in Figure (C). Thirdly, for elderly population density, the highest decile (22.22 - 24.40) was concentrated in seven provinces: Lampang, Sing Buri, Lamphun, Chai Nat, Samut Songkhram, Ang Thong, and Phayao, as shown in Figure 2(D). Finally, the highest decile (49.8 - 149.1) for $PM_{2.5}$ concentration was identified in seven provinces: Chiang Mai, Lampang, Nonthaburi, Pathum Thani, Phra Nakhon Si Ayutthaya, Ratchaburi, and Udon Thani, as presented in Figure 2(E).

The univariate Moran's I of COPD prevalence rates demonstrated positive spatial autocorrelation. The Moran's I value was 0.313 ($p < 0.05$) (Table 1). LISA analysis revealed that hot spots (i.e., High-High clusters of COPD prevalence rates) were primarily located in the northern region of Thailand, including Chiang Mai, Lamphun, Lampang, and Phayao. Conversely, cold spots (i.e., Low-Low clusters of COPD) were scattered, with one located in the eastern region (Prachinburi, Chachoengsao, Samut Prakan) and another in the lower northeastern region (Surin).



(A) Spatial distribution of COPD prevalence. | (B) Spatial distribution of Smoke shop area | (C) Spatial distribution of NTL density | (D) Spatial distribution of concentration of elderly | (E) Spatial distribution of $PM_{2.5}$

Figure 2. Spatial distribution of various factors

Table 1. Geographical distribution of prevalence of COPD

Factor	Moran's I	LISA			
		High-Hight (4 Provinces)	High-Low (6 Provinces)	Low-Low (4 Provinces)	Low-Hight (0 Provinces)
COPD preva lence	0.454	Lampang* Chiang Mai** Lamphun** Phayao**	Ang Thong* Samut Songkhram* Nakhon Nayok* Ubon Ratchathani* Samut Sakhon*** Chanthaburi***	Samut Prakan* Surin* Prachinburi** Chachoengsao**	

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

Table 2. Spatial clusters of tobacco outlet

Factor	Moran's I	LISA			
		High-Hight (0 Provinces)	High-Low (0 Provinces)	Low-Low (11 Provinces)	Low-Hight (5 Provinces)
Smoke shop area	-0.008			Tak* Kamphaeng Phet* Nong Khai* Udon Thani* Nong Bua Lamphu* Kalasin* Mukdahan* Maha Sarakham* Roi Et* Surin* Buriram**	Phang Nga* Trang* Satun* Songkhla* Nakhon Si Thammarat***

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

Table 3. Spatial clusters of NTL density

Factor	Moran's I	LISA			
		High-Hight (11 Provinces)	High-Low (0 Provinces)	Low-Low (7 Provinces)	Low-Hight (3 Provinces)
Night time light	0.404	Saraburi** Chonburi** Bangkok*** Ang Thong*** Phra Nakhon Si Ayutthaya*** Nakhon Pathom*** Nonthaburi*** Pathum Thani*** Samut Prakan*** Samut Sakhon*** Samut Songkram***		Phichit* Sakon Nakhon* Nakhon Phanom* Mukdahan* Roi Et* Yasothon* Amnat Charoen*	Ratchaburi* Nakhon Nayok** Chachoengsao***

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

Table 4. Spatial clusters of elderly population density

Factor	Moran's I	LISA			
		High-Hight (14 Provinces)	High-Low (0 Provinces)	Low-Low (4 Provinces)	Low-Hight (2 Provinces)
Density of elderly inhabitants	0.514	Lamphun* Uttaradit* Phitsanulok* Uthai Thani* Suphan Buri* Sing Buri* Ang Thong* Phra Nakhon Si Ayutthaya* Nonthaburi* Lopburi** Phrae** Lampang*** Chai Nat*** Nakhon Sawan***		Phang Nga** Pattani** Yala** Narathiwat**	Saraburi* Pathum Thani*

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

Table 5. Spatial clusters of $PM_{2.5}$ density.

Factor	Moran's I	LISA			
		High-Hight (11 Provinces)	High-Low (1 Provinces)	Low-Low (7 Provinces)	Low-Hight (5 Provinces)
Density of $PM_{2.5}$	0.234	Lamphun* Pathum Thani* Bangkok* Chai Nat* Lopburi* Sing Buri** Samut Prakan** Phra Nakhon Si** Nonthaburi** Ang Thong*** Saraburi***	Surat Thani**	Nakhon Si T* Krabi* Phatthalung* Songkhla* Satun* Phuket* Trang***	Samut Songkhram* Suphan Buri*** Nakhon Pathom*** Samut Sakhon*** Nakhon Nayok***

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

Spatial autocorrelation analysis identified geographical clustering patterns of tobacco outlets per area. Table 2 shows that these tobacco outlet clusters were significant at $p < 0.05$. The univariate Moran's I for tobacco outlet density revealed negative spatial autocorrelation, with a value of -0.008. LISA analysis identified 11 cold spots located in Tak, Kamphaeng Phet, Nong Khai, Udon Thani, Nong Bua Lamphu, Kalasin, Mukdahan, Maha Sarakham, Roi Et, Buri Ram, and Surin.

Table 3 presents the average NTL values. The univariate Moran's I statistic revealed moderate positive spatial autocorrelation of NTL density with a value of 0.404 at $p < 0.05$, LISA analysis revealed 11 hot spots in Bangkok, Ang Thong, Ayutthaya, Saraburi, Nakhon Pathom, Nonthaburi, Pathum Thani, Samut Prakan, Samut Sakhon, Samut Songkhram, and Chonburi. Seven cold spots were located in Phichit, Sakon Nakhon, Nakhon Phanom, Mukdahan, Roi Et, Yasothon, and Amnat Charoen.

Table 4 presents the clustering pattern of population density. The univariate Moran's I statistic for the distribution of these population densities demonstrated positive spatial autocorrelation. The Moran's I value of 0.514 was statistically significant ($p < 0.05$), therefore exhibiting clustering. LISA analysis revealed 14 hot spots in Lamphun, Lampang, Phrae, Uttaradit, Phitsanulok, Nakhon Sawan, Uthai Thani, Suphan Buri, Chai Nat, Lopburi, Sing Buri, Ang Thong, Ayutthaya, and Nonthaburi. Meanwhile, two cold spots were found in Saraburi and Pathum Thani.

Table 5 presents the clusters of $PM_{2.5}$ concentration. The univariate Moran's I statistic of $PM_{2.5}$ concentration demonstrated positive spatial autocorrelation. The value of 0.234 was statistically significant ($p < 0.05$), revealing spatial concentration in several areas. LISA analysis identified 11 hot spots in Lamphun, Chai Nat, Lopburi, Sing Buri, Ang Thong, Ayutthaya, Nonthaburi, Samut Prakan, Pathum Thani, Saraburi, and Lopburi. Conversely, seven cold spots were found in Krabi, Nakhon Si Thammarat, Trang, Phatthalung, Satun, and Songkhla.

3.2 Factors associated with COPD

The Moran's I indicated significant statistical association patterns of an independent factor and COPD (p-value < 0.05). There was a spatial correlation between the distribution pattern of tobacco outlet in the same direction as the COPD pattern. The outcomes of the bivariate LISA revealed the statistically significant positive correlation between tobacco outlet density and COPD (Moran's I = -0.047). LISA indicated areas with a concentration of tobacco outlet and high prevalence of COPD with low values in the surrounding 7 provinces (Cold-spot or low-low clusters) in Prachin Buri, Chachoengsao, Chanthaburi, Surin, Ubon Ratchathani, Samut Sakhon, and Samut Songkhram provinces as can be seen in Table 6 (Figure 3).

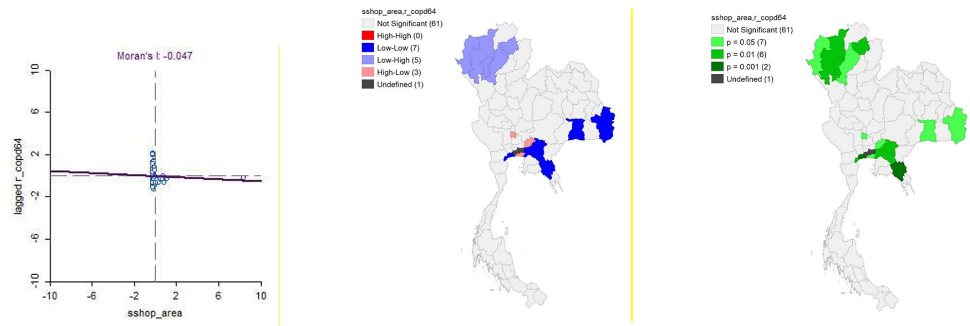


Figure 3. LISA and Moran's I scatter plot matrix of tobacco outlet density on COPD

Table 6. Geographical distribution of tobacco outlet density on COPD

Factor	Moran's I	LISA			
		HH (0 province)	**HL** (3 province)	**LL** (7 province)	**LH** (5 province)
Tobacco outlet	-0.047		Ang Thong* Nakhon Nayok* Samut Prakan*	Surin* Ubon Ratchathani* Samut Sakhon* Samut Songkhram* Prachinburi** Chachoengsao** Chanthaburi***	Mae Hong Son* Lampang* Phayao** Chiang Mai** Lamphun**

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

There was a spatial autocorrelation of Night time light and a distribution pattern in the same direction with COPD (Moran's I of -0.099). The LISA analysis showed clusters of a province with a low concentration of tobacco store and stroke with the low values of surrounding 6 provinces (Cold spot). 6 low-low clusters were found in Prachinburi, Chachoengsao, Chanthaburi, Surin, Amnat Charoen, and Ubon Ratchathani provinces as can be seen in Table 7 (Figure 4).

It has been revealed that the provinces having high number of elderly populations high prevalence of COPD with a Moran's I of 0.221. The LISA analysis indicated 4 Hot-spots or High-High clusters of the high concentration of elderly population and patients with COPD with high values in the surrounding 4 provinces in Chiang Mai, Lamphun, Lampang, and Phayao. LISA analysis showed clusters of a province with a concentration of elderly population and prevalence of stroke was low values of surrounding 6 provinces (Cold-spot or low-low clusters). There were 6 low-low clusters found Surin, Ubon Ratchathani, Prachinburi, Chachoengsao, Samut Prakan, and Samut Sakhon provinces as can be seen in Table 8 (Figure 5).

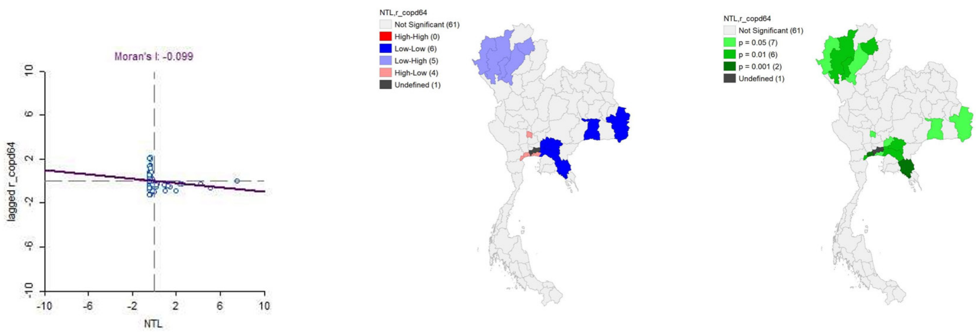


Figure 4. LISA and Moran's I scatter plot matrix of Night time light on COPD

Table 7. Geographical distribution of Night time light on COPD

Factor	Moran's I	LISA			
		HH (0 province)	**HL** (4 province)	**LL** (6 province)	**LH** (5 province)
Night time light	-0.099		Ang Thong* Samut Songkhram* Samut Prakan* Samut Sakhon***	Prachinburi* Chachoengsao* Surin* Amnat Charoen* Ubon Ratchathani* Chanthaburi***	Mae Hong Son* Lampang* Chiang Mai** Lamphun** Phayao**

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

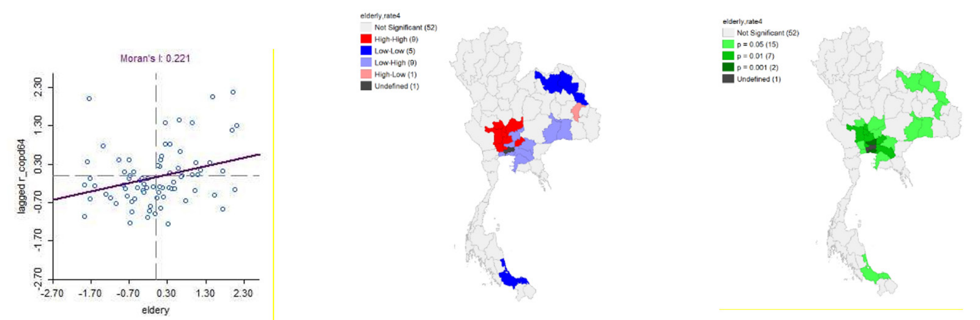


Figure 5. LISA and Moran's I scatter plot matrix of smoke density of elderly inhabitants on COPD

In addition, the bivariate LISA revealed a statistically significant positive correlation between $PM_{2.5}$ density and prevalence of COPD (Moran's I = 0.080). LISA indicated areas with a concentration of $PM_{2.5}$ density and high prevalence of COPD with high values in the surrounding 3 provinces (Hot-spot or High-High cluster) in Chiang Mai, Lamphun, and Lampang. LISA analysis showed clusters of a province with a $PM_{2.5}$ density and COPD patients with low values of surrounding 8 provinces (Cold-spot or low-low clusters). There were 8 low-low clusters found Surin, Ubon Ratchathani, Nakhon Nayok, Prachinburi, Chachoengsao, Chanthaburi, Samut Sakhon, and Samut Songkhram provinces as can be seen in Table 9 (Figure 6).

Table 8. Geographical distribution of density of elderly inhabitants on COPD

Factor	Moran's I	LISA			
		HH (4 province)	**HL** (4 province)	**LL** (6 province)	**LH** (1 province)
Density of elderly inhabitants	0.221	Chiang Mai** Lamphun** Lampang** Phayao**	Nakhon Nayok* Ang Thong* Samut Songkhram** Chanthaburi**	Surin* Ubon Ratchathani* Samut Prakan* Prachinburi** Chachoengsao** Samut Sakhon***	Mae Hong Son*

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

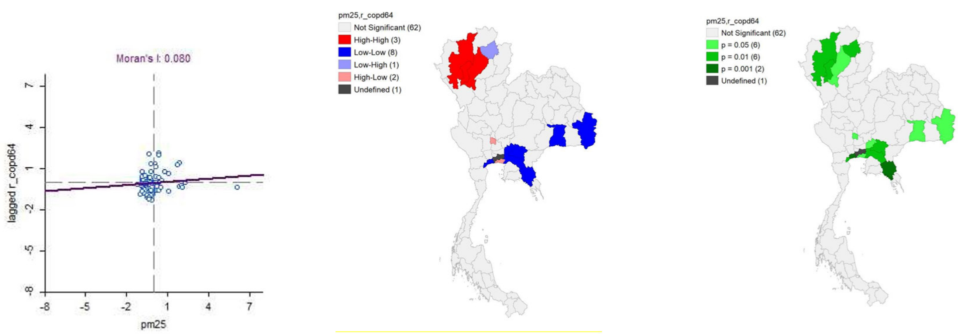


Figure 6. LISA and Moran's I scatter plot matrix of $PM_{2.5}$ density on COPD

Table 9. Geographical distribution of $PM_{2.5}$ density on COPD

Factor	Moran's I	LISA			
		HH (3 province)	**HL** (2 province)	**LL** (8 province)	**LH** (1 province)
Density of $PM_{2.5}$	0.080	Lampang* Chiang Mai** Lamphun**	Samut Prakan* Ang Thong*	Surin* Ubon Ratchathani* Nakhon Nayok* Prachinburi** Chachoengsao** Samut Songkhram** Chanthaburi*** Samut Sakhon***	Phayao*

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

Table 10. OLS and spatial regression results.

Factors	OLS	Spatial regression model	
		SLM	SEM
Tobacco outlet	0.216	0.223*	0.220*
	(0.139)	(0.12)	(0.128)
Night time light	-23.870***	-20.976**	-22.202**
	(6.86)	(6.458)	(7.045)
Density of elderly inhabitants	19.581**	16.914**	17.145**
	(5.935)	(5.537)	(6.259)
$PM_{2.5}$	-0.037	-0.253	-0.396
	(0.986)	(0.911)	(0.923)
Constant	127.393		
	(104.637)		
p		63.956	
		(103.973)*	
λ			180.142
			(113.764)
F-stat	7.645		
R-Squared	0.301	0.361	0.349
Log Likelihood	-489.434	-486.792	-487.547
AIC	988.869	985.584	985.094
BIC	1000.52	999.568	996.748
Moran's I	2.223		
LM_{tag}	3.867		
LM_{eror}	1.050		

*Correlation is significant at the 0.05 level

**Correlation is significant at the 0.01 level

***Correlation is significant at the 0.001 level

3.3 Spatial regression analysis

A comparative assessment of spatial and non-spatial models for predicting COPD prevalence revealed that the Spatial Lag Model (SLM) is the most suitable for predicting COPD incidence. This determination was based on a comparison of model selection statistics, including R-squared, AIC, and BIC, across all three candidate models, with the SLM exhibiting the best fit. Analysis of variables for predicting COPD prevalence revealed statistically significant associations between tobacco outlet density, average nighttime light, and elderly population density, and the prevalence of COPD in Thailand. Of the four factors evaluated through spatial regression modeling, the SLM identified statistically significant spatial associations between COPD incidence and tobacco outlet density (coefficient = 0.223), average nighttime light (coefficient = 20.976), and elderly population density (coefficient = 16.914). Therefore, the SLM was selected as the most appropriate spatial regression model. The analysis, incorporating these coefficients, demonstrated that tobacco outlet density, average nighttime light, and elderly population density collectively accounted for 36.10% (R^2 = 0.361) of the variance in COPD prevalence in Thailand (Table 10).

The increasing density of tobacco outlets in Thailand, fueled by aggressive tobacco industry marketing and easy accessibility, has led to greater accessibility of cigarettes for the population (World Health Organization, 2022; Tobacco Control Research and Knowledge Management Center, 2022; Safiri S, 2022; Bhutani M, *et al.,* 2022). Multiple studies have established a correlation between the number of tobacco retailers and increased smoking rates, raising significant concerns about associated health impacts, particularly the development of chronic obstructive pulmonary disease (COPD) (Tobacco Control Research and Knowledge Management

Center, TRC, 2022; Lugg, *et al.,* 2022; He, *et al.,* 2023). Consequently, stringent governmental regulations are required to control tobacco outlet density, encompassing licensing, zoning regulations, advertising restrictions, and the promotion of strict legal compliance among vendors to mitigate the long-term health consequences of smoking among the Thai population.

The density of nighttime light (NTL) serves as an indicator of urbanization, which is linked to a higher prevalence of COPD (Moitra, *et al,* 2022; Zhang, *et al.,* 2023). Urbanization brings about various risk factors, including pollution, chemical exposure, and stress (Zhang, *et al,* 2023). Studies conducted in several countries, including Thailand, have revealed that urban populations exhibit a higher susceptibility to COPD compared to their rural counterparts (Wang, *et al.,* 2022), attributable to lifestyle choices and environmental factors conducive to disease development. This highlights the substantial impact of urban social and environmental factors on public health.

The rising density of the elderly population is another crucial aspect. Currently, Thailand is transitioning into an aged society, characterized by a continuously growing proportion of senior citizens, especially in the northern and northeastern regions (Chuakhamfoo, *et al,* 2022). This demographic shift poses significant implications for the public health system, particularly regarding COPD (Zhu, *et al.,* 2023; Adeloye, *et al.,* 2022). Elderly individuals are more susceptible to age-related physiological changes, especially within the respiratory system, making them more prone to COPD. This vulnerability subsequently translates into increased burdens on families and society as a whole. Therefore, the expanding elderly population contributes to a heightened risk of elevated COPD prevalence within specific regions.

4. Conclusion

This study initiated the identification of spatial association between sociodemographic, environment factors and prevalence of COPD in Thailand. A wide variation in COPD prevalence was found among populations in Thailand. COPD clusters were found in almost every region of the country. Our findings suggested that sociodemographic and environmental factors are significantly positively correlated to the prevalence of COPD, including tobacco outlet density, Average nighttime light, and elderly population density. This study described the overall situation of the sample population residing in provincial areas by linking data from various sources. However, it is important to acknowledge that residential mobility during the study period could have influenced exposure to risk factors for COPD. The main findings of this study could be useful for policymakers, medical practitioners, and researchers to reduce COPD burden in Thailand owing to regional differences in COPD burden. Specifically, the obtained analytical results could help policymakers priorities programs aimed at reducing COPD prevalence relevant to the geographic and socio-demographic context of the region, especially the north 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 behaviors (especially in elderly). 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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Conflicts of Interest

The authors declare no competing interests.

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Ethics approval and consent to participate

Ethics approval was received from the Vongchavalitkul University Ethics Committee for Human Research (Reference No. 096/2023).

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