# Socio-economic and environmental factors are related to acute exacerbation of chronic obstructive pulmonary disease incidence in Thailand

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## Abstract

Chronic Obstructive Pulmonary Disease (COPD) is a significant global health issue, leading to high rates of sickness and death worldwide. In Thailand, there are over 3 million patients with the COPD, with more than a million patients admitted to hospitals due to symptoms of the disease. This study investigated factors influencing the incidence of acute exacerbations among COPD patients in Thailand, including the spatial autocorrelation between socio-economic and environmental factors. We conducted a spatial analysis using Moran's *I*, Local Indicators Of Spatial Association (LISA), and spatial regression models, specifically the Spatial Lag Model (SLM) and the Spatial Error Model (SEM), to explore the relationships between the variables. The univariate Moran's *I* scatter plots showed a significant positive spatial autocorrelation of 0.606 in the incidence rate of COPD among individuals aged 15 years and older across all 77 provinces in Thailand. High-High (HH) clusters for the COPD were observed in the northern and southern regions, while Low-Low (LL) clusters were observed in the northern and north-eastern regions. Bivariate Moran's *I* indicated a spatial autocorrelation between various factors and acute exacerbation of COPD in Thailand. LISA analysis revealed 4 HH clusters and 5 LL clusters related to average income, 12 HH and 8 LL clusters in areas where many people smoke, 5 HH and 8 LL clusters in areas with industrial factory activities, 11 HH and 9 LL clusters associated with forested areas, and 6 LL clusters associated with the average rice field. Based on the Akaike information criterion (AIC). The SLM outperformed the SEM but only slightly so, with an AIC value of 1014.29 compared to 1019.56 and a Lagrange multiplier value of $p<0.001$. However, it did explain approximately 63.9% of the incidence of acute exacerbations of COPD, with a coefficient of determination ($R^2 = 0.6394$) along with a Rho (ρ) of 0.4164. The results revealed that several factors, including income, smoking, industrial surroundings, forested areas and rice fields are associated with increased levels of acute COPD exacerbations.

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## Introduction

Chronic Obstructive Pulmonary Disease (COPD) is as a major cause of morbidity and mortality worldwide, significantly impacting public health and healthcare systems. In 2019, there were approximately 3.2 million deaths globally due to COPD (Li *et al.*, 2023). This alarming trend is evident in both developed and developing countries. According to the Health Data Center (HDC) of the Ministry of Public Health, Thailand, the statistics regarding chronic COPD are concerning, with approximately 35,500 new cases of COPD reported annually, and the cumulative total of cases, including both new and existing patients, stood at 150,549 in 2022 (HDC, 2023). Notably, the mortality rate associated with COPD has shown a consistent increase each year from 2019 to 2022. These data highlights the growing burden of this chronic disease in the country and underscores the need for effective public health interventions to manage and mitigate its impact (Samarnkongsak *et al.*, 2019; Kitjakrancharoensin *et al.*, 2020).

The pathogenesis and progression of COPD are influenced by a complex interplay of precipitating factors, encompassing environmental exposures, genetic predisposition and individual susceptibility factors (Hardin & Silverman, 2014; Kim & Lee, 2017). This variability underscores the importance of region-specific analyses to tailor effective interventions (Jenkins, 2021). Although the precipitating factors of COPD are well-documented (Gou *et al.*, 2023), the spatial distribution and geographic interactions of

COPD exacerbation patterns remain underexplored, particularly in relation to their region-specific risk factors. The application of Geographic Information Systems (GIS) and spatial statistical analysis presents a valuable opportunity to comprehensively examine these relationships, particularly in areas where such methodological approaches have not been extensively utilized (Gou *et al.*, 2023).

Given the high prevalence of COPD and its increasingly significant impacts, it is essential to highlight important factors that must be considered for effective prevention and control strategies. Multiple precipitating factors contribute to both the pathogenesis and progression of COPD. By employing advanced spatial analytical approaches, we aimed to elucidate the patterns and determinants of COPD exacerbations, ultimately providing critical insights that can inform region-specific public health interventions. Hence, this study utilized sophisticated analytical techniques to examine the geographic heterogeneity of COPD risk factors and their associations with disease outcomes.

COPD exacerbation can be defined as an acute worsening of respiratory symptoms that requires additional therapy, thereforer the specific aim was to conduct a spatial analysis to identify and examine the geographic heterogeneity of COPD exacerbation risk factors and their associations with disease outcomes in Thailand.

## Material and Methods

### Study site

The research presented here was based on data from 2022 in Thailand, a Southeast Asian country covering an area of 513,120 km$^2$, with a population of approximately 71.6 million people (National Statistical Office of Thailand, 2022). The country is divided into four regions: North, Northeast, Central, South and further into 77 provinces spanning latitudes 20°28'N to 5°36'S and longitudes 105°38'E to 97°22'W. Thailand experiences three seasons: rains from mid-May to mid-October followed by winter from mid-February and summer until mid-May.

### Study design and data sources

This cross-sectional, spatial analysis examined the geographic distribution and risk factors associated with exacerbations of COPD across all 77 provinces in Thailand. It integrated multiple data sources to analyze spatial patterns and associations between COPD exacerbations and various socio-economic and environmental determinants.

### COPD exacerbation data

In this study, the primary outcome measure was the rate of acute COPD exacerbations per 100,000 population aged ≥15 years during 2022 (HDC, 2023). Cases were identified by the diagnostic codes J440 and J441 based on the tenth revision of international statistical classification of diseases (ICD-10) as delivered by the World Health Organization (WHO).

### Determinants of risk

Five potential risk factors were selected based on their theoretical associations with COPD outcomes: Household income level (economic indicator), smoking prevalence (behavioural risk factor), density of industrial activity (environmental exposure), forested area adjacent to industrial zones (air quality indicator) and rice field coverage (agricultural air quality indicator). These variables were obtained from the National Statistical Office of Thailand (National Housing Information Center, 2023) and were selected based on their established relationships with respiratory health outcomes in previous literature.

### Spatial analysis

Geographic analysis utilized QGIS version 3.28 (https://qgis.org/) for initial exploratory spatial data analysis and visualization, while spatial patterns and clustering were examined using GeoDa software version 1.18 (https://geodacenter.github.io/download.html). The analysis encompassed three stages: the exploratory spatial data analysis, spatial autocorrelation analysis using Global Moran's *I* and Local Indicators of Spatial Association (LISA) following methods described by Anselin (2022), and spatial regression analysis including Ordinary Least Squares (OLS), the Spatial Lag Model (SLM) and the Spatial Error Model (SEM) following Steiniger and Hunter's methodology (2013). Spatial regression models were constructed to examine associations between risk factors and COPD exacerbation rates while accounting for spatial dependence, with model diagnostics including tests for spatial autocorrelation, heteroskedasticity and model fit ($R^2$, Akaike Information Criterion (AIC) and Log likelihood), all conducted at a significance level of $\alpha = 0.05$. In the analysis, "areas of concentration" refer to regions with a high incidence of acute COPD exacerbations, identified through clustering patterns in the data. High-risk values or "hotspots" and High-High (HH) areas represent zones where both the incidence of COPD exacerbations and also neighbouring areas show consistently high rates of the disease. These high-risk areas were defined by statistically significant spatial clusters measured by Moran's *I*.

## Results

### Global spatial patterns

The concentration of incidents, quantified through spatial autocorrelation, identified provinces where acute exacerbations are more frequent among people aged ≥15 years old. Provinces identified as high-risk areas for acute COPD exacerbations include Chiang Mai, Mae Hong Son, Lamphun, Lampang, Chumphon, Surat Thani, Krabi, Phatthalung, Songkhla, Pattani, Yala and Narathiwat (Figure 1). The unchanged Moran's *I* value of 0.606 for the incidence of acute COPD exacerbations among individuals ≥15 years old in Thailand in 2022 indicated stable and moderately strong positive spatial autocorrelation. This value suggests that areas with high rates of exacerbations are spatially clustered, meaning that neighbouring provinces tend to have similarly high or low rates. The stability of the value implies a consistent clustering pattern across the provinces, as shown in Tables 1 and 2 together with Figure 2, reflects provincial-level cluster trends.

Moran's *I* identified a statistically significant association between the incidence of acute COPD exacerbations in the age group ≥15 years old ($p$<0.05), thereby indicating a strong spatial correlation. The distribution pattern aligned with the incidence of acute exacerbations among COPD patients belonging to this age group but exhibited different patterns in each province. The analysis revealed areas of concentration and incidence of acute COPD exacerbations in those aged ≥15 years old, with high-risk values or areas (hotspot or HH). These provinces were identified as Chiang

Mai, Mae Hong Son, Lamphun, Lampang, Chumphon, Surat Thani, Krabi, Phatthalung, Songkhla, Pattani, Yala and Narathiwat (Figure 1). The unchanged Moran's *I* value for the incidence of acute exacerbations of COPD in this age group in Thailand in 2022 showed a spatial Moran's *I* autocorrelation of 0.606. Values varied depending on the variables examined overall in Thailand. Tables 1 and 2 together with Figure 2 show the distribution of cluster trends at the provincial level.

The LISA results are presented in Tables 2, 3, 4, 5, 6 and 7, and Figures 3, 4, 5, 6 and 7. Our analysis revealed significant associations between COPD exacerbations and several factors. Income and forest coverage demonstrated negative correlations, suggesting protective effects, while smoking and the presence of industrial plants showed positive associations with exacerbation rates. Rice field exposure exhibited variable relationships, influenced by environmental factors such as air quality and pesticide use.

LISA analysis was conducted to explore the relationship between average income, median income, and the incidence of acute exacerbations of COPD among individuals aged ≥15 years old. The analysis revealed hotspots (HH) with the highest values in four provinces Lamphun, Krabi, Surat Thani and Nakhon Si Thammarat. Conversely, a coldspot cluster (LL) was identified covering Suphan Buri, Ang Thong, Udon Thani, Bueng Kan, and Mukdahan provinces (Table 3 and Figure 3). High values indicating a significant association between smoking and the incidence of acute exacerbations of COPD among ≥15 years olds were observed in 12 provinces, with HH clusters identified in Lamphun, Tak, Ranong, Krabi, Surat Thani, Nakhon Si Thammarat, Phatthalung, Songkhla, Trang, Yala, Pattani, and Narathiwat. Conversely, LISA analysis also revealed clusters of provinces where smoking prevalence and COPD exacerbation incidence were low. Such values (coldspot cluster and LL) were found in eight provinces, including Mukdahan, Bangkok, Suphanburi, Phra Nakhon Si Ayutthaya, Ang Thong, Lopburi, Saraburi, and Nakhon Nayok (Table 4 and Figure 4).

LISA analysis was conducted to explore the relationship between the proportion of industrial factories and the incidence of acute exacerbations of COPD among individuals aged ≥15 years old. High values are indicative of significant associations and they were observed in hotspot areas in five provinces: Chiang Rai, Chiang Mai, Surat Thani, Nakhon Si Thammarat and Songkhla. Conversely, LL clusters were identified in Loei, Bueng Kan, Mukdahan, Suphanburi, Ang Thong, Lopburi, Saraburi, and Nakhon Nayok (Table 5 and Figure 5). When the relationship

**Table 1.** The variation of the global autocorrelation according to the study variables.

| Variable | Moran' *I* |
|---|---|
| Income | -0.197 |
| Smoking | 0.296 |
| Industrial plant | -0.115 |
| Forested area | 0.393 |
| Rice field | -0.409 |



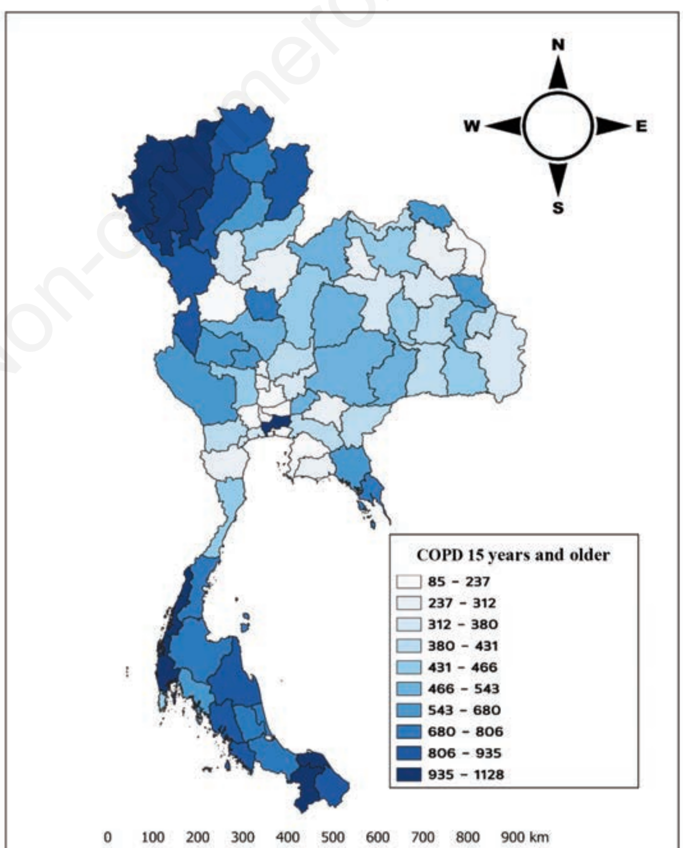


**Figure 1**. Incidence of acute exacerbations of COPD in ≥15 years olds in Thailand in 2022.

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between the proportion of forested areas and the incidence of acute COPD exacerbations among individuals of this age group, we found high values and hotspot areas in eleven provinces, including Mae Hong Son, Chiang Rai, Chiang Mai, Lampang, Lamphun, Phayao, Tak, Ranong, Yala, Narathiwat, and Surat Thani. LL clusters were identified in the provinces of Bueng Kan, Udon Thani, Nakhon Ratchasima, Bangkok, Phra Nakhon Si Ayutthaya, Suphanburi, Ang Thong, Lopburi and Saraburi (Table 6 and Figure 6). Additionally, LISA analysis was employed to investigate the relationship between the proportion of rice fields and the incidence of acute COPD exacerbations among those aged ≥15 years old. While no high values were found, LL clusters were identified in six provinces: Bangkok, Lopburi, Saraburi, Loei, Bueng Kan and Mukdahan (Table 7 and Figure 7).

**Table 2.** Geographic distribution of the incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

| Local indicators of spatial association (LISA) | | | |
|---|---|---|---|
| High-high (HH) | High-low (HL) | Low-low (LL) | Low-high (LH) |
| Chiang Mai*** | Bangkok*** | Sukhothai* | |
| Mae Hong Son* | Chai Nat* | Udon Thani* | |
| Lamphun* | | Samut Prakan** | |
| Lampang** | | Samut Sakhon*** | |
| Chumphon | | Samut Songkhram** | |
| Surat Thani** | | Nakhon Pathom** | |
| Sword* | | Nonthaburi** | |
| Phatthalung* | | Pathum Thani*** | |
| Songkhla* | | Ayutthaya** | |
| Pattani* | | Suphan Buri*** | |
| Yala* | | Ang Thong* | |
| Narathiwat** | | Sing Buri** | |
| | | Ratchaburi** | |
| | | Lop Buri* | |
| | | Saraburi** | |
| | | Nakhon Nayok** | |
| | | Prachin Buri** | |
| | | Chachoengsao* | |

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



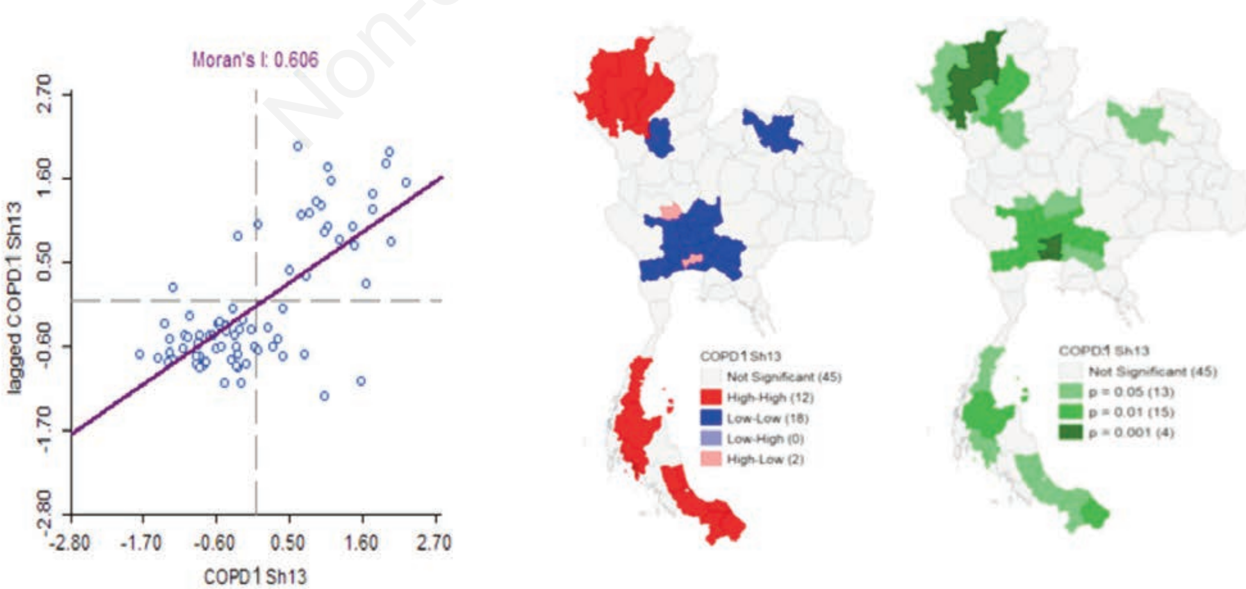


**Figure 2.** Diagram of LISA and Moran's *I* distribution of the incidence of acute exacerbations of COPD among people in ≥15 years olds in Thailand.

**Table 3.** Geographic distribution of income and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

| Local indicators of spatial association (LISA) High-high (HH) | High-low (HL) | Low-low (LL) | Low-high (LH) |
|---|---|---|---|
| Lamphun** | Bangkok*** | Suphan Buri* | Chiang Rai* |
| Krabi** | Ayutthaya*** | Ang Thong* | Chiang Mai*** |
| Surat Thani** | Saraburi* | Udon Thani* | Mae Hong Son* |
| Nakhon Si Thammarat* | Lop Buri* | Bueng Kan* | Lampang** |
| | Nakhon Nayok* | Mukdahan* | Phayao* |
| | Nakhon Ratchasima* | | Tak* |
| | Loei* | | Ranong* |
| | | | Phatthalung** |
| | | | Trang* |
| | | | Songkhla** |
| | | | Yala* |
| | | | Pattani* |
| | | | Narathiwat** |

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



**Table 4.** Geographic distribution of smoking and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

| Local indicators of spatial association (LISA) High-high (HH) | High-low (HL) | Low-low (LL) | Low-high (LH) |
|---|---|---|---|
| Lamphun** | Nakhon Ratchasima* | Mukdahan* | Chiang Rai* |
| Tak* | Loei* | Bangkok*** | Chiang Mai*** |
| Ranong* | Udon Thani* | Suphan Buri* | Mae Hong Son* |
| Krabi** | Bueng Kan* | Ayutthaya*** | Lampang** |
| Surat Thani** | | Ang Thong* | Phayao* |
| Nakhon Si Thammarat* | | Lop Buri* | |
| Phatthalung** | | Saraburi* | |
| Songkhla** | | Nakhon Nayok* | |
| Trang* | | | |
| Yala* | | | |
| Pattani* | | | |
| Narathiwat** | | | |

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

**Table 5.** Geographic distribution of industrial plant and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

| Local indicators of spatial association (LISA) High-high (HH) | High-low (HL) | Low-low (LL) | Low-high (LH) |
|---|---|---|---|
| Chiang Rai* | Bangkok*** | Loei* | Mae Hong Son* |
| Chiang Mai*** | Ayutthaya*** | Bueng Kan* | Lampang** |
| Surat Thani** | Udon Thani* | Mukdahan* | Lamphun** |
| Nakhon Si Thammarat* | Nakhon Ratchasima* | Suphan Buri* | Phayao* |
| Songkhla** | | Ang Thong* | Tak* |
| | | Lop Buri* | Ranong* |
| | | Saraburi* | Krabi** |
| | | Nakhon Nayok* | Phatthalung** |
| | | | Trang* |
| | | | Yala* |
| | | | Pattani* |
| | | | Narathiwat** |

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

## Spatial regression analysis

The outcomes of spatial modelling are summarized in Table 8, which encompasses the results of the OLS, SLM and SEM analyses. The table compiles data on average income, smoking prevalence, proportion of nearby industrial factories, forested areas and proportion of rice fields. These factors are believed to be associated with the incidence of acute exacerbations of COPD among individuals from 15 years and up. The OLS model explains approximately **51.6%** of the incidence in all ≥15 years olds (**$R^2$ = 0.5156).** The final SLM explains approximately 63.9% of this incidence in this age group ($R^2$ = 0.6394) along with a Rho (ρ) of 0.4164. The SEM indicates that the factors mentioned were all significant predictors, explaining approximately **61.1%** of the incidence of acute exacerbations of COPD in the age group of ≥**15** years and older ($R^2$= **0.6112)**, along with a Lambda (λ) value of 0.4741**.** These results make SLM the best regression model in this case and demonstrate that these particular variables are positively associated with the incidence of acute exacerbation of COPD in the age group investigated. $R^2$ confirmed the **63.9%** figure given above for SLM and this was repeated by the AIC that also indicated that SLM slightly outperformed SEM with the values **1014.29** vs. **1019.56, respectively.** The conclusion of SLM as the best regression model is further strengthened by highlighting its ability to account for spatial autocorrelation, which OLS and SEM do not

**Table 6.** Geographic distribution of forest area and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

| Local indicators of spatial association (LISA) | | | |
|---|---|---|---|
| High-high (HH) | High-low (HL) | Low-low (LL) | Low-high (LH) |
| Mae Hong Son* | Loei* | Bueng Kan* | Krabi** |
| Chiang Rai* | Mukdahan* | Udon Thani* | Trang* |
| Chiang Mai*** | Nakhon Nayok* | Nakhon Ratchasima* | Phatthalung** |
| Lampang** | | Bangkok*** | Nakhon Si Thammarat* |
| Lamphun** | | Ayutthaya*** | Songkhla** |
| Phayao* | | Suphan Buri* | Pattani* |
| Tak* | | Ang Thong* | |
| Ranong* | | Lop Buri* | |
| Yala* | | Saraburi* | |
| Narathiwat** | | | |
| Surat Thani** | | | |

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

**Table 7.** Geographic distribution of forest area and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

| Local indicators of spatial association (LISA) | | | |
|---|---|---|---|
| High-high (HH) | High-low (HL) | Low-low (LL) | Low-high (LH) |
| | Ayutthaya*** | Bangkok*** | Mae Hong Son* |
| | Suphan Buri* | Lop Buri* | Chiang Rai* |
| | Ang Thong* | Saraburi* | Chiang Mai*** |
| | Nakhon Nayok* | Loei* | Lampang** |
| | Nakhon Ratchasima* | Bueng Kan* | Lamphun** |
| | Udon Thani* | Mukdahan* | Phayao* |
| | | Tak* | |
| | | Ranong* | |
| | | Surat Thani** | |
| | | Nakhon Si Thammarat* | |
| | | Krabi** | |
| | | Phatthalung** | |
| | | Trang* | |
| | | Songkhla** | |
| | | Yala* | |
| | | Pattani* | |
| | | Narathiwat** | |

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

handle as effectively. The positive Moran's $I$ value (0.606) indicates spatial clustering, which means that the incidence of acute COPD exacerbations is not randomly distributed. The SLM adjusts for these spatial dependencies by incorporating the influence of neighbouring areas, leading to more accurate predictions compared to OLS and SEM, which may underestimate the spatial effect.

## Discussion

The study revealed several significant spatial relationships between environmental factors and COPD exacerbations in Thailand in 2022. A positive correlation was found between smoking prevalence and COPD exacerbations, particularly in areas with high population density and economic growth. This finding aligns with previous research by Laohasiriwong and Thammawongsa

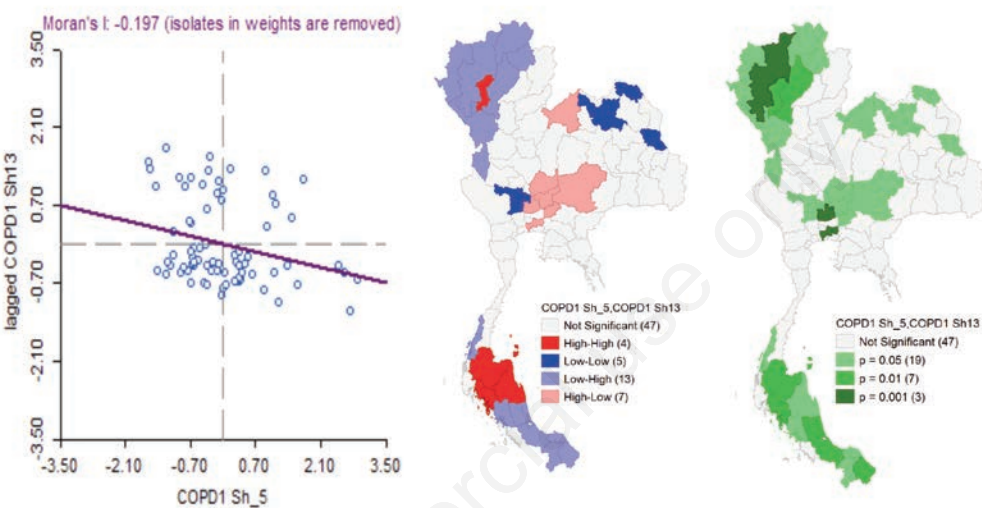


**Figure 3**. LISA and Moran's *I* scatterplot matrix of income and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

**Table 8.** Spatial regression analysis between socio-economic and environmental factors on the incidence of acute exacerbations among COPD patients in ≥15 years olds in Thailand 2022.

| Independent variable | OLS (SE) | Spatial Regression Model SLM (SE) | SEM (SE) |
|---|---|---|---|
| Income | -0.012*** (0.004) | -0.008** (0.003) | -0.009** (0.004) |
| Smoking | 22.057*** -6.713 | 13.555** -5.733 | 10.684** -7.225 |
| Industrial plant | 52.432*** -14.088 | 48.255*** -11.718 | 47.896*** -11.998 |
| Forest area | 4.525*** -1.406 | 3.554*** -1.214 | 4.728*** -1.423 |
| Rice field | -3.382** -1.413 | -1.901 -1.180 | -1.432 -1.465 |
| Constant | 328.452 (213.231) | 182.633 (179.831) | 441.526 (199.657) |
| ρ | - | 0.416 | - |
| λ | - | - | 0.474 |
| R2 | 0.516 | 0.639 | 0.611 |
| Log Likelihood | -509.292 | -500.145 | -503.781 |
| Akaike information criterion (AIC) | 1030.58 | 1014.29 | 1019.56 |
| Bayes information criterion (BIC) | 1044.65 | 1030.7 | 1033.63 |
| Lagrange Multiplier | - | P<0.001*** | P<0.001*** |

*correlation significant at the 0.05 level; **correlation significant at the 0.01 level; ***correlation significant at the 0.001 level; OLS= ordinary least squares; SLM = spatial lag model; SEM = spatial error model; SE is standard error; Constant = the regression model intercept (the expected mean value of Y when all X=0); ϱ = SLM lag coefficient; λ = SEM lag coefficient; $R^2$ = coefficient of determination.*

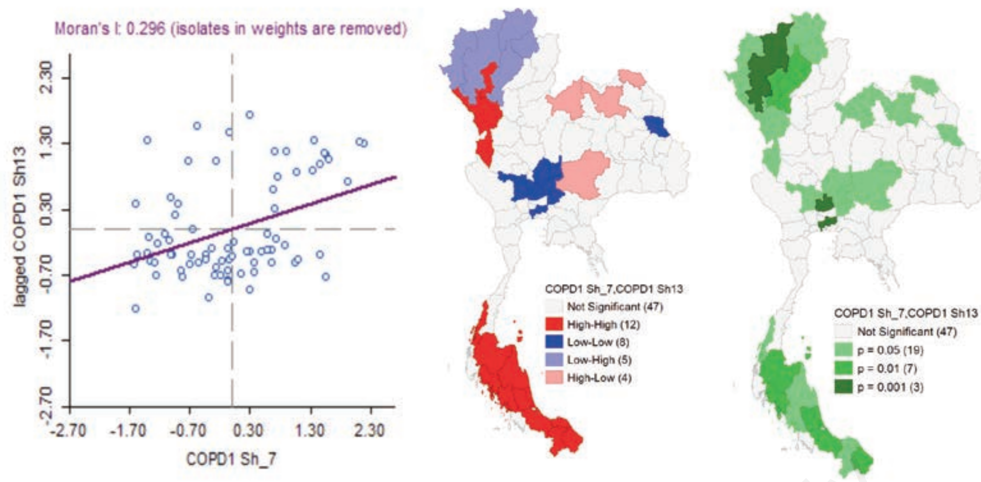


**Figure 4**. LISA and Moran's *I* scatterplot matrix of smoking and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

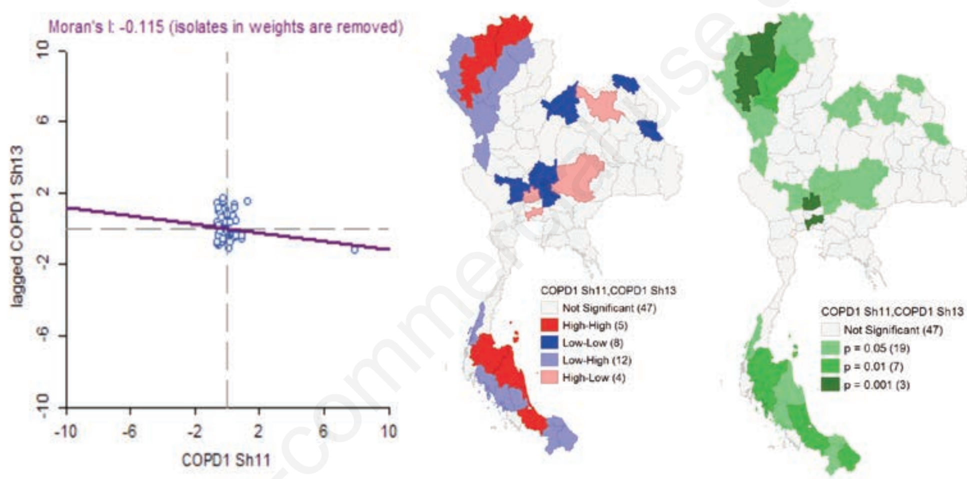


**Figure 5**. LISA and Moran's *I* scatterplot matrix of industrial plant and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

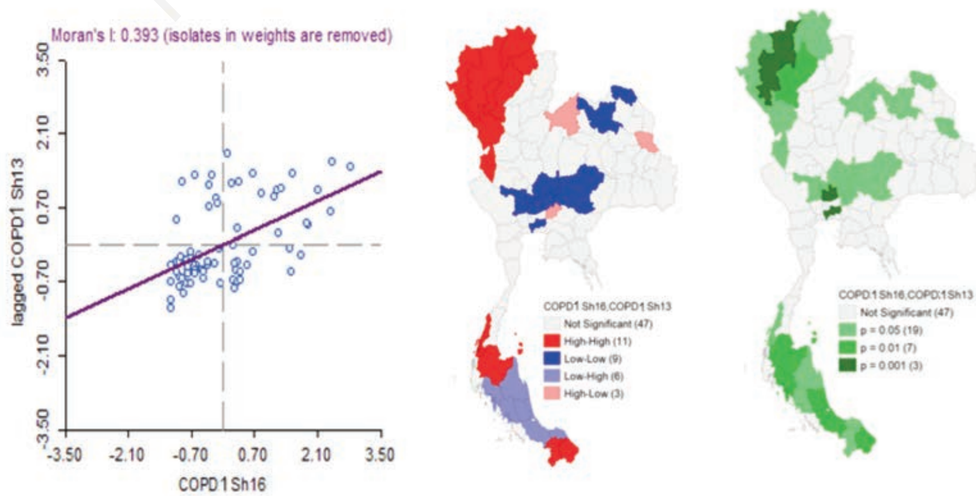


**Figure 6**. LISA and Moran's *I* scatterplot matrix of forest area and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.

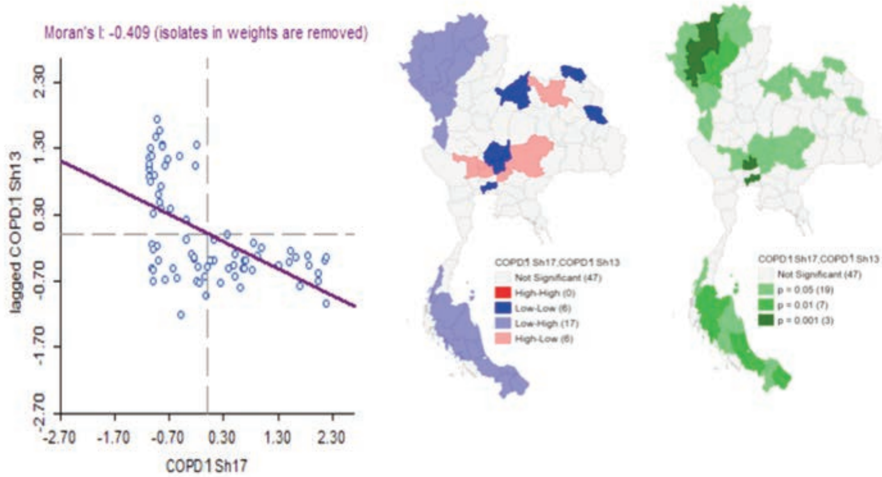


**Figure 7**. LISA and Moran's *I* scatterplot matrix of rice field and incidence of acute exacerbations of COPD in ≥15 years olds in Thailand.



(2021), who identified similar patterns in tobacco sales concentration. The significance of this relationship is further emphasized through data published by WHO (2019) showing that smokers face a mortality rate approximately three times higher than non-smokers. Industrial presence also showed a positive spatial correlation with COPD exacerbations, consistent with findings of higher COPD incidence in urban and industrial areas, particularly in central and northern Thailand (Luenam & Puttanapong, 2022). This relationship likely stems from increased air pollution in these regions as evidenced by the 200% increase in air pollution from 2016 to 2019 (Department of Medical Services, 2023).

Interestingly, the study found a positive association between forested areas and COPD exacerbations, supporting the observa*tions by Zhang* et al. (2023), who reported increased respiratory issues in regions with higher forest coverage. This unexpected relationship might be attributed to forest fire pollution and allergens present in forested environments. Conversely, a negative correlation was observed between rice field areas and COPD exacerbations, supporting Pattanaphong's (2017) hypothesis that agricultural expansion may improve air quality through reduced exposure to industrial pollutants. These findings have significant implications for public health policy. First, stricter tobacco control measures and expanded smoke-free zones should be implemented in high-density urban areas. Second, industrial emission standards should be strengthened, particularly in urban centres where pollution concentration is the highest (Bureau of Noncommunicable Diseases, 2022). Third, forest fire prevention and control measures need enhancement, especially in regions where forested areas intersect with populated zones. Fourth, the preservation and potential expansion of agricultural areas, particularly rice fields, might serve as a natural buffer against air pollution. Additionally, the healthcare system should be strengthened through the establishment of specialized respiratory clinics in high-risk areas and the development of comprehensive COPD care networks (Hartford *et al.*, 2021). To address these challenges effectively, a multi-sectoral approach is crucial. Local governments should collaborate with environmental agencies to monitor air quality, healthcare providers to track COPD exacerbations, and agricultural departments to maintain beneficial land use patterns. Future research should focus on understanding the mechanisms behind these spatial relationships, particularly the protective effect of agricultural areas and the impact of forest-related pollutants on respiratory health. Such understanding would enable more targeted and effective public health interventions to reduce the burden of COPD exacerbations in Thailand.

## Conclusions

This study marks a significant advancement in understanding the geographic distribution of COPD exacerbations in Thailand through comprehensive spatial analysis. The SLM's strong explanatory power (63.9%) reveals that COPD exacerbations follow distinct geographical patterns influenced by urbanization, industrial presence, and environmental factors. These findings fundamentally shift our understanding of COPD risk from purely individual health factors to a broader environmental and socioeconomic context. This research provides crucial insights for developing targeted, location-specific interventions and evidence-based environmental policies, potentially transforming COPD management approaches across Thailand's diverse regions.

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