GIS-Based Spatio-temporal Analysis of COPD Incidence Rates and High-risk Clusters in Suphan Buri, Thailand

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Abstract
Chronic obstructive pulmonary disease (COPD) remains a major public health challenge, particularly in provinces with persistent environmental and demographic risk factors. This study aimed to investigate the spatio-temporal distribution and clustering of COPD incidence in Suphan Buri province from 2019 to 2024 using village-level health records and geographic information systems (GIS). Annual incidence rates were calculated and stabilized using Empirical Bayes Smoothing, and spatial clustering was assessed using global Moran's I and local Moran's I. The analysis revealed consistent spatial clustering across all study years, with persistent hotspot villages primarily located in Si Prachan, Song Phi Nong, Dan Chang, and Doem Bang Nang Buat districts. In addition, 30 villages transitioned from outlier status to hotspot status, indicating the emergence of new high-risk areas. These findings highlight the uneven spatial distribution of COPD burden and emphasize the need for targeted surveillance, proactive case detection, and focused resource allocation in both persistent and emerging hotspot locations.

Keywords: Chronic Obstructive Pulmonary Disease, Geographic Information System, Local Indicators of Spatial Association, Spatial Autocorrelation

1. Introduction

Chronic obstructive pulmonary disease (COPD) is recognized as a critical chronic respiratory illness contributing substantially to illness and death globally. In the Thai context, it consistently ranks among the ten primary causes of mortality [1]. COPD results in a permanent and progressive reduction of airflow in the lungs, affecting quality of life and increasing patient mortality. At present, a large number of COPD patients remain undiagnosed or inadequately treated. Moreover, the risk factors of COPD are associated with social, economic, behavioral, and environmental aspects, such as smoking and exposure to air pollution [2], including geographic factors that may contribute to the risk of COPD incidence [3].

During the past decade (2014–2024), the national trend of COPD incidence in Thailand has shown a gradual decline followed by a slight resurgence in recent years. According to the Ministry of Public Health's Open Data Portal, the national incidence decreased from approximately 35.0 to 12.2 per 100,000 population between 2015 and 2022, before rising again to about 20.7 per 100,000 in 2024. The total number of registered COPD cases nationwide increased from around 180,000 in 2014 to 191,829 cases in 2023, corresponding to a prevalence of 420 per 100,000 population, which represented an increase of 5.78% compared with 2020 [4]. These observations suggest an overall decreasing trend of COPD incidence across Thailand during 2014–2022, with a moderate increase in the most recent years.

Suphan Buri province consistently reports a higher COPD burden than the national average, with incidence rates ranging from 60.8 per 100,000 in 2015 to 14.3 per 100,000 in 2024, and prevalence rates fluctuating between 480 and 510 per 100,000 population during 2019–2024 [4]. The province is geographically diverse, encompassing extensive agricultural plains, urban centers, and lowland river basins (Figure 1). Seasonal post-harvest burning of rice straw, particularly during February–April, produces particulate matter (PM 2.5) that represents a recognized environmental risk for COPD [5]. Suphan Buri has also been recognized as one of the provinces prioritized for accelerated implementation of national air-quality and respiratory-health policies.

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This prioritization has led to provincial level directives, including actions coordinated by the governor, to strengthen local responses to air-quality concerns and associated health impacts. The province also hosts several stone-milling and quarrying industries and contains agricultural areas that may periodically experience smoke episodes from open-field burning. These factors have contributed to its designation as one of the twelve target provinces in the national initiative promoting open burn free agricultural networks. Although these environmental conditions vary across districts, they collectively reflect the province's heightened policy attention and its relevance to national efforts addressing environmental determinants of respiratory health. Since 2019, when PM 2.5 mitigation was designated a national agenda item, Thailand has progressively intensified nationwide monitoring of air quality related respiratory health conditions, and this sustained effort provides a consistent backdrop for examining recent COPD patterns in the province [6]. When considered together with Suphan Buri's consistently higher than average COPD incidence and prevalence, these policy, demographic, and environmental characteristics underscore the province's relevance within the national context of respiratory health monitoring.

The study of spatio-temporal patterns of COPD is therefore essential, as it provides insight into the geographic and temporal distribution of disease and supports evidence-based planning and control policies. Geographic information system (GIS) technology has been widely used to examine spatial patterns of chronic diseases and to support epidemiological surveillance [7]. Spatial statistics such as global Moran's I and local Moran's I have been applied to identify local clusters and to assess spatial dependence of disease incidence [8]. Previous studies further demonstrated that combining GIS with spatial autocorrelation analysis improves the identification of high-risk areas and supports the development of disease distribution maps for public health decision making [9]. However, most COPD studies in Thailand have been conducted at provincial or regional levels, while fine scale spatio-temporal analysis at the village level remains limited. This gap restricts the understanding of local disease dynamics and targeted prevention. Using village level data allows more precise hotspot detection and better allocation of health resources. Empirical Bayes Smoothing (EBS) was adopted to stabilize incidence rates in small populations, while Monte Carlo simulations (999 permutations) were used to enhance the reliability of spatial significance testing [10] and [11]. EBS and Moran's I were selected as robust exploratory tools suitable for small area health data where case numbers are sparse, offering computational efficiency compared with Bayesian or SaTScan space time models [12][13] and [14].

This study aimed to analyze the spatio-temporal distribution of COPD incidence rates in Suphan Buri province, identify high-risk clusters at the village level, and monitor annual changes and transitions of risk areas. The findings are expected to provide actionable evidence for targeted COPD screening, proactive surveillance, and improved allocation of health resources. This evidence can support provincial health offices in designing village level interventions and contribute to Thailand's long-term health information systems for chronic respiratory disease control.

2. Materials and Methods

2.1 Study Area

Suphan Buri province is located in central Thailand and covers approximately 5,358 square kilometers. It comprises 10 districts, 110 subdistricts, and 1,008 villages, with a landscape characterized by lowland floodplains, extensive agricultural plains, upland terrain in the west, and forested mountainous areas in the northwest. Land use is dominated by rice cultivation, which accounts for more than 68% of agricultural land, particularly in the southern, central, and eastern zones. The western area contains higher elevation sugarcane fields, while quarrying and stone milling industries are situated in the northwestern uplands. Industrial facilities are concentrated mainly in the southern and eastern parts of the province. Seasonal increases in fine particulate matter (PM 2.5) commonly occur between February and April, influenced by agricultural residue management [5]. In 2023, PM 2.5 concentrations ranged from 7.1 to 53.8 μg/m³, with an annual average of 24.4 μg/m³ [15]. These diverse agricultural, industrial, and topographic settings create spatial variability in particulate exposure across districts, providing important context for understanding potential differences in respiratory health risks within the province.

2.2 Data Sources

Data on COPD patients aged 15 years and older for the period 2019–2024, identified using ICD-10 code J44, along with annual population statistics, were obtained from the Health Data Center (HDC), Ministry of Public Health [4]. The use of the ≥15-year age threshold reflects the standard demographic structure employed in the HDC reporting system.

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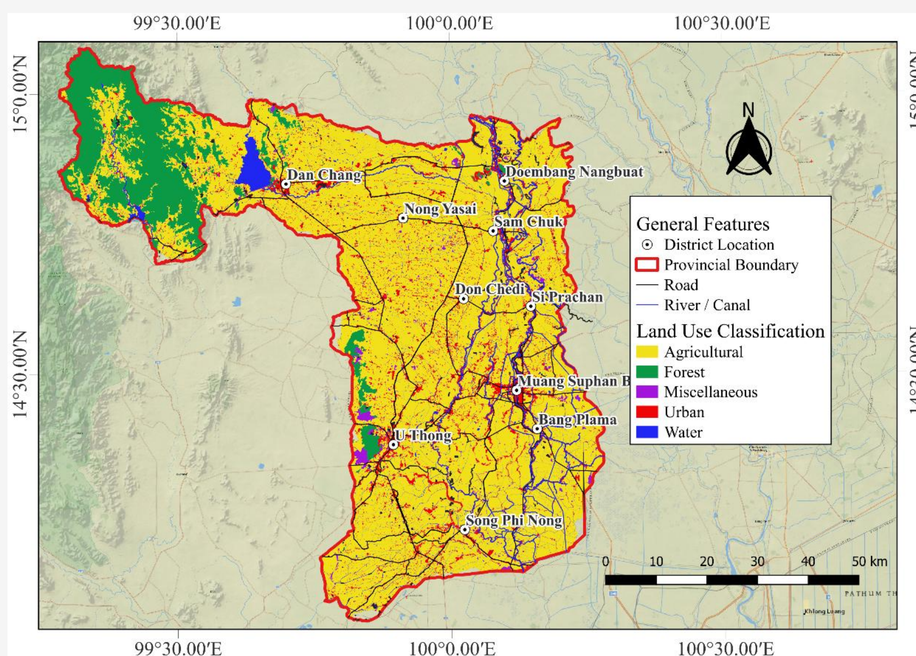

Figure 1: Suphan Buri province, Thailand

All COPD case records were derived from routine diagnostic reports issued by healthcare facilities and had undergone formal verification procedures within the Ministry of Public Health's health information system. Prior to analysis, duplicate, miscoded, and temporally incomplete entries were removed. Population figures were sourced from the Ministry's official demographic database and harmonized with annual civil registration counts to ensure consistency between case data and population denominators [4]. Village location data were collected using GNSS and stored as point-based shapefiles. A standard handheld GPS receiver was used to record village coordinates, and all recorded points were checked against administrative boundary layers to confirm positional correctness. Completeness was verified through cross referencing with the official village registry maintained by the Department of Provincial Administration. Field based GNSS acquisition was necessary because no complete or up to date village level geospatial dataset was publicly available, consistent with recommended practices in spatial epidemiological data preparation [9].

2.3 Data Processing

Village coordinates (point data) obtained from field surveys were integrated with COPD patient and population data. Because official village boundary polygons for Suphan Buri province were not available, Thiessen polygons were generated from village centroids and applied as the spatial unit for all analyses, including incidence rate calculation, Spatial autocorrelation and Local Indicator of Spatial autocorrelation (LISA) (Figure 2). This approach provides a continuous, non-overlapping tessellation appropriate for village level epidemiological analysis when administrative boundaries are unavailable, although we acknowledge that Thiessen polygons remain a geometric approximation. The incidence rate (IR) for each village was calculated using Equation 1:

$$IR = \frac{n}{P} \times 100$$

Equation 1

Where: n is the number of new COPD cases, and P is the total population of the village.

To address instability in rates due to small populations or zero case villages, Empirical Bayes Smoothing (EBS) was performed using GeoDa, which implements a moment based empirical bayes estimator. In this procedure, GeoDa automatically computes the variance components required for the shrinkage calculation and generates the smoothed incidence rates. Villages with zero observed cases were assigned adjusted values through the EBS shrinkage process, improving stability before LISA computation. These procedures follow standard practices in spatial epidemiology to minimize rate volatility across heterogeneous population sizes [12].

2.4 Spatial Analysis

Spatial analysis was performed by constructing a spatial weight matrix using the queen contiguity method [13] and [14]. Global Moran's I was applied to examine spatial autocorrelation of COPD incidence rates, to determine whether the distribution was clustered, random, or dispersed (Table 1), while local Moran's I (Local indicators of spatial association: LISA) was used to identify High–High (HH), Low–Low (LL), High–Low (HL), and Low–High (LH) categories (Table 2). Statistical significance was evaluated using a Monte Carlo randomization procedure with 999 permutations, in which the observed values are repeatedly reshuffled to create a reference distribution of Moran's I under spatial randomness ($p < 0.05$) [9]. The overall analytical workflow is summarized in Figure 2. The queen contiguity weighting scheme was selected because village polygons in Thailand are irregular and often share edges as well as vertices, allowing adjacency relationships to be captured more realistically for potential disease diffusion.

Table 1: Interpretation of Global Moran's I

Moran's I	Spatial Pattern
0 > E(I)	Clustered: areas with similar values are located near each other
0 = E(I)	Random: no clear pattern of clustering or dispersion
0 < E(I)	Dispersed: areas with dissimilar values are located near each other

Table 2: Interpretation of Local Moran's I (LISA)

LISA Cluster Type	Description
High-High (HH) or Hotspot	Areas with high values surrounded by other high values
Low-Low (LL) or Coldspot	Areas with low values surrounded by other low values
High-Low (HL) or Outlier (OL)	Areas with high values surrounded by low values
Low-High (LH) or Outlier (OL)	Areas with low values surrounded by high values

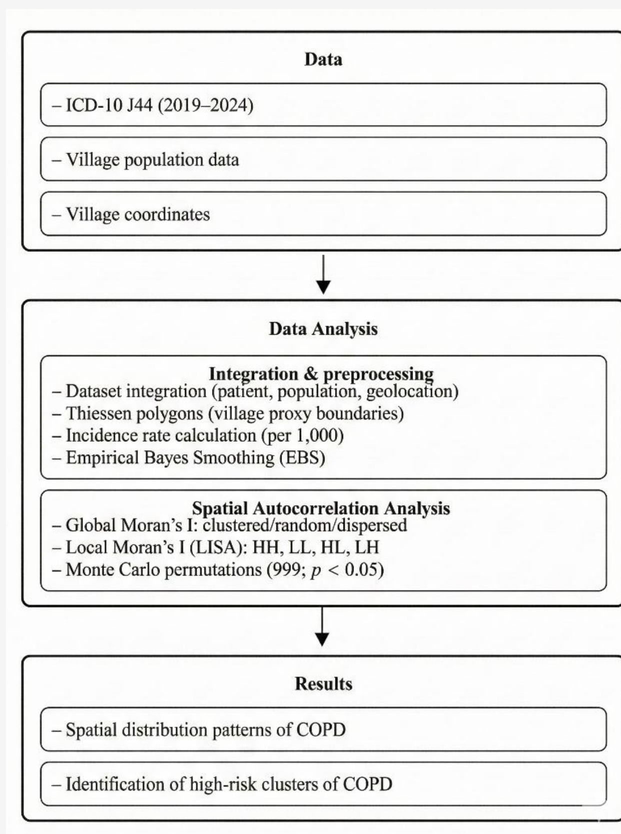

Figure 2: COPD cluster analysis methodology

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Sensitivity checks using k-nearest neighbor and distance-based matrices yielded similar clustering patterns, confirming the robustness of the queen contiguity approach. Given the multi-year but limited case data, exploratory global Moran's I and local Moran's I were preferred over more complex space time models (e.g., SaTScan or Bayesian hierarchical frameworks) that require larger samples and additional covariates. Together, these spatial statistics provide both an overall measure of spatial dependence and detailed local cluster identification suitable for village level COPD analysis.

2.5 Software

Spatial data analysis and map visualization were performed using QGIS and GeoDa. QGIS was employed for spatial data management, integration of patient and population datasets, and preparation of village boundary layers. GeoDa was used for applying Empirical Bayes Smoothing (EBS), constructing spatial weight matrices, and performing global Moran's I and local Moran's I analysis. The overall analytical workflow comprised five sequential steps: (1) data acquisition and pre-processing in QGIS, (2) implementation of EBS and spatial autocorrelation analysis in GeoDa, (3) generation of global Moran's I and local Moran's I maps, (4) identification of persistent hotspots and transitional clusters, and (5) temporal validation and summary of findings (Figure 2). This workflow was adapted from established GIS-based spatial analytical frameworks [9] and [14].

3. Results

The spatial analysis of COPD in Suphan Buri province was conducted using spatial statistical techniques, including global Moran's I and local Moran's I, in combination with Empirical Bayes Smoothing (EBS) to reduce variability in incidence rates among areas with different population sizes, as follows:

3.1 COPD Incidence Rates in Suphan Buri Province

The annual COPD incidence rates in Suphan Buri province from 2019 to 2024 are summarized. The overall provincial population declined slightly during the study period, ranging from 835,572 in 2020 to 793,439 in 2024. The number of new COPD cases ranged from 50 to 164 cases annually. The crude incidence rate was highest in 2019 (0.19 per 1,000 population), then decreased gradually to the lowest level in 2022 (0.06 per 1,000). Subsequently, the rate increased again, reaching 0.14 per 1,000 in 2024 (Figure 3). These fluctuations indicate the dynamic burden of COPD in the province and provide essential baseline context for subsequent spatial autocorrelation analyses. At the village level, most villages reported no new cases each year, while non-zero incidence appeared in scattered locations across the province and varied from year to year (Figure 4). Villages with incidence rates ≥3.0 per 1,000 were observed sporadically and did not persist in the same locations across all years, instead shifting over time. This reflects unstable patterns of risk at the local scale, indicating temporal and spatial variability in the burden of COPD. Such variation underscores the need for spatial statistical analysis to confirm clustering and to identify persistent hotspot areas.

3.2 Spatial Distribution Patterns of COPD Incidence Rates in Suphan Buri Province

The results of the global Moran's I analysis of COPD incidence rates adjusted by Empirical Bayes Smoothing (EBS) between 2019 and 2024 showed positive values for all years, indicating spatial clustering of COPD incidence (Figure 5). All Moran's I statistics were statistically significant ($p < 0.01$) based on 999 Monte Carlo permutations. The highest Moran's I (0.143) occurred in 2020, representing the strongest spatial dependence, whereas the lowest value (0.058) in 2022 reflected a weaker clustering pattern. Overall, COPD incidence exhibited significant positive spatial autocorrelation throughout the study period.

3.3 Identification of Hotspots of COPD Incidence Rates in Suphan Buri Province

Although the crude incidence rate declined between 2019 and 2022, spatial clustering remained statistically significant throughout the study period, suggesting that localized hotspots persisted despite overall reductions. The local Moran's I (LISA) analysis was used to identify local clusters of COPD incidence rates, with results presented as annual LISA cluster maps (Table 3) (Figure 6). The analysis of local Moran's I revealed that risk areas in Suphan Buri province, particularly certain villages, emerged as hotspots (HH). These were located in the eastern part of the province (Si Prachan District), the southern part (Song Phi Nong District), the northwestern part (Dan Chang District), and the northeastern part (Doem Bang Nang Buat District). During 2019–2024, a total of 82 hotspots were identified, of which 14 villages repeatedly appeared as persistent hotspots across more than one year (Figure 7). Specifically, 29 hotspots (HH) were identified in 2019, 31 in 2020, 11 in 2021, 6 in 2022, 10 in 2023, and 11 in 2024.

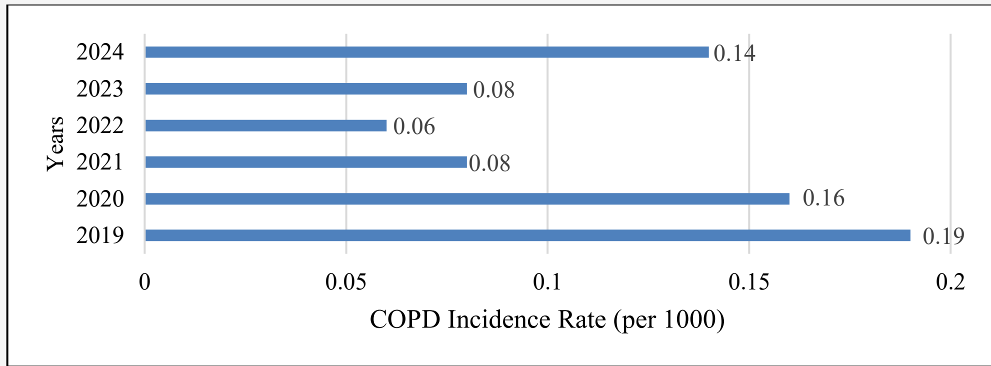

Figure 4: Annual COPD incidence rates in Suphan Buri province, 2019–2024

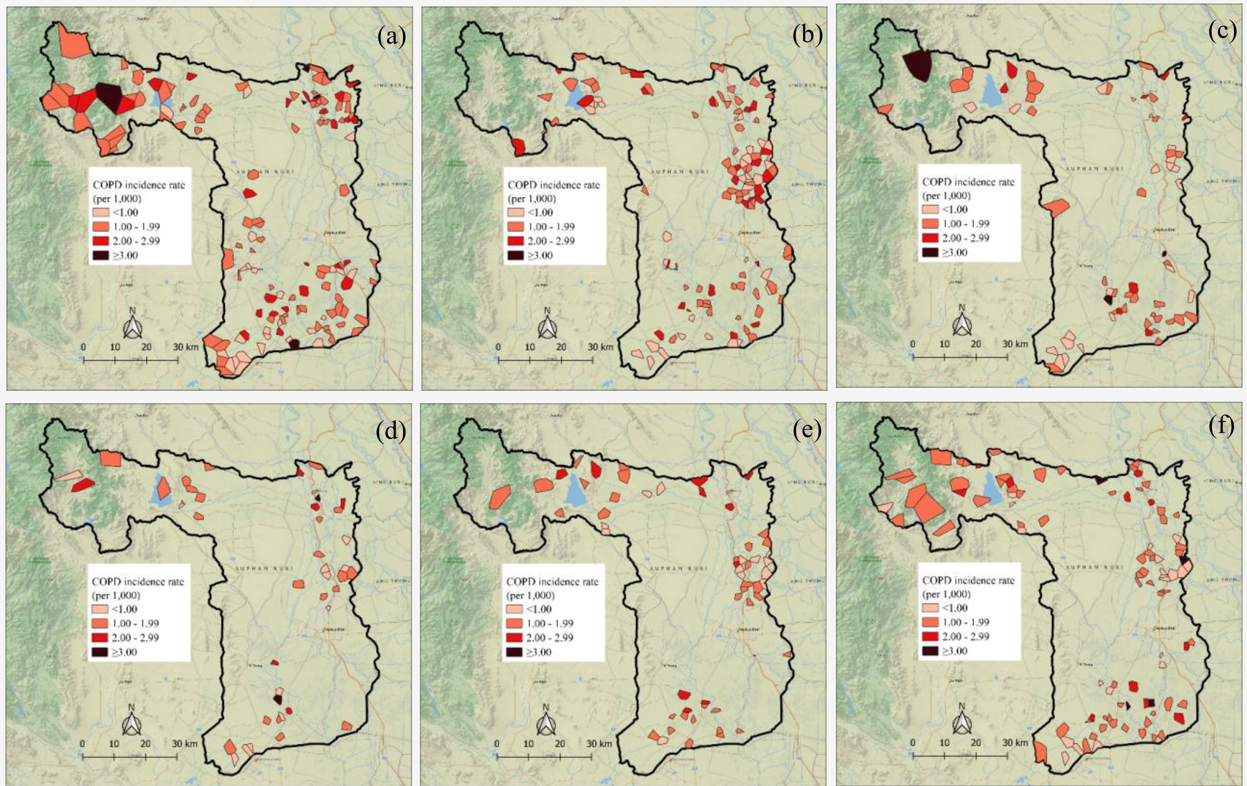

Figure 4: Annual COPD incidence rates per 1,000 population in Suphan Buri province: (a) 2019, (b) 2020, (c) 2021, (d) 2022, (e) 2023, and (f) 2024

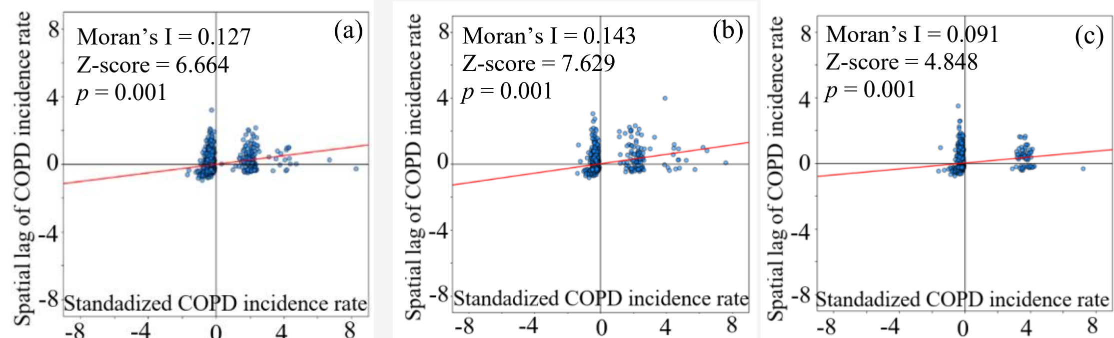

Figure 5: Spatial autocorrelation of COPD incidence rates using Moran's I, Suphan Buri province: (a) 2019, (b) 2020, (c) 2021 (Continue next page)

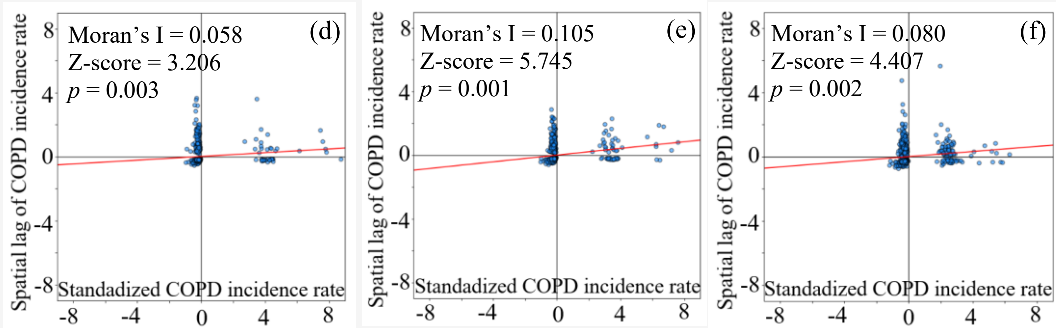

Figure 5: Spatial autocorrelation of COPD incidence rates using Moran's I, Suphan Buri province: (d) 2022, (e) 2023, (f) 2024 (Continue previous page)

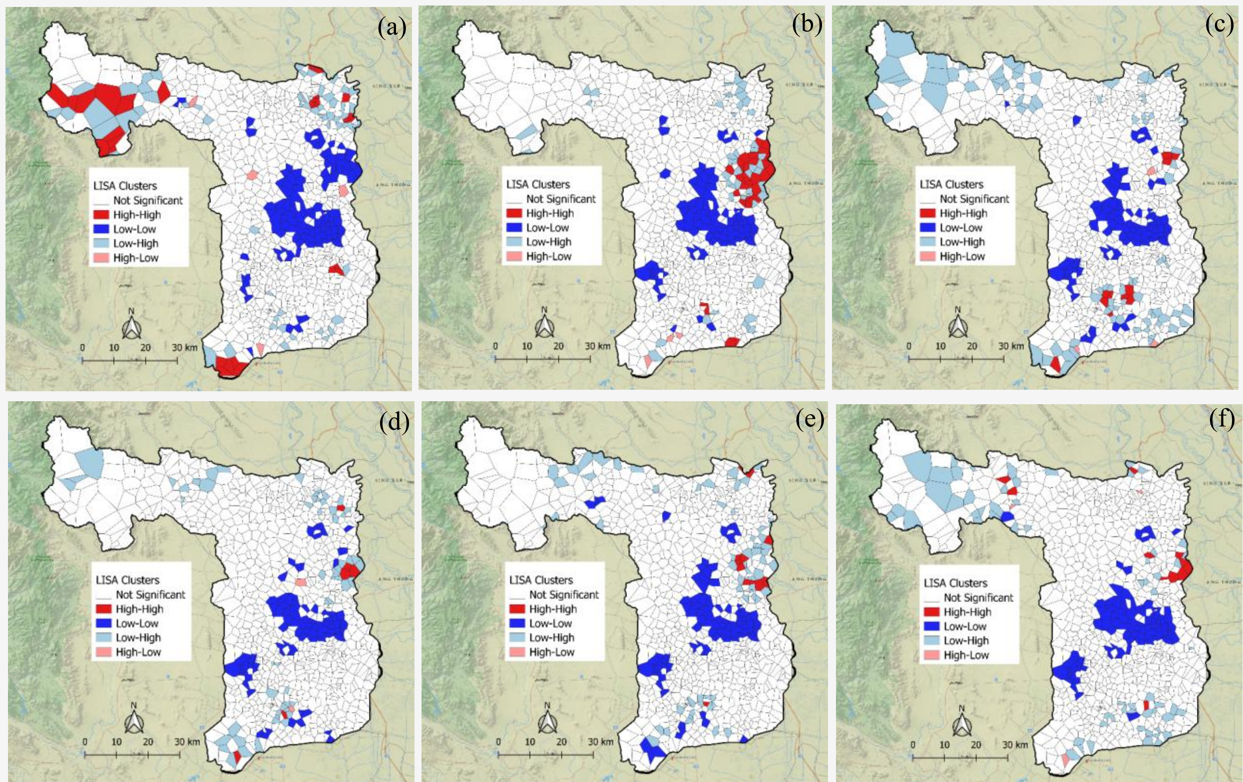

Figure 6: LISA cluster maps of COPD incidence rates using local Moran's I, Suphan Buri province: (a) 2019, (b) 2020, (c) 2021, (d) 2022, (e) 2023, and (f) 2024

Table 3: Distribution of LISA cluster types of COPD incidence rates in Suphan Buri province, 2019–2024

Year	Numbers of clusters and outliers			
	HH	LL	HL	LH
2019	29	126	4	60
2020	31	100	3	49
2021	11	105	3	84
2022	6	95	2	57
2023	10	106	0	61
2024	11	103	3	61

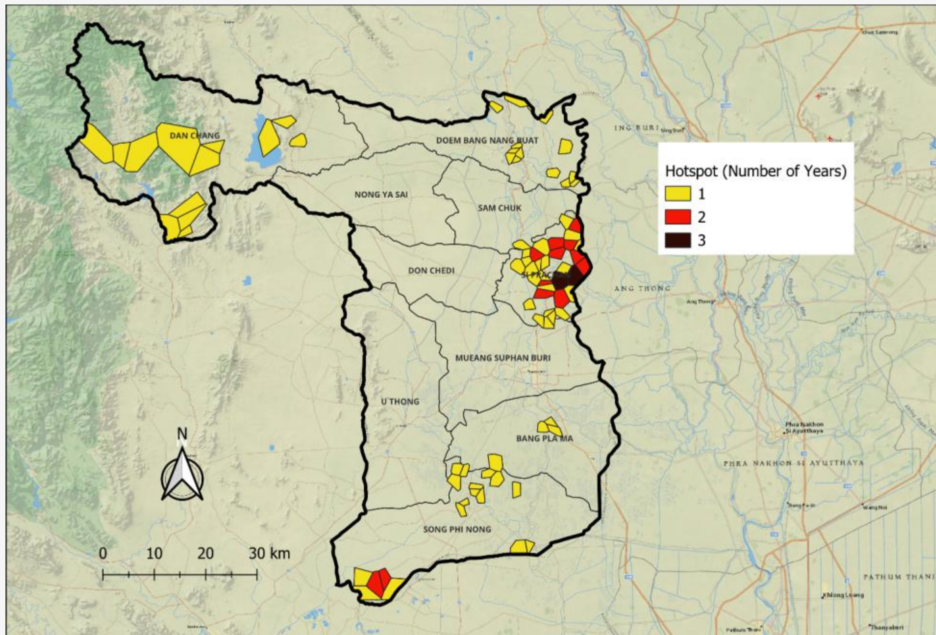

Figure 7: Frequency map of hotspot of COPD incidence rates in Suphan Buri province, 2019–2024

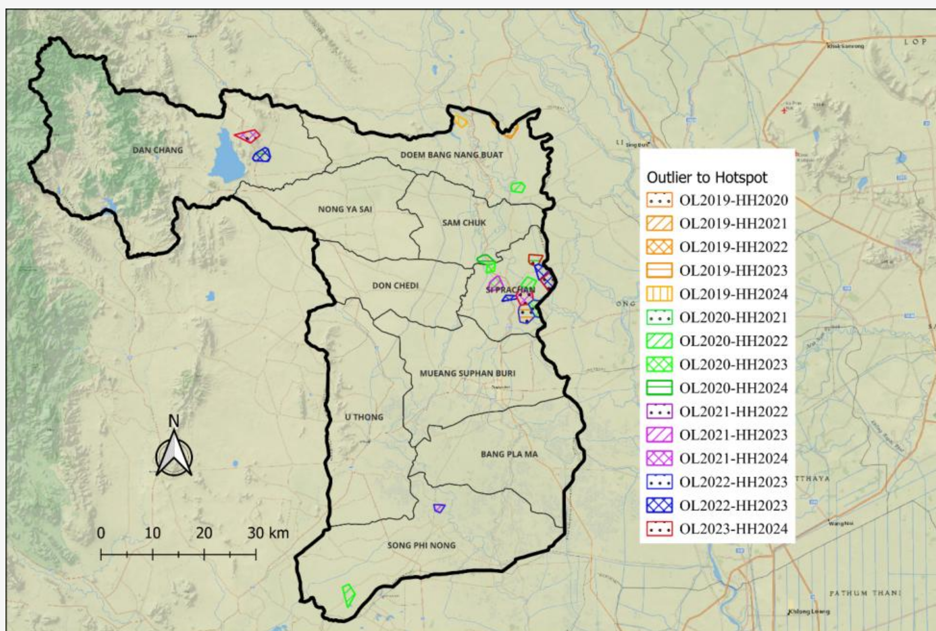

Figure 8: Map of spatial transitions from outlier (HL, LH) to hotspots (HH) of COPD incidence rates in Suphan Buri province, 2019–2024

Table 4: Number of areas transitioning from outlier clusters (HL or LH) to hotspots (HH) of COPD incidence rates in Suphan Buri Province, 2019–2024

Base year	Transition to HH in year	Number of villages
2019	2020, 2023, 2024	4
2020	2022, 2023, 2024	9
2021	2022, 2023, 2024	6
2022	2023, 2024	8
2023	2024	3

Among these, 2 clusters (Si Prachan District) persisted for three consecutive years, while 12 clusters (Si Prachan District and Song Phi Nong District) persisted for two consecutive years (Figure 7). Outlier clusters (HL or LH) were identified in all years, and 30 outlier villages later transitioned into hotspot (HH) status during the study period (Table 4). These transitions were concentrated in the eastern part of the province (Si Prachan District), followed by the northeastern (Doem Bang Nang Buat District), southern (Song Phi Nong District), and northwestern areas (Dan Chang District) (Figure 8).

Analysis of spatio-temporal transitions indicated that 30 outlier clusters (HL or LH) evolved into hotspots clusters (HH) during 2019–2024 (Table 4). These transitions were recurrently concentrated in the eastern part of the province (Si Prachan), followed by the northeastern (Doem Bang Nang Buat), southern (Song Phi Nong), and northwestern areas (Dan Chang). Notably, multiple clusters in Si Prachan District repeatedly shifted from outlier to HH status across consecutive years (Figure 8), highlighting this district as the most dynamic hotspot zone. In summary, a total of 82 hotspots were detected, with 14 villages showing recurrent hotspot status across multiple years. Additionally, 30 villages transitioned from outlier status to hotspot status in subsequent years, reflecting dynamic spatial changes that may evolve into persistent hotspots in the future.

4. Discussion

The findings of this study demonstrated that the COPD incidence rates in Suphan Buri province between 2019 and 2024 exhibited statistically significant clustered spatial patterns in every year ($p < 0.01$). This result is consistent with previous research that reported adjusted COPD incidence rates displaying clustered distributions [16]. Similar observations were made in another study, which indicated that COPD cases tend to concentrate in specific areas associated with environmental and socioeconomic factors such as proximity to industrial zones, major roads, or areas with elevated air pollution [8]. Comparable evidence was also reported in Bangladesh, where the spatio-temporal distribution of COPD patients showed similar clustering patterns [7]. Year to year variation in global Moran's I values may be related to environmental and seasonal influences. Stronger spatial clustering in 2020 coincided with intense post-harvest burning and drier meteorological conditions, whereas the lower value in 2022 corresponded with reduced agricultural fires and wetter La Niña conditions. Such temporal correspondence should be interpreted as contextual patterns that may reflect prevailing environmental conditions. These findings may be consistent with previous observations that climatic variability and burning activity influence spatial patterns of respiratory diseases. The results are consistent with previous studies that linked particulate-matter levels and respiratory morbidity in agricultural regions [2][3] and [7]. Additional analysis revealed that industrial areas carried a higher risk of COPD-related hospital admissions compared to other areas [17]. Research conducted in Spain identified clear high-risk clusters of respiratory diseases using the LISA technique, supporting the findings in Suphan Buri province where persistent high-risk points were observed [18]. The values of Moran's I varied between years. In 2020, the value was highest (0.143), indicating stronger clustering compared to other years. In 2022, the lowest value (0.058) suggested potential changes in contextual conditions, such as climatic patterns or air quality levels, that may have influenced spatial clustering [11].

Further studies demonstrated that increases in particulate matter in agricultural and urban areas of central Thailand were associated with rising rates of respiratory diseases, including COPD [3]. Geographic and social structures were also found to play an important role in the occurrence and distribution of disease [19]. Although clustered spatial patterns were clearly identified, the overall incidence of COPD remained low throughout the study period, which aligns with the epidemiological characteristics of COPD as a chronic, slowly progressive disease that typically presents modest annual incidence. National surveillance data show incidence levels ranging between 0.12 and 0.35 per 1,000 population [4], with provincial trends in Suphan Buri falling within a comparable range. The village level incidence observed in this study (0.06–0.19 per 1,000 population) therefore lies within expected epidemiological levels, particularly in communities with smaller populations where annual case counts naturally fluctuate around low baselines. These findings indicate that low incidence values likely reflect the underlying nature of COPD rather than data anomalies and underscore the value of multi-year spatial analysis in revealing patterns that may not be evident from single-year data.

An investigation in Thailand covering 2016–2019 revealed significant clustering of chronic respiratory diseases related to population density, households, vehicles, factories, and agricultural areas [20]. Another study confirmed that COPD prevalence clusters were positively associated with tobacco-outlet density, elderly population density, and PM 2.5 concentrations [21]. Research conducted in Iran showed that high-risk clusters were concentrated in dense and environmentally stressed

zones [22], while a study in Pakistan found clustering across both spatial and temporal dimensions linked with climatic and pollution factors [23]. These findings are broadly consistent with the spatial distribution observed in this study, where hotspots occurred in districts characterized by agricultural activity or industrial operations. The analysis using local Moran's I (LISA) identified a total of 82 hotspots, including 14 that recurred in the same locations across multiple years. These clusters were distributed across Si Prachan, Song Phi Nong, Dan Chang, and Doem Bang Nang Buat districts.

This observation is consistent with research that reported areas with repeated open burning were more likely to develop into respiratory disease hotspots [2]. The recurrence of these high-risk points may be related to surrounding agricultural activity and seasonal burning patterns that are common in these areas. Most of the districts mentioned are dominated by rice farming with year-round burning. Song Phi Nong and Si Prachan districts also contain numerous factories, and Dan Chang district includes hotspots located near stone mills and quarries [5]. The spatial concentrations of hotspots observed in this study appear to align with broader geographic characteristics of Suphan Buri, although the present data do not allow for causal inference. The districts in which hotspots recurred Si Prachan, Song Phi Nong, Dan Chang, and Doem Bang Nang Buat are situated in areas that differ from other parts of the province in terms of agricultural activity, industrial presence, and general land use patterns [5]. While the study was not designed to measure these factors directly, the geographic correspondence suggests that local environmental or structural conditions may contribute to the persistence of hotspot areas. Similarly, villages that transitioned from outlier status to hotspot status were often located along the same regional corridors, indicating that gradual changes in these areas may be related to shifts in spatial risk patterns over time. Other studies demonstrated that COPD clustering is more common in rural areas than in urban settings [24]. Similar findings were observed among veterans in the United States, where disadvantaged rural populations exhibited higher COPD prevalence rates [25]. Nevertheless, COPD is also influenced by additional determinants such as smoking exposure, genetic predisposition, congenital lung abnormalities, severe respiratory infections, and asthma [26]. This is further supported by global evidence showing the burden and attributable risk factors of COPD worldwide [27]. In addition, 30 outlier areas were observed to transition into hotspots in subsequent years. This pattern may suggest a potential increase in localized vulnerability in such areas, although further investigation would be needed to identify the underlying factors. Previous research highlighted that monitoring outliers transitioning into hotspots could serve as an important indicator for preventive planning [10].

Consistent evidence was also reported in another study, which emphasized the importance of early identification of such transitions [7]. The use of GIS in risk assessment and hotspot identification was also demonstrated in this study. Prior research applied global Moran's I and LISA to identify statistically significant clustering and to distinguish high- and low risk areas [20]. Additional work confirmed the ability of global Moran's I and LISA to correctly identify both high and low risk clusters [18]. Combining Empirical Bayes Smoothing with global Moran's I and LISA improved the detection of community level hotspots [9], and Monte Carlo simulations enhanced the reliability of spatial-pattern detection [3]. These results, consistent with the present study, highlight the robustness of GIS based spatial statistics for analyzing chronic respiratory diseases. Collectively, these findings underscore the importance of integrating spatial analysis with longitudinal health data to identify COPD hotspot areas and monitor spatio-temporal changes. This approach supports precise resource allocation and targeted prevention strategies. The present findings also have practical implications for public health policy in Thailand. The identification of persistent and emerging COPD hotspots in Suphan Buri province suggests the need for integrating GIS based spatial monitoring into local health information systems. Such tools could support proactive COPD screening programs, targeted health education, and resource allocation in high risk villages. Moreover, given the strong association between COPD and environmental exposures such as agricultural burning and particulate matter, collaboration between the health and environmental sectors is essential for risk reduction. Embedding these spatial approaches into provincial surveillance frameworks would allow timely detection of new hotspots, inform evidence based interventions, and ultimately improve disease prevention strategies at both provincial and national levels.

5. Conclusion

This study demonstrated that the application of spatial autocorrelation, spatial statistics, and GIS based cluster detection methods provides a useful exploratory framework for analyzing the COPD incidence rates in Suphan Buri province. Using Empirical Bayes Smoothing, global Moran's I, and local Moran's I, the analysis confirmed that COPD incidence rates between 2019 and 2024 exhibited

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statistically significant clustered patterns across all years. Although crude incidence rates fluctuated during the study period, the overall spatial dependence remained consistent. Persistent hotspot clusters were repeatedly observed in Si Prachan, Song Phi Nong, Dan Chang, and Doem Bang Nang Buat districts, and 30 villages transitioned from outlier status to hotspot status in subsequent years, reflecting patterns of spatial change that may warrant continued monitoring. The analysis provides additional insight into how COPD incidence varies across communities within the province, complementing findings from broader scale studies.

The findings highlight that the COPD burden in Suphan Buri province is unevenly distributed and concentrated in specific geographic areas with persistent or emerging risks. By integrating GIS and spatial statistics, this study provides practical tools for visualizing spatio-temporal disease patterns, identifying persistent hotspots, and detecting transitional risk areas. Such evidence should be viewed as exploratory and supportive of further investigation rather than prescriptive guidance for direct intervention. Importantly, this study addresses a critical research gap by presenting one of the first integrated spatio temporal analyses of COPD at the village level in Thailand, offering higher spatial resolution than previous provincial or district based investigations. This study also has several limitations. It relied on secondary health service data that may be subject to underreporting or diagnostic variation. Individual level risk factors such as smoking, occupation, and health behaviors were not included and therefore could not be linked to the observed spatial patterns. Spatial representation using Thiessen polygons may differ from actual administrative boundaries, and spatial misalignment across datasets cannot be ruled out. In addition, the ecological scale of the analysis means that village-level associations may not reflect individual level risks. Only Moran's I and LISA were applied, and other spatial modelling approaches could offer complementary or more explanatory insight.

Future research could build on these findings by incorporating environmental, demographic, or socioeconomic variables into spatial regression or spatial econometric models to examine potential drivers of COPD clustering more formally. Integrating high resolution environmental data such as PM 2.5 levels, humidity, and wind characteristics or applying Bayesian or SaTScan space-time models may further improve understanding of local risk patterns. Comparative multi-provincial studies would also strengthen national surveillance and inform the development of data-driven public-health strategies for chronic respiratory diseases.

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