A spatial lag model analysis of lung cancer incidence and satellite-derived data on air pollution in Thailand from 2020 to 2023

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Abstract

This study aimed at investigating the association between satellite-based remotely sensed data on particulate matter with diameters less than 2.5 microns ($PM_{2.5}$), sulphur dioxide (SO_2), nitrogen dioxide (NO_2) and carbon monoxide (CO) on the one hand, with the incidence of lung cancer in Thailand on the other. Regression analyses on a nationwide dataset comprising 604,460 confirmed cases reported between 2020 and 2023 were conducted using the Spatial Lag Model (SLM) to assess the relationship between the ambient air pollutants and lung cancer incidence. The results revealed that provinces with the highest cancer incidence rates were consistently found to be located in the eastern part of north-eastern Thailand and the far North as well as some provinces in the South. The SLM accounted for a moderate proportion of variance in lung cancer incidence, with R^2 values ranging from 0.1548 to 0.1755 over the study period. $PM_{2.5}$ concentrations were positively and significantly associated with incidence rates each year, an effect increasing from 2020 (0.2160, p=0.0075) to 2023 (0.3096, p=0.0102). These findings highlight the potential of satellite-based air quality data, particularly $PM_{2.5}$ for predicting and monitoring lung cancer incidence, thereby supporting evidence-based public health planning and environmental policy in Thailand. The results add empirical evidence to the growing body of literature demonstrating the public health consequences of ambient air pollution.

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Introduction

Despite growing interest in the health impacts of air pollution, a critical research gap remains regarding the spatial association between atmospheric pollutant concentrations and lung cancer incidence, particularly in low- and middle-income countries. While satellite-based remote sensing has been increasingly used to monitor air quality, few studies have integrated these data with nation-scale cancer incidence records to produce spatially explicit models. This gap is particularly pronounced in Southeast Asia, including Thailand, where lung cancer rates continue to rise alongside deteriorating air quality (Sakti *et al.*, 2023)

Remote sensing technologies have become indispensable in air quality monitoring for health-related research. Unlike ground-based monitoring stations, which provide limited, point-based datasets often constrained by predominantly covering urban areas, satellite observations offer spatially continuous coverage across extensive geographic regions (Putrenko & Pashynska, 2017; Fernandes *et al.*, 2019; Filonchyk *et al.*, 2020). In recent years, this type of data have been widely employed to assess atmospheric pollutants, such particulate matter with diameters less than 2.5 microns ($PM_{2.5}$), sulphur dioxide (SO_2), nitrogen dioxide (NO_2) and carbon monoxide (CO) (Prunet *et al.*, 2020; Kang *et al.*, 2021; Saw *et al.*, 2021; Xia *et al.*, 2021). These pollutants are classified as human carcinogens and pose significant public health risks, particularly in industrialised and densely populated regions (Cetin, 2016; Oliveira *et al.*, 2021; Maharjan *et al.*, 2022). As urbanisation continues to increase, pollution levels are expected to rise leading to greater health impacts, including higher cancer incidence (Çetin & Sevik, 2016; Ozel *et al.*, 2019). In Thailand alone, 604,460 lung cancer cases linked to long-term air pollution exposure were reported for the period 2020-2023 (Ministry of Public Health - MoPH, 2024).

This study addressed the research gap regarding the spatial distribution of lung cancer by investigating the potential relationships between major air pollutants and lung cancer incidence in Thailand using satellite-derived data. A further objective was to develop a predictive spatial model that can estimate lung cancer incidence based on pollutant exposure levels, thereby informing environmental health risk assessments and public health strategies. The findings from this study should provide empirical evidence of pollution-related cancer risks and contribute to the development of data-driven tools for public health monitoring and environmental policymaking.

Materials and Methods

This retrospective study examined the association between long-term exposure to ambient air pollutants and lung cancer incidence in Thailand from 2020 to 2023. Addressing this urgent public health concern, we integrated remotely sensed data and epidemiological statistics to identify geographic patterns and model pollution-related cancer risk.

Study area and seasons

This study focused on Thailand, an upper-middle-income country with a total area of 514,000 km^2 comprising 511,770 km^2 of land and 2,230 km^2 of water. The geographically administrative hierarchy includes 77 provinces, 878 districts (amphoes), 7,225 sub-districts (tambons) and 74,965 villages. Located in a tropical zone, it has three seasons: winter from November to February, summer from March to May and rainy season from June to October.

Data sources

The dependent variable was the annual lung cancer incidence rate, calculated as the number of confirmed cases per 100,000 population. Morbidity data, classified under the ICD-10 code C34 (malignant neoplasm of bronchus and lung), were obtained from the Centre of Epidemiological Information, Bureau of Epidemiology, MOPH. A total of 122,104 cases were reported in 2020, followed by 183,632 in 2021, 189,722 in 2022, and 109,002 in 2023 across all 77 provinces. The data are publicly available via the Department of Disease Control, MOPH (2024). The independent variables were the annual average concentrations of the four major air pollutants $PM_{2.5}$, NO_2, SO_2 and CO estimated using remotely sensed data from two satellite sources as described below.

$PM_{2.5}$ data were derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument (https://modis.gsfc.nasa.gov/about/) aboard the Terra and Aqua satellites launched by NASA in 1999 and 2002, respectively. We used the Aerosol Optical Depth (AOD) data retrieved (NASA, 2024) based on the multi-angle implementation of atmospheric correction (MAIAC) algorithm (https://modis-land.gsfc.nasa.gov/ MAIAC.html) applied to the MODIS satellite observation at 1-km spatial resolution. The annual $PM_{2.5}$ concentrations were computed by aggregating daily AOD values to the provincial level, matching the spatial and temporal resolution of lung cancer data. The Deep Blue algorithm (https://earth.gsfc.nasa.gov/climate/data/deep-blue) provides useful proxies for estimating ground-level $PM_{2.5}$ concentrations with high spatial resolution (Lyapustin *et al.*, 2011; Peng *et al.*, 2022).

The NO_2, SO_2, and CO concentrations were obtained from the TROPOspheric Monitoring Instrument (TROPOMI) aboard the Sentinel-5P satellite (https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5) launched 2017 by the European Space Agency (ESA). The near-daily global coverage and a spatial resolution of approximately 1 km, enables TROPOMI to produce a detailed, global mapping of pollutant distributions (Prunet *et al.*, 2020; Kang *et al.*, 2021; Saw *et al.*, 2021; Xia *et al.*, 2021).

The analytical methods used included standard regression and the Spatial Lag Model (SLM), which accounts for spatial dependencies between neighbouring areas (Anselin, 2003; Ward & Gleditsch, 2018; Wu *et al.*, 2020; Luenam & Puttanapong, 2022). By incorporating indirect spatial effects, SLM improves model reliability in detecting the influence of environmental factors on health outcomes.

Data analysis

For an exploratory spatial data analysis, QGIS version 3.8.3 (Steiniger & Hunter, 2013) and GeoDa version 1.20.0.8 (Anselin *et al.*, 2006) were used. QGIS was applied to integrate all data before transfer to GeoDa for regression computation.

Regression analysis

The relationship between air pollutant concentrations and lung cancer incidence across the 77 provinces in Thailand was examined using spatial regression, specifically SLM implemented in GeoDa. All variables were log-transformed to stabilise variance and 'linearise' relationships. Statistical significance was assessed at the 0.05 level using two-sided tests.

To account for spatial dependence, a spatial weights matrix (W_{ij}) was constructed based on first-order queen contiguity, whereby provinces were defined as neighbours if they shared either a common boundary or a vertex. This matrix was row-standardised, such that the influence of neighbouring provinces sums to one for each observation. The matrix 'operationalises' the spatial structure of the data, which allows estimation of spill-over effects, *i.e.,* situations where pollutant levels in one province may be influenced by those in adjacent provinces (Anselin & Arribas-Bel, 2013; Mollalo *et al.*, 2020). The SLM was specified as follows:

$$\Delta logAP_i = \beta_0 + \beta_1 logLC_i + \rho W_{ij} \Delta logAP_j + \varepsilon_i \qquad \text{Eq. 1}$$

where $\Delta logAP_i$ stands for $\Delta logAirpollutants_i$ *i.e.,* the year-on-year change in the log-transformed concentration of air pollutants (dependent variable); $logLC_i$ for *logLungCancerincidencei, i.e.*, the log-transformed lung cancer incidence rate (independent variable); ρ for the spatial lag coefficient that represents the strength of spatial dependence; W_{ij} for the spatial weight matrix that indicates the influence of neighbouring province *i* on province *j*; β_0 for the intercept coefficient; β_1 for the slope coefficient; and for a normally distributed error term.

To justify the use of a spatial model, global Moran's *I* was first applied to the residuals of an Ordinary Least Squares (OLS) model to test for spatial autocorrelation. Since a statistically significant, positive Moran's *I* indicates spatial clustering and violation of the OLS independence assumption, Lagrange Multiplier (LM) diagnostics were employed to determine the most appropriate spatial model specification. The significant LM-lag test supported the use of the SLM over alternative models such as the Spatial Error Model (SEM), suggesting the presence of substantive spatial interaction in the dependent variable. The SLM approach is particularly appropriate in this context as it incorporates the direct influence of neighbouring provinces on pollutant levels, thereby improving model accuracy and accounting for spatial spill-over effects that are otherwise undetectable through traditional regression techniques (Wu *et al.*, 2020).

Results

Lung cancer in Thailand

Out of the total of 604,460 lung cancer cases reported in Thailand between 2020 and 2023 (MoPH, 2024), the provinces with the highest incidence rates of lung cancer were found in the eastern part of the Northeast, near the border to Lao People's Democratic Republic. Provinces with the highest incidence rates were also found in the far northern part of the country near the Myanmar border. Moreover, there were also high incidence rates in some provinces in the South each year (Figure 1).

SLM estimations

The outcome obtained by regression using SLM is presented in Table 1. Given the longitudinal dataset, a comparative analytical framework was applied across four consecutive years (2020-2023). For each year, the SLM generated province-specific coefficient estimates for each independent variable ($PM_{2.5}$, SO_2, NO_2 and CO) across all 77 provinces in Thailand. This resulted in annual pollutant coefficients for each province. To enable comparison between the study years and enhance interpretability, the average of the 77 provincial coefficients for each pollutant was computed and shown as the representative estimates in Table 1. These averaged coefficients reflect the national-level association between each pollutant and the incidence rate of lung cancer, controlling for spatial dependence and other covariates.

Across all the study years analysed, the SLM consistently revealed a statistically significant positive association at the level of $p<0.05$ between $PM_{2.5}$ concentrations and lung cancer incidence, with the average slope coefficients increasing over time. Although none of the associations found were stronger than $p<0.05$, it was close to $p<0.01$ in 2023, the latest year studied (Table 1). In addition, SO_2 only exhibited a significant positive association in 2020 (0.4709, p=0.0384), while its effect in subsequent years diminished and no longer statistically significant. The situation with respect to NO_2 and CO was similar showing statistical significance only in one of the study years, 2020 for the former (0.01601, p=0.0360) and 2021 for the latter (1.9976, p=0.0435), with the associative effect weaker and statistically marginal in other years.

The model's explanatory power, as measured by R^2, ranged from 15.5% to 17.6% across the study period. The spatial lag parameter (ρ), confirmed the presence of spatial autocorrelation, thereby validating the appropriateness of the SLM framework.

Discussion

This study provides robust evidence of the association between $PM_{2.5}$ exposure and lung cancer incidence in Thailand, with spatial regression analysis identifying elevated risks in the north-eastern, northern and southern border provinces. The use of satellite-derived AOD data enabled high-resolution assessment of air pollution in areas lacking ground-based monitoring, offering a practical approach for identifying localised health risks. By integrating spatial epidemiology with remote sensing, this research could address key data limitations in low- and middle-income settings and contributes a novel framework for environmental health surveillance and policy development.

The regression analysis revealed a statistically significant positive correlation between $PM_{2.5}$ concentrations and lung cancer incidence, even after adjusting for relevant covariates, suggesting a strengthening association between $PM_{2.5}$ exposure and lung cancer incidence in recent years (Table 1). These findings reinforce the well-established health risks associated with long-term exposure to fine particulate matter (Badyda *et al.*, 2017; Chen *et al.*, 2016; Cao *et al.*, 2018). Notably, the strength of this relationship varied spatially across Thai provinces, with more pronounced associations in regions exhibiting higher $PM_{2.5}$ levels, a heterogeneity that highlights the uneven burden of air pollution.

Our spatial analysis identified persistent clusters of high lung

Table 1. Regression coefficients for air pollutants and lung cancer incidence in Thailand 2020-2023.

Independent variable	2020	2021	2022	2023
Constant	0.0239 (p=0.9932)	435.235 (p=0.0791)	33.417 (p=0.1804)	23.719 (p=0.2218)
$PM_{2.5}$	0.2160 (p=0.0075)	0.2781 (p=0.0150)*	0.2551 (p=0.0322)*	0.3096 (p=0.0102)*
SO_2	0.4709 (p=0.0384)*	0.0656 (p=0.2681)	0.0566 (p=0.3450)	0.2268 (p=0.2633)
NO_2	0.1469 (p=0.1636)	0.01601 (p=0.0360)*	0.01277 (p=0.0945)	0.1675 (p=0.3521)
CO	0.1834 (p=0.8776)	19.976 (p=0.0435)*	15.787 (p=0.1115)	13.449 (p=0.0914)
R^2	0.1751	0.1548	0.1654	0.1755
ρ (rho)	0.1010	0.1477	0.1579	0.2007
Province (no.)	77	77	77	77

The values represent the average coefficient estimates across all 77 provinces in Thailand derived from the spatial lag model (SLM); *statistically significant at p<0.05).

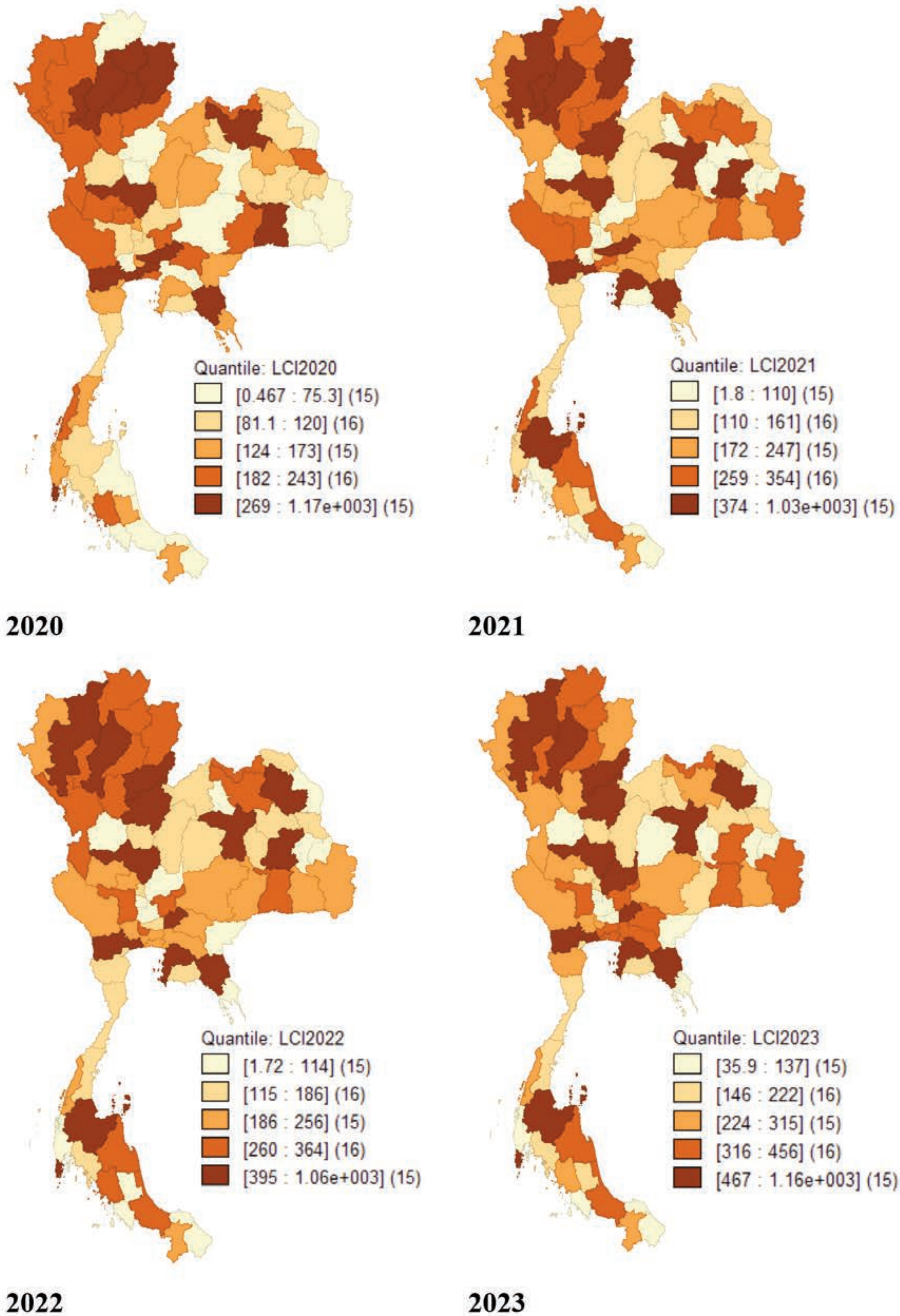

Figure 1. Spatial distribution of lung cancer incidence across Thailand between 2020 and 2023. The legend for each map indicates the range of [incidence rates] and the number of (provinces) within each range.

cancer incidence across the study period, predominantly in the eastern part of the north-eastern provinces bordering Lao People's Democratic Republic. Additional high-risk areas were observed in several northern provinces adjacent to Myanmar and also in some southern provinces. These regional hotspots coincide with areas frequently affected by forest fires and agricultural crop burning, practices prevalent under the slash-and-burn farming system (Chen *et al.*, 2019; Wang *et al.*, 2022). Transboundary air pollution originating from neighbouring countries Myanmar, Laos, Vietnam, Cambodia and Malaysia further exacerbates the situation through further addition of $PM_{2.5}$, thereby increasing the health risks across borders (Amnuaylojaroen *et al.*, 2023).

The spatiotemporal distribution of lung cancer cases corresponds with periods and locations where $PM_{2.5}$ pollution has recently intensified. The role of biomass burning with regard to elevating ambient $PM_{2.5}$ levels remains a critical environmental health concern (Lee *et al.*, 2018; Yin *et al.*, 2019; Amnuaylojaroen *et al.*, 2020). This study adds empirical evidence to the growing body of literature demonstrating the public health consequences of ambient air pollution, particularly in the context of rapidly developing economies such as Thailand, where environmental sustainability often lags behind industrial and agricultural expansion.

The biological possibility of $PM_{2.5}$ as a risk factor for lung cancer is supported by its composition. Fine particulate matter typically contains black carbon with toxic components such as sulphates and nitrate that are considered particularly hazardous due to the ability of deep penetration into the pulmonary system (Li *et al.*, 2018). Exposure to these particles has been associated with various respiratory disorders, as they can infiltrate and become retained within lung tissue (Shu *et al.*, 2016). Such exposure has been identified as an etiological factor in the development of lung cancer. Indeed, numerous studies have suggested that $PM_{2.5}$ may act as a significant risk factor for this disease (Bowe *et al.*, 2019; Yang *et al.*, 2020; Sang *et al.*, 2022).

The use of satellite-derived AOD as a proxy for $PM_{2.5}$ exposure offers a valuable methodological contribution, particularly in regions with sparse ground-based monitoring. The validity of AOD-based $PM_{2.5}$ estimates has been substantiated by previous studies (Lee *et al*., 2011; Kloog *et al.*, 2011, 2012; Chudnovsky *et al.*, 2013). In the Thai context, satellite-derived data provide a practical means of identifying pollution and disease clusters in real time, especially given the variability in emissions influenced by both socioeconomic and meteorological factors.

The SLM approach was employed to further strengthen the model's predictive capabilities. The results affirm the robustness of the positive association between $PM_{2.5}$ and lung cancer incidence ($p<0.05$), even after accounting for spatial dependencies. This is consistent with prior applications of remotely sensed data in public health surveillance (Jechow *et al.*, 2020; Elvidge *et al.*, 2020; Beyer, 2021) suggesting that $PM_{2.5}$ data can effectively serve as a predictive indicator of lung cancer.

While comprehensive in scope, this study is subject to several limitations. First, the reliance on AOD-$PM_{2.5}$ as a proxy for the risk of lung cancer, although validated, may still introduce spatial estimation errors in regions with frequent cloud cover or complex terrain. Second, the study design is ecological in nature and does not account for individual-level risk factors such as smoking status, occupational exposure or genetic predisposition. Third, the model does not incorporate long-term latency effects of carcinogen exposure, which are critical in cancer epidemiology. Future research should adopt a multi-level modelling approach that combines spatial data with individual-level health records to improve causal inference. Incorporating time-lagged exposure assessments, high-resolution meteorological data, and urban development indices could significantly enhance model precision. In addition, the rising level of statistical significance for the association between $PM_{2.5}$ and lung cancer reaching close to level of $p<0.01$ (Table 1) in the last study year warrant continued follow-up in the following years.

Conclusions

While the current analytical framework offers statistically significant findings, its predictive capacity could be improved by incorporating additional variables such as meteorological conditions, land use, socioeconomic status, and healthcare access. Future research should explore the application of machine learning techniques, such as random forest, gradient boosting, and neural networks as they can uncover non-linear relationships and complex interactions among variables that traditional regression methods may overlook. These models can also be continuously trained and updated with new satellite and epidemiological data, enabling dynamic and real-time prediction systems. The integration of LM into environmental health modelling holds substantial promise for enhancing both the predictive accuracy and explanatory power of disease risk assessments. The findings underscore the urgent need for strengthened environmental regulation, enhanced air quality monitoring, and regional cooperation to mitigate the significant and preventable health burden posed by ambient air pollution in Thailand.

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