

Spatial distribution of COVID-19 infection in Thailand and its related factors during 2020-2021

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ABSTRACT

Background: The COVID-19 pandemic, with over 759 million confirmed cases and 6.8 million deaths globally as of March 2023, underscores the critical need for effective control measures.

Objectives: This study investigates the spatial dynamics of the disease in Thailand from 2020 to 2021, focusing on the association between demographic, environmental, and socioeconomic factors and COVID-19 infection rates, utilizing Geographic Information Systems.

Methods: In this cross-sectional study, QGIS and GeoDa were employed to analyze the spatial pattern of COVID-19 infection rates using Local Moran's I statistics for spatial autocorrelation. Spatial regression, specifically the Spatial Lag Model and Spatial Error Model was utilized to identify factors related to the observed spatial patterns.

Results: The study identified high incidence clusters in southern and central Thailand. Population density, age demographics, and urbanization were found to be positively correlated with incidence rates. Environmental factors such as temperature showed a negative correlation, while forest area coverage exhibited a complex influence. Socioeconomic variables, including income and alcohol density, displayed varying effects, while tobacco density was positively associated with incidence.

Conclusion: This comprehensive study underlines the importance of considering spatial dynamics in pandemic analysis. It reveals the multifaceted interplay between demographic, environmental, and socioeconomic factors in COVID-19 transmission. These findings provide valuable insights for targeted interventions and effective pandemic control strategies in Thailand and similar regions.

Keywords: COVID-19 pandemic, Demographics, Environmental factors, Geographic Information Systems, Socio-economic variables, Spatial dynamics, Thailand

1. Introduction

The COVID-19 pandemic, declared by the World Health Organization (WHO) in March 2020, has presented unprecedented challenges globally, affecting healthcare systems, economies, and daily lives worldwide [1]. As of March 7, 2023, the pandemic has recorded a staggering 759,408,703 confirmed cases and 6,866,434 deaths globally, underscoring the urgent need for effective control measures [2]. This global crisis has prompted researchers and policymakers to explore innovative approaches to understanding and mitigating the spread of the virus.

Understanding the spatial dynamics of COVID-19 is crucial for effective control and response measures. Geographic Information Systems (GIS) have emerged as indispensable tools for analysing infectious disease distribution and identifying risk factors [3-6]. It can provide not only hotspot clustering of diseases [7-8], but also valuable insights into the spatial relationships between environmental factors [9-10], demographic factors [11-13] and health care factors [11] which are important in shaping disease dynamics. Sandar et al. (2023) identified the spatial autocorrelation and heterogeneity of demographic and healthcare factors in Thailand's COVID-19 epidemic, shedding light

on the spatial determinants of transmission [11]. Similarly, Ganslmeier et al. (2021) explored the impact of weather on the COVID-19 pandemic, highlighting the intricate interplay between environmental factors and disease transmission [10]. Moreover, the spatial-temporal patterns of COVID-19 transmission identified by a study in the United States, emphasizing the role of geographic factors in shaping disease dynamics [12].

By elucidating spatial patterns and determinants of transmission on COVID-19 infection, evidence-based decision-making, targeted interventions, and appropriate pandemic response efforts can be applied. Therefore, this study aimed to describe the spatial distribution of COVID-19 incidence rate within provinces of Thailand during 2020 and 2021 and to explore the impact of demographic factors, environmental factors, and socioeconomic factors on COVID-19 incidence rate and its spread within provinces of Thailand by employing geospatial analysis.

2. Methods

The incidence rate of COVID-19 during 2020-2021 and its relationship with demographic, environmental, and socio-economic factors determinants at the provincial level in Thailand were explored through geospatial analysis using QGIS and GeoDa.

2.1 Study Area

This study was carried out in Thailand, which is located in Southeast Asia and has an upper-middle-income economy. Thailand covers a size of 514,000 km² and shares borders with Myanmar, Cambodia, Laos, and Malaysia. It is divided into 77 provinces, which are organized into four regions: Central, North, Northeast, and South.

The publicly available data from Government of Thailand were utilized to conduct this study (<https://data.go.th/en/dataset?groups=publichealth&groups=research&organization=epidemiologists>).

2.2 Study Design

This cross-sectional study was conducted by analyzing secondary data using spatial analysis techniques.

2.3 Sample size and sampling

The present cross-sectional study employed a dataset of COVID-19 cases reported by the Centre of Epidemiological Information, Bureau of Epidemiology, Ministry of Public Health (MoPH) in Thailand. The dataset covered the period from January 2020 to 2022 and included a total of 1,669,080 confirmed cases from all 77 provinces in Thailand. However, to maintain homogeneity, the study excluded non-residents, such as foreigners

working, studying, traveling, or living in Thailand, who accounted for a significant proportion of total confirmed cases. Therefore, only the cases of Thai citizens were included in the analysis after data cleaning. After data cleaning, the study ultimately included 1,669,080 Thailand citizens.

A total of 1,669,080 confirmed cases of COVID-19 were obtained from the COVID-19 report of Thailand data, covering a two-year period from 2020 to 2022 [14]. The incidence rate of COVID-19 for each province in Thailand was calculated by dividing the number of confirmed new cases by the total population of that province and multiplying the result by 100,000.

$$\text{Incidence Rate} = \frac{\text{New cases in Province}}{\text{Total population in Province}} \times 100,000 \text{ population}$$

This calculation was performed to account for potential variations due to differences in population size across provinces. The resulting incidence rate per 100,000 population was used as the dependent variable in the regression models to investigate potential factors associated with COVID-19 transmission.

2.4 Data Collection

In this study, a range of demographic, environmental, and socioeconomic factors

were compiled and included as explanatory variables. The dataset was obtained from

commonly cited open data sources for Thailand during the epidemic (Table 1).

Table 1: List of explanatory variables in the study

Description of Variable	Sources
Administrative Map of Thailand	Geographic (GIS) data[15]
COVID-19 Confirmed Cases 2020 January to 2022 December	Open Government Data of Thailand[16]
Demographic Factors	
Percentage of Child age of Population	National Statistical Office[17]
Percentage of Working age Population	
Percentage of Old age Population	
Percentage of Urban population	
Environmental Factors	
Lowest Temperature 2020	National Statistical Office[17]
Highest Temperature 2020	
Forest Area Coverage	
Socio-economic Factors	
Per Capita income (baht)	National Statistical Office[17]
Alcohol Density	Centre of Alcohol Studies (http://cas.or.th/cas/)
Tobacco Density	Centre of Tobacco Studies (https://cts.rutgers.edu/)

2.5 Data Analysis

To describe the spatial distribution patterns of COVID-19 incidence rate, QGIS version 3.20.3 (Odense) [18] and GeoDa version 1.18.0.16 [19] were applied to find out the measure of spatial autocorrelation analysis for an exploratory spatial data analysis. After collecting the data, it was input into an Excel file and then uploaded into Quantum GIS. This software was used to integrate all the data before transferring it to GeoDa for LISA analysis and spatial regression. The geographical coordinates of administrative areas of province-specific database of provincial maps were processed using Quantum GIS. This allowed for the description of spatial distribution patterns of demographic,

healthcare, and socioeconomic factors, as well as the COVID-19 incidence rate, across the 77 provinces of Thailand.

2.5.1 QGIS (Quantum Geographic Information System)

QGIS offers a wide range of tools to analyse various spatial statistics of epidemic risk areas, including spatial distribution, hotspots, orientation, and trajectories of spread. In this study, QGIS techniques were used to examine spatial variations in COVID-19 incidence, visualize epidemic waves, and track pandemic hotspots throughout the study period. This analysis was a primary step in understanding the spatial variability of incidence in relation to demographic, healthcare, and socioeconomic

variables, and for spatiotemporal prediction of regional transmission speed and magnitude.

2.5.2 GeoDa Program

Spatial autocorrelation analysis was performed in this study using the GeoDa program, with a 3 k-Nearest neighbour criterion used to identify spatial groupings and form a weight matrix for analysing spatial correlation [19, 20]. The spatial weight matrix was carefully formulated to ensure an appropriate selection of neighbouring provinces, as this factor can significantly influence the outcome of Local Indicators of Spatial Autocorrelation (LISA) computation. For example, given the distinct geographic features of Phuket and Krabi, as well as the 23 coastal and 32 border provinces included in this study, the spatial weight matrix was optimized to maintain localized characteristics while including sufficient neighbouring provinces. By employing a 3 k-Nearest neighbour criterion, the spatial weight matrix accurately captured the spatial relationships and dependencies among neighbouring provinces, which is essential for reliable LISA analysis [19, 20].

In this study, the spatial regression analysis was performed using the GeoDa program. The Queen's contiguity with a distance of 1 was used as a criterion to identify the grouping of

neighbouring provinces for the analysis. This approach utilized a weight matrix to examine the spatial correlation among provinces, which is important for modelling and understanding the spatial patterns of COVID-19 incidence rates. The use of weight matrix allowed the spatial dependence among neighbouring provinces to be taken into account, which was crucial for accurate spatial regression analysis [21].

2.6 Ethical Clearance

The researcher submitted the proposal and obtained approval from the Human Ethical Committee of the Khon Kaen University, Khon Kaen, Thailand. Since this study is based on secondary data, there is no harm to the study population. The Ethics Committee in Human Research of Khon Kaen University, Thailand approved the study under reference number HE662188.

3. Results

The following figures describe distribution of COVID-19 rate per 100,000 Population 2020-2021. The clusters were observed to be concentrated in the central and southern regions of Thailand. In the central region, the concentration was evident in five provinces: Samut Songkhram, Samut Sakhon, Bangkok Metropolis, Samut Prakan, Chon Buri, and

Rayong. In the southern region, the Songkhla, Pattani, Yala, and Narathiwat concentration was notable in four provinces: (Figure 1).

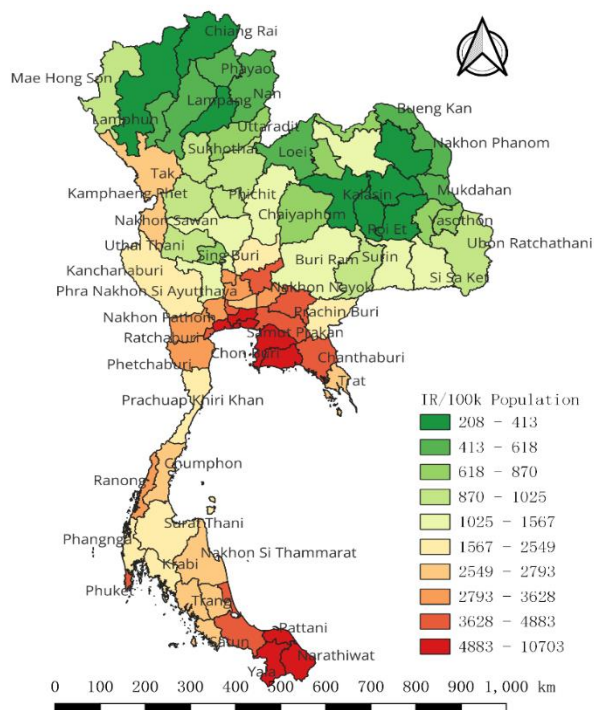


Figure 1. COVID-19 incidence rate per 100,000 population

3.1 Exploring COVID-19 Infection Clusters Revealed by LISA Analysis: IR/100k Population Incidence Rate

Analysing the COVID-19 Incidence Rate per 100,000 population, the study revealed a

positive spatial autocorrelation, as indicated by a Moran's I value of 0.690 and a p-value of 0.001. Particularly, the data revealed the presence of distinct clusters (Figure 2).

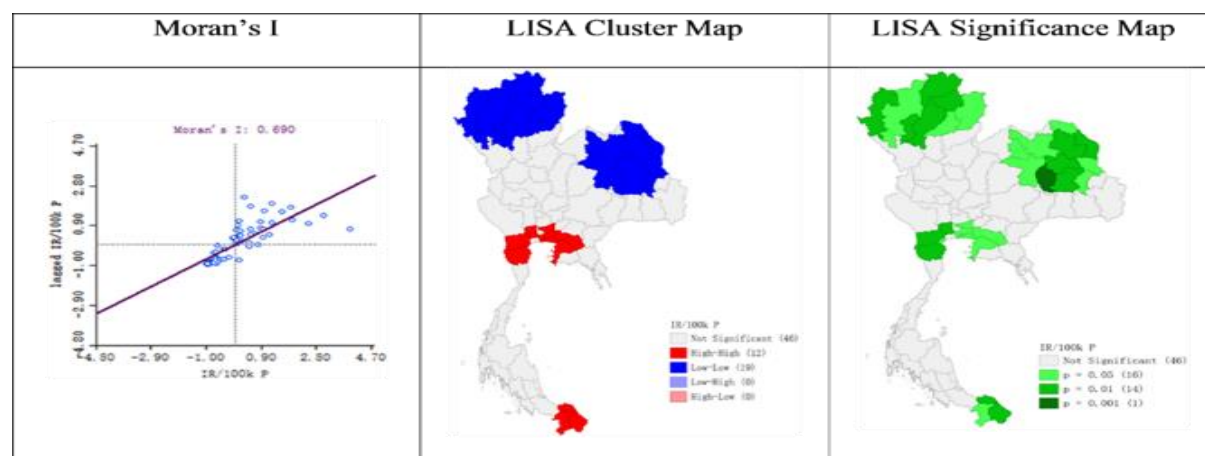


Figure 2. Univariate analysis of COVID-19 incidence rate per 100,000 Population

3.2 Exploring COVID-19 Infection Clusters through Child Age (0-14 Years) Incidence Rate

Analysing the COVID-19 Incidence Rate within the 0-14 Years Child Age Group, the

study revealed a notable positive spatial autocorrelation, as indicated by a Moran's I value of 0.353 and a p-value of 0.001. Notably, the data revealed the presence of distinct cluster patterns (Figure 3).

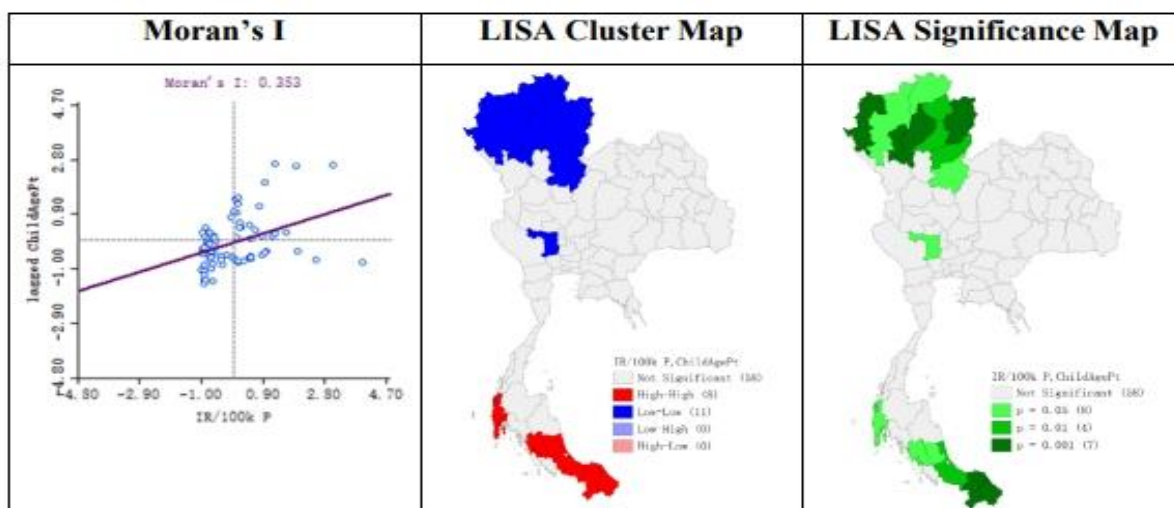


Figure 3. Bivariate analysis of Child Age (0-14 Years) Percent and COVID-19 Incidence Rate

3.3 Exploring COVID-19 Infection Clusters among Working Age (15-59 Years) Population

Analyzing the COVID-19 Incidence Rate within the Working Age (15-59 Years)

Group, the study unveiled a noteworthy negative spatial autocorrelation, as indicated by a Moran's I value of -0.057 and a p-value of 0.185. Notably, the data revealed the presence of distinct cluster patterns (Figure 4).

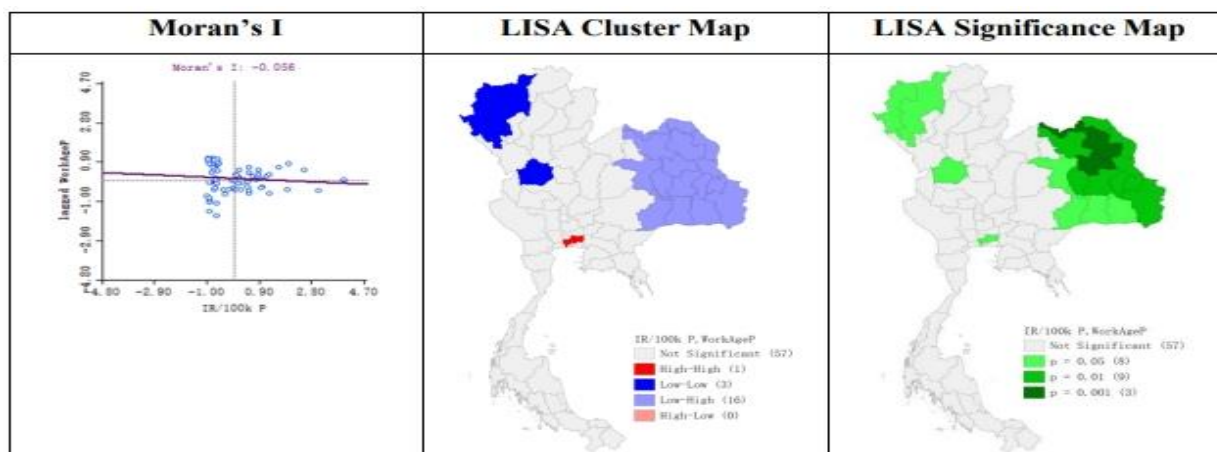


Figure 4. Bivariate analysis of Working Age (15-59 Years) Percent and COVID-19 Incidence Rate

3.4 Exploring COVID-19 Infection Clusters among the Elderly (60 Years and Over) Population

Analysing the COVID-19 Incidence Rate within the Old Age (60 Years and over) Group, the study unveiled a remarkable

negative spatial autocorrelation, as indicated by a Moran's I value of -0.269 and a p-value of 0.001. Notably, the data revealed the presence of distinct cluster patterns (Figure 5).

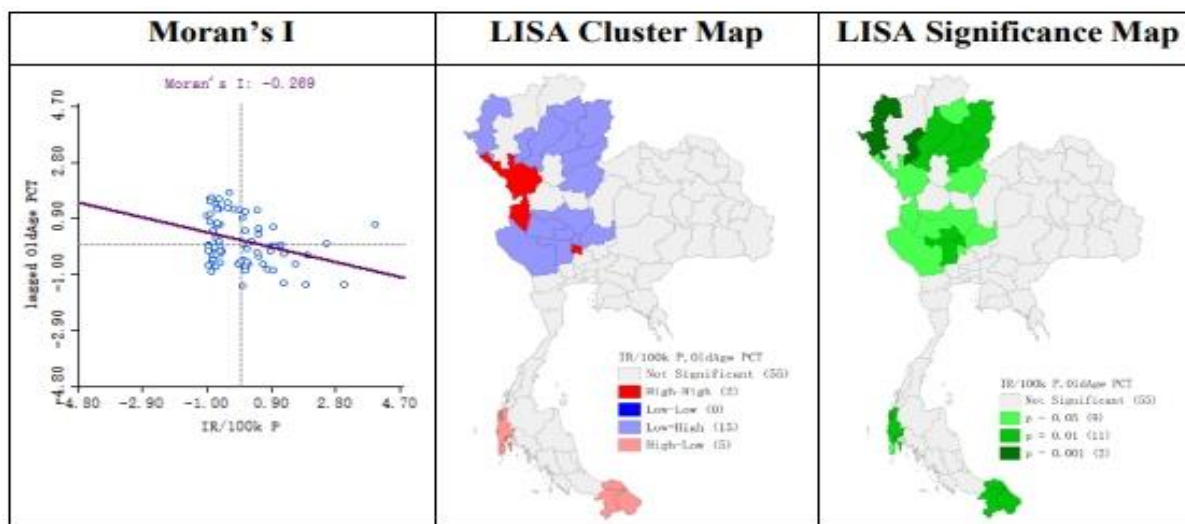


Figure 5. Bivariate analysis of Old Age (60 Years and over) Percent and COVID-19 Incidence Rate

3.5 Exploring Impact of Urban Population Percentage on COVID-19 Incidence Rate

Analysing the COVID-19 Incidence Rate within the Percentage of Urban population

Group, the study unveiled a noteworthy positive spatial autocorrelation, as indicated by a Moran's I value of 0.379 and a p-value of 0.001. Notably, the data revealed the presence of distinct cluster patterns (Figure 6).

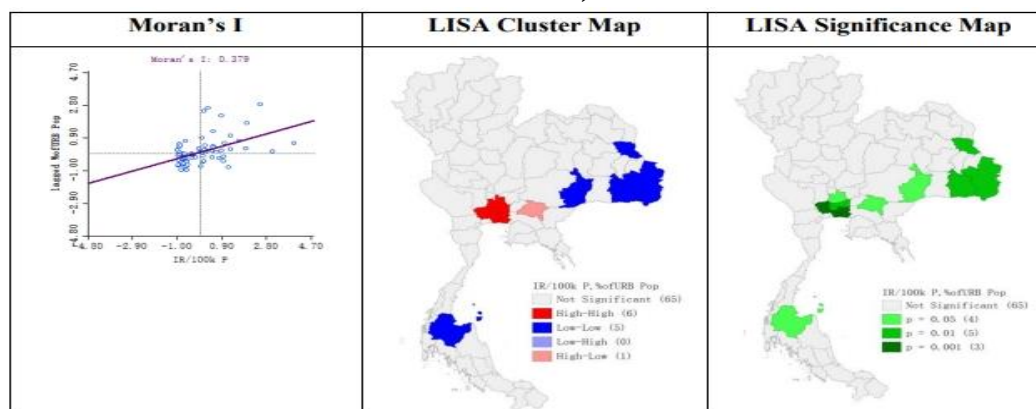


Figure 6. Bivariate analysis of Percent of Urban Population and COVID-19 Incidence Rate

3.6 Exploring the Relationship between Lowest Temperature in 2020 and COVID-19 Incidence Rate

Analysing the COVID-19 Incidence Rate within the Lowest Temperature 2020 Group,

the study unveiled a noteworthy positive spatial autocorrelation, as indicated by a Moran's I value of 0.108 and a p-value of 0.046. Notably, the data revealed the presence of distinct cluster patterns (Figure 7).

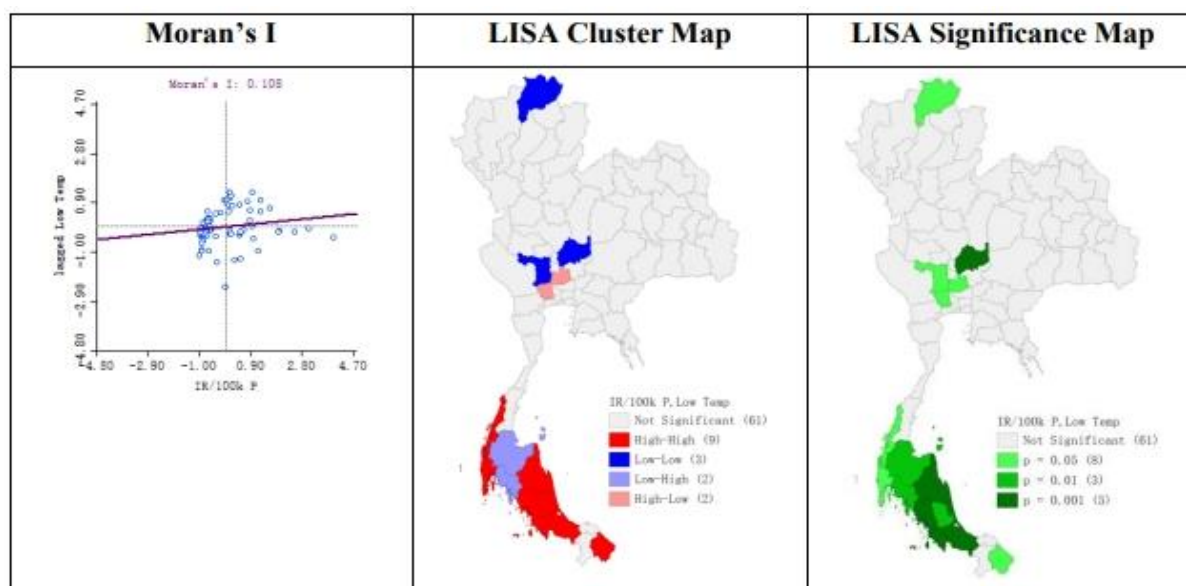


Figure 7. Bivariate analysis of Lowest Temperature 2020 and COVID-19 Incidence Rate

3.7 Analysing the Relationship between Highest Temperature in 2020 and COVID-19 Incidence Rate

Analysing the COVID-19 Incidence Rate within the Highest Temperature 2020 Group,

the study unveiled a noteworthy negative spatial autocorrelation, as indicated by a Moran's I value of -0.320 and a p-value of 0.001. Notably, the data revealed the presence of distinct cluster patterns (Figure 8).

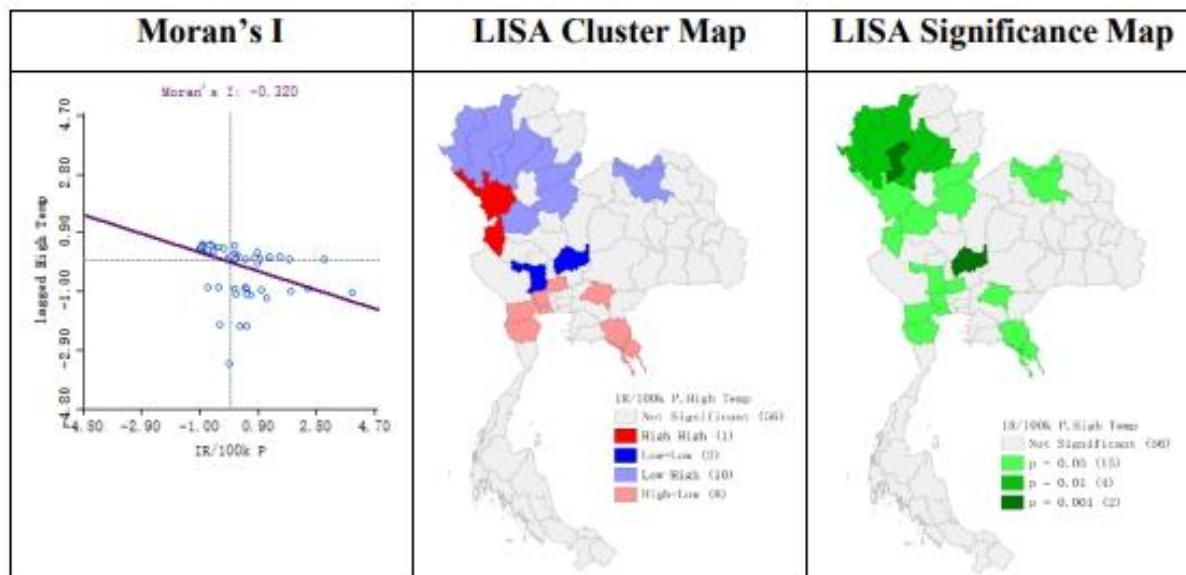


Figure 8. Bivariate analysis of Highest Temperature 2020 and COVID-19 Incidence Rate

3.8 Examining COVID-19 Incidence Rate in Relation to Forest Area from Remote Sensing 2020 (Rai)

Analysing the COVID-19 Incidence Rate within the Forest Area from Using Remote Sensing 2020 (Rai) Group, the study showed

a significant negative spatial autocorrelation, as indicated by a Moran's I value of -0.288 and a p-value of 0.001. Remarkably, the data revealed the presence of distinct cluster patterns (Figure 9).

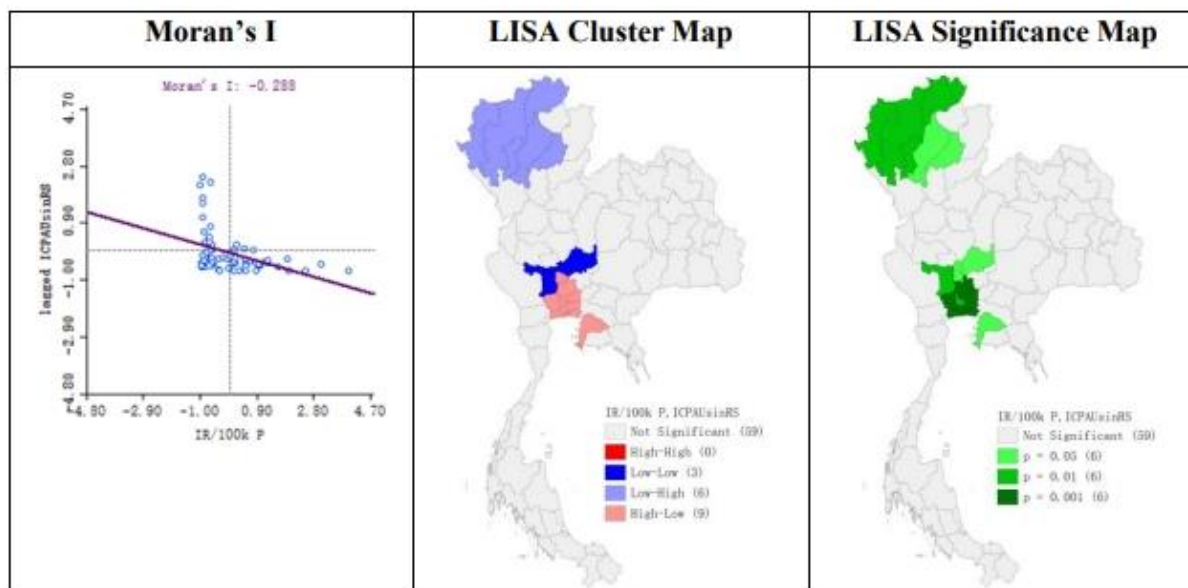


Figure 9. Bivariate analysis of Forest Area from Using Remote Sensing 2020 (Rai) and COVID-19 Incidence Rate

3.9 Exploring Per Capita Income (in Baht) and COVID-19 Incidence Rate 2020

Analysing the COVID-19 Incidence Rate within the Per Capita Income (in Baht) 2020

Group, the study unveiled a noteworthy positive spatial autocorrelation, as indicated by a Moran's I value of 0.410 and a p-value of 0.001. Notably, the data revealed the presence of distinct cluster patterns (Figure 10).

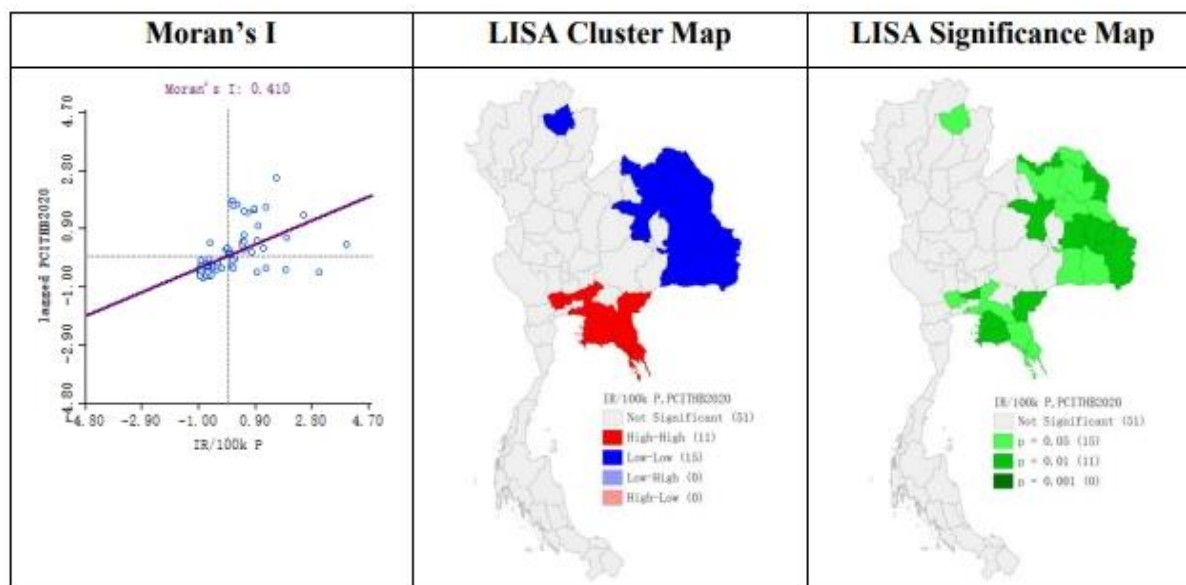


Figure 10. Bivariate analysis of Per Capita Income Baht 2020 and COVID-19 Incidence Rate

3.10 Exploring Correlation between Density of Alcohol Stores per Kilometres (Km) 2020 and COVID-19 Incidence Rate

Analysing the COVID-19 Incidence Rate within the Density of Alcohol Store Per Km

2020 Group, the study unveiled a noteworthy positive spatial autocorrelation, as indicated by a Moran's I value of 0.400 and a p-value of 0.001. Notably, the data revealed the presence of distinct cluster patterns (Figure 11).

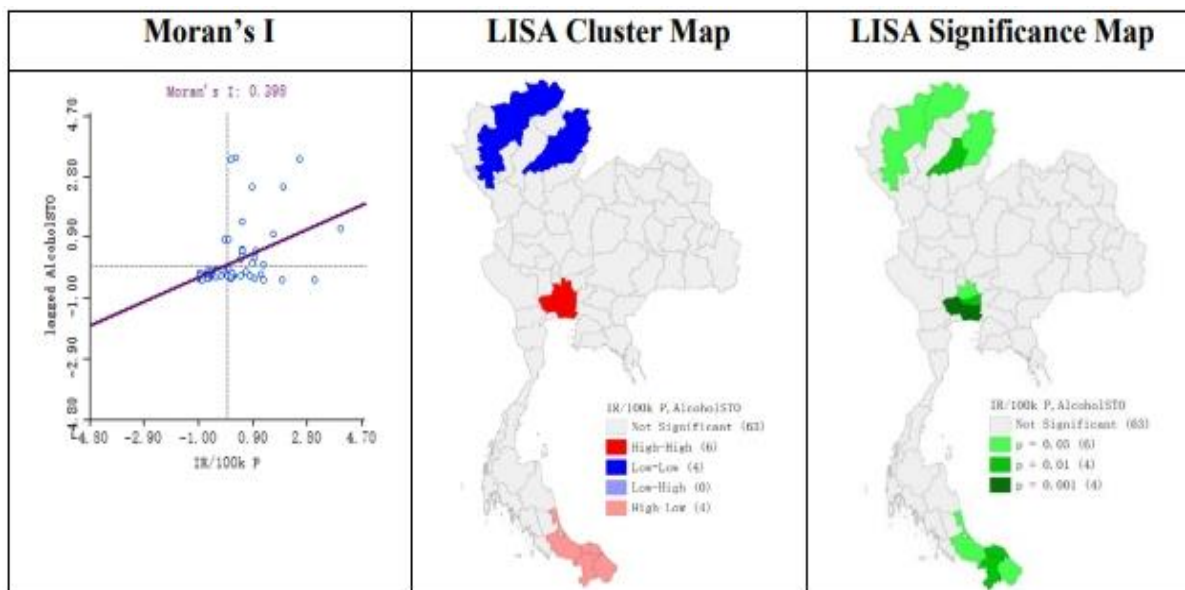


Figure 11. Bivariate analysis of Density of Alcohol Store Per Km 2020 and COVID-19 Incidence Rate

3.11 Exploring COVID-19 Incidence Rate in Relation to Density of Tobacco Stores per Kilometres (Km) KM 2020

Analysing the COVID-19 Incidence Rate within the Density of Tobacco Store Per KM 2020 Group, the study unveiled a noteworthy

positive spatial autocorrelation, as indicated by a Moran's I value of 0.427 and a p-value of 0.001. Notably, the data revealed the presence of distinct cluster patterns (Figure 12).

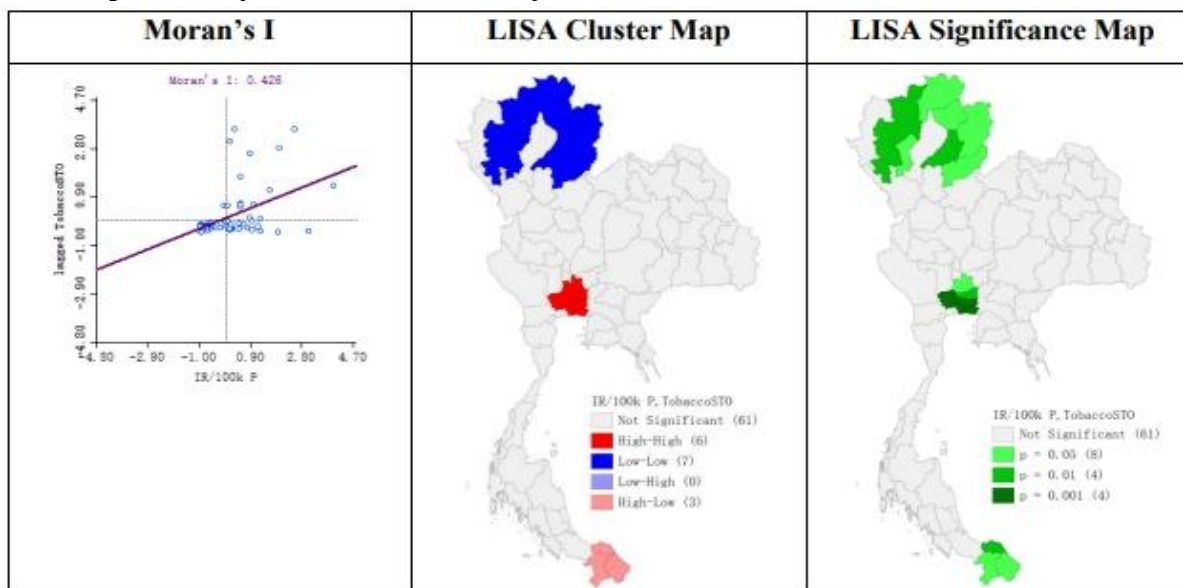


Figure 12. Bivariate analysis of Density of Tobacco Store Per Km 2020 and COVID-19 Incidence Rate

3.12 Spatial regression of factors of interest and COVID-19 incidence rate

Comparison of the Ordinary Least Squares (OLS), Spatial Lag Model (SLM), and Spatial Error Model (SEM) using various metrics and estimation results:

Coefficient Estimates:

The coefficient estimated in the SLM model slightly differ from other models, likely due to SLM's consideration of spatial correlation. For instance, the "Percentage of Child age of Population" is estimated at 222.88 in SLM compared to 342.37 in OLS. This indicated that accounting for geographical influence may alter coefficient estimations.

Statistical Significance:

Most variables in the SLM model exhibited low p-values for their coefficients, implying potential significance in influencing the dependent variable. This reinforced the reliability of the SLM model in capturing influential factors.

Fit Metrics:

The SLM model excelled in fit metrics. Its R^2 value of 0.82 implied that the model can

explain 82% of the variance in the dependent variable, far surpassing other models. Additionally, the SLM model demonstrated the lowest AIC and BIC values, indicating lower model complexity while maintaining a good fit.

Statistical Tests:

The LaGrange multiplier test in the Spatial Lag Model showed significance, signifying the model's substantial spatial dependency. This further supported the advantage of SLM model in considering spatial correlation.

Considering these factors collectively, the SLM stood out as the most appropriate model for this dataset. Its superior performance lied in its ability to better explain the variability in the data when considering spatial relationships. With higher statistical significance and better fit, the SLM not only captured relationships between variables more accurately but also predicted the dependent variable more reliably. This makes it a more dependable choice for modelling and forecasting based on this dataset.

Table 2: Estimated parameters obtained from ordinary least square model, spatial lag model and spatial error model models.

Variable	OLS Coefficient (SE)	SLM Coefficient (SE)	SEM Coefficient (SE)
Constant	7148.75(3202.69) *	5529.81(2561.02) ***	7991.61(3319.19) *
Percentage of Child age of Population (%)	342.366 (54.056) ***	222.878(45.561) *	217.576(69.564) **
Percentage of Working age Population (%)	-154.469 (47.252) **	-119.109 (37.951) ***	-136.919 (47.305) **

Variable	OLS Coefficient (SE)	SLM Coefficient (SE)	SEM Coefficient (SE)
Highest Temperature 2020 (%)	-75.7519 (16.349) ***	-42.427 (14.734) **	-70.747 (16.653) **
Lowest Temperature 2020 (%)	73.7896 (32.773) ***	31.992 (27.784) *	80.257 (33.419) *
Per Capita income (baht) (%)	0.006(0.001) ***	0.004(0.001) ***	0.005 (0.001) ***
Tobacco Density	105.096 (24.080) ***	89.172 (19.067) ***	79.888 (21.322) ***
Rho		0.44	
Lambda			0.53
R –squared	0.74	0.82	0.79
Log likelihood	-646.883	-634.508	-641.448
AIC	1307.77	1285.02	1296.9
BIC	1324.17	1303.77	1313.3
Lagrange Multiplier (lag)		P<0.001	P= 0.272

Note: *correlation significance at the 0.05 level; **correlation significance at the 0.01 level; ***correlation significance at the 0.001 level; OLS, ordinary least squares; SLM, spatial lag model; SEM, spatial error model; SE; standard error; Constant, the regression model intercept (the expected mean value of Y when all X=0); p, spatial autoregressive parameter; AIC, Akaike's information criterion; BIC, Bayesian information criterion, R', the goodness of fit.

4. Discussion

Our study contributed to a deeper understanding of COVID-19 transmission by unravelling the intricate interplay of demographic, environmental, and socioeconomic factors. These findings emphasize the need for tailored and targeted interventions that consider spatial distribution, age demographics, urbanization, and other influential variables. By taking these multifaceted dynamics into account, policymakers and public health authorities can develop more effective strategies to control the spread of COVID-19 and future pandemics, ultimately safeguarding the well-being of the population. As the global fight against COVID-19 continues, the insights gained from this study serve as a valuable

resource for evidence-based decision-making and pandemic management strategies.

In our in-depth study of the dynamics of COVID-19 transmission in Thailand from 2020 to 2021, we actively referred to previous literature on the global prevalence of COVID-19 to better understand the virus's transmission mechanisms and design effective public health strategies.

Spatial Dynamics and Intervention Effects:

Our study underscores the importance of considering spatial dynamics when analysing COVID-19 transmission. We observed high incidence rates concentrated in the southern and central regions of Thailand. Spatial autocorrelation remained consistent throughout the pandemic, suggesting the

influence of government interventions, widespread testing, travel restrictions, and vaccination efforts on the spatial dynamics of the virus. The study by Kraemer et al. (2020) indicates that human mobility and control measures significantly impact the spread of COVID-19 in China. Our findings align with the critical role of these interventions in the dynamics of disease transmission[22].

Population Density and Age Structure:

Population density, the presence of children and seniors, and the percentage of urban population were positively correlated with COVID-19 incidence rates. This emphasizes the need for targeted interventions for specific age groups and densely populated areas. A study focused on the transmission and impact of COVID-19 in different population groups, providing further support for our findings [23].

Environmental Factors:

We observed a negative correlation between the highest temperature in 2020 and the incidence rate, suggesting that higher temperatures may have limited the virus's spread. Forest area coverage also showed a significant linkage to the incidence rate, highlighting the complex relationship between ecological variables and disease

transmission. The study by Bashir et al. (2020) demonstrated the correlation between environmental pollution indicators and COVID-19, supporting our observations regarding temperature and forest coverage [24].

Socioeconomic Factors:

Socioeconomic factors exhibited complex associations with COVID-19 incidence rates. Higher per capita income was correlated with elevated incidence rates, while alcohol density showed a negative correlation, and tobacco density showed a positive correlation. This underscores the influence of cultural behaviours and health conditions on transmission dynamics. Bambra et al.'s (2020) study delving into the relationship between the COVID-19 pandemic and health inequalities provides background support for our observations on the correlation between economic factors and incidence rates [25].

5. Conclusion

This study examined COVID-19 transmission in Thailand from 2020 to 2021, analysing demographic, environmental, and socioeconomic factors. The findings highlighted the importance of spatial analysis in understanding disease spread. Clusters of high incidences were identified in southern

and central regions, influenced by government interventions, testing, travel restrictions, and vaccination efforts. Demographics played a significant role, with higher population density, the presence of children and seniors, and urbanization correlating with increased incidence. Environmental factors, such as temperature and forest coverage, also impacted transmission dynamics. Socioeconomic factors exhibited complex associations, with income affecting incidence rates and cultural behaviours influencing transmission. Therefore, this study deepens our understanding of COVID-19 transmission, emphasizing the need for tailored interventions considering spatial distribution,

demographics, and various factors. These insights can guide effective strategies for pandemic control, benefiting public health decision-makers worldwide.

Acknowledgement

I would like to take this opportunity to express my deepest gratitude to those who have contributed to the completion of this research paper. I dedicated this paper to anyone who seeks to advance knowledge, solve problems, and make a positive impact through research. It is my hope that this work contributes, in some measure, to the collective understanding of the subject matter.

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