Geospatial Health 2023; volume 18:1183

Spatial autocorrelation and heterogenicity of demographic and healthcare factors in the five waves of COVID-19 epidemic in Thailand

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Abstract

A study of 2,569,617 Thailand citizens diagnosed with COVID-19 from January 2020 to March 2022 was conducted with the aim of identifying the spatial distribution pattern of incidence rate of COVID-19 during its five main waves in all 77 provinces of the country. Wave 4 had the highest incidence rate (9,007 cases per 100,000) followed by the Wave 5, with 8,460 cases per 100,000. We also determined the spatial autocorrelation between a set of five demographic and health care factors and the spread of the infection within the provinces using Local Indicators of Spatial Association (LISA) and univariate and bivariate analysis with Moran's *I*. The spatial autocorrelation between the variables examined and the incidence rates was particularly strong during the waves 3-5. All findings confirmed the existence of spatial autocorrelation and heterogenicity of COVID-19 with the distribution of cases with respect to one or several of the five factors examined. The study identified significant spatial autocorrelation with regard to the COVID-19 incidence rate with these variables in all five waves. Depending on which province that was investigated, strong spatial autocorrelation of the High-High pattern was observed in 3 to 9 clusters and of the Low-Low pattern in 4 to 17 clusters, whereas negative spatial autocorrelation was observed in 1 to 9 clusters of the High-Low pattern and in 1 to 6 clusters of Low-High pattern. These spatial data should support stakeholders and policymakers in their efforts to prevent, control, monitor and evaluate the multidimensional determinants of the COVID-19 pandemic.

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Key words: demographic; healthcare; spatial distribution; COVID-19, Thailand.

Acknowledgments: we thank Dr. Roshan Kumar Mahato, Assistant Professor in Faculty of Public Health, KhonKaen University, for helpful discussions and comments on the manuscript.

Conflict of interest: the Authors declare no conflict of interest.

Ethical considerations: the Ethics Committee in Human Research of Khon Kaen University, Thailand approved the study under reference number HE652161.

Received for publication: 8 January 2023.
Accepted for publication: 26 February 2023.

Geospatial Health 2023; 18:1183
doi:10.4081/gh.2023.1183

Introduction

As reported by the World Health Organization (WHO), COVID-19 has caused 6 million deaths and 512 million confirmed cases globally of 15 March 2022 (WHO, 2022). In December 2019, the primary cases were reported in China and the infection was declared a pandemic in March the following year (WHO, 2020). On January 13th, 2020, Thailand reported its first case and has subsequently seen multiple waves of the virus (Kunno *et al.*, 2021), with a total of 4,281,536 cases and 28,778 deaths reported by May 5th, 2022 (WHO-Thailand 2022a). The COVID-19 pandemic presented a major challenge for health authorities, who are working to develop effective preventive and control measures to curb its spread. It is crucial to identify risk factors related to both demographic and healthcare factors so as to effectively manage and control the pandemic. It has become mandatory to identify risk factors related to healthcare and demography.

The application of geographic information systems (GIS) and spatial statistics have proved effective in analyzing and controlling the spread of the disease (Lovett *et al.*, 2014). These tools provide important data and information for policy makers to make informed decisions in controlling the pandemic (Ramírez-Aldana *et al.* 2020). By envisage the relationship between related variables and disease, GIS helps stakeholders from various sectors to identify the most effective measures for controlling the pandemic, while decisions based on spatial analysis provide relevant guidelines and regulations for controlling the spread of COVID-19 (Sornlorm *et al.* 2022).

Recent studies have explored demographic risk factors for spread and severity of the pandemic, such as urbanization (Kwok *et al.* 2021) and population density (Dutta *et al.*, 2021; Pedorsa and Albuquerque, 2020). Additionally, the availability of medical resources has been linked to COVID-19 infection rates (Alcântara *et al.*, 2020; Liu *et al.*, 2020; Ribeiro *et al.*, 2020; Su *et al.*, 2020;

Wu *et al.*, 2021; You *et al.*, 2020). Despite the limited number of GIS-based studies in Thailand, research has been conducted on the impact of factors such as night-time light (Sangkasem and Puttanapong, 2020), air quality in Greater Bangkok (Wetchayont, 2021) and the spread of the disease in different regions in Thailand (Zhang *et al.*, 2021). However, there is a lack of studies specifically focusing on the demographic and healthcare factors that impact the spread of COVID-19. To develop effective plans and policies for controlling the pandemic, it is necessary to understand its distribution and the spatial autocorrelation of demographic and healthcare factors. Thus, this study aimed to identify spatial patterns of COVID-19 in five specific waves in Thailand, and its incidence during these waves based on demographic and healthcare factors.

Materials and Methods

Study area

This study was conducted in Thailand, which is located in Southeast Asia and considered an upper-middle-income country. Thailand has a total area of 514,000 km^2 and shares borders with Myanmar, Cambodia, Laos and Malaysia. It is divided into 77 provinces, which are grouped into four regions named Central, North, Northeast and South. Geographical mapping of the administrative areas with geographic coordinates was done assisted by DIVA-GIS (http://www.diva-gis.org/). All these datasets used in the study are publicly available.

Study design and data collection

The number of confirmed COVID-19 cases in Thailand from January 2020 to March 2022 was used as the dependent variable in this study. These data were collected from the Centre of Epidemiological Information, Bureau of Epidemiology, Ministry of Public Health and included a total of 2,569,617 confirmed cases. The monthly incidence rate was calculated as the number of confirmed cases per 100,000 population, data were divided into five phases based on the progression of the pandemic as follows: First wave (January-May 2020), Second wave (September 2020-March 2021), Third wave (April-June 2021), Fourth wave (July-October 2021), and Fifth wave (November 2021-March 2022). The data were provided by WHO-Thailand (2022b).

The independent variables were demographic data and healthcare data. The former included population density, household density and percentage of people residing in urban areas by the year 2020, which were obtained from the Department of Provincial Administration and the Ministry of Interior. The healthcare data, collected by the Office of the Permanent Secretary of the Ministry of Public Health, consisted of the total number of hospitals; of other medical establishments with beds; and of physicians per 10,000 population. These data were obtained from the National Statistical Office, Thailand (2020), and covered the years 2016-2020.

Statistical analysis

We employed well-established geospatial statistics such as global and local Moran's *I* and the Local Indicator of Spatial Association (LISA) for autocorrelation studies (Steiniger and Hunter 2013). GeoDa v. 1.18.0.16, developed by Anselin, was used for spatial data analysis, with QGIS v. 3.20.3 (https://www.qgis.org) utilized to combine and integrate all the data into one dataset, which was then imported into GeoDa for analysis by LISA.

Moran's *I* is a statistical tool used to measure the strength of the relationship between variables in a spatial context. It produces values ranging from -1 to 1, where +1 indicates strong positive spatial autocorrelation (*i.e.* similar values clustering together), 0 indicates random spatial patterns, and -1 indicates negative spatial autocorrelation (*i.e.* dissimilar values clustering together)(Anselin and Bao 1997; Anselin, Syabri and Kho 2006; Anselin 2020). To assess spatial autocorrelation reliably, this study was performed with 999 permutation simulations at the significance level p=0.05. The Moran's *I* test is calculated as follows:

$$I = \frac{\Sigma_i \Sigma_j w_{ij} z_i . z_j / S_0}{\Sigma_i z_i^2 / n} \quad \text{(Eq.1)}$$

where Σ_i is the sum of variable of interest at the location *I*; Σ_j the sum of variable of interest at the location *j*; w_{ij} the elements of the spatial weight matrix; z_i the term $i - \bar{x}$(where $\bar{x}$ expresses the mean of variable *x* for an observation at location *i*); z_j the term $x_j - \bar{x}$ (where $\bar{x}$ expresses the mean of variable *x* for an observation at location *j*); S_0 the sum of all weights $\Sigma_i \Sigma_j w_{ij}$; and *n* the number of observations. A limitation of Global Moran's *I* is its inability to find the local spatial autocorrelation. To overcome this, Anselin (2020) extended this statistic to a version offering the specific loca-

Table 1. Univariate analysis of COVID-19 incidence rate among waves.

Variable	Moran's *I*	P
COVID-19 phase		
Wave 1	0.145	0.051
Wave 2	0.043	0.040
Wave 3	0.622	0.001
Wave 4	0.535	0.001
Wave 5	0.454	0.001

Table 2. Univariate analysis of COVID-19 incidence rate per 100,000 population.

Correlation type	HH (no. of provinces)	HL (no. of provinces)	LL (no. of provinces)	LH (no. of provinces)
Wave				
Wave 1	4	0	6	2
Wave 2	4	0	4	4
Wave 3	7	1	10	2
Wave 4	8	1	16	1
Wave 5	7	1	15	1

tions of spatial autocorrelation, which is calculated as follows:

$$I_i = c.z_i \sum_j w_{ij} z_j \quad \text{(Eq.2)}$$

where Σ_j is summation of all variables of interest at location j that borders location i; z_i the deviation of the variable of interest from its mean value at location i; z_j the deviation of the variable of interest from its mean value at location j; w_{ij} the elements of the spatial weight matrix; and c a constant that is typically set to 1/n.

GeoDa was utilized to analyse spatial autocorrelation by employing the k-nearest neighbours approach (Anselin *et al.*, 2006; Cliff and Ord, 1981) using k=3. The spatial weight matrix was carefully selected in computing Moran's *I* and LISA. The spatial weight matrix was designed to account for geographical features such as island provinces (Phuket and Krabi) as well as coastal and border provinces to ensure enough neighbouring areas were included and to maintain local characteristics.

A scatterplot in spatial analysis can be represented by four quadrants based on the standardized variables. These quadrants represent different patterns of spatial autocorrelation, with positive autocorrelation indicated by High-High (HH) and Low-Low (LL) correlations in upper right and lower left positions, and negative autocorrelation indicated by High-Low (HL) and Low-High (LH) correlation in the lower right and upper left positions.

LISA maps indicate spatial clustering patterns (in this case COVID-19 incidence). From univariate maps, HH clusters depict high-incidence provinces surrounded by other high-incidence provinces, while LL clusters show low-incidence provinces surrounded by other low-incidence provinces. We used bivariate maps with colour to depict the pattern of factors of interest, where dark red represents HH areas (hotspots) and dark blue LL areas (coldspots); light red represents high-density areas surrounded by low-density areas (HL) and light bluerepresents low-density areas surrounded by high-density areas (LH).

Results

COVID-19 incidence rate by province

There was a significant spatial dependency with respect to the incidence rate across the five phases of the pandemic. Moran's *I* was high in all waves indicating that there was a strong spatial correlation between COVID-19 cases in the country as a whole (Table 1, online supplementary materials for details).

Figure 1 displays the incidence rate per 100,000 population (displayed as 10 levels, each in a different colour) among the provinces during each of the five waves of the pandemic. The highest numbers reached per wave were 44 cases in Phuket during Wave, 474 cases in Samut Sakhon during Wave 2, 1,356 cases in Bangkok Metropolis during Wave 3, 9,007 cases in Samut Sakhon during Wave 4, and 8,460 cases in Phuket during Wave 5.

In the LISA analysis, hotspots of high incidence rate were found in a varying number of provinces during the different waves, with the highest during Waves 4 and 5; there was also a maximum of coldspots during these two last waves, but they appeared in the northern and north-eastern regions (Table 2). Significant spatial COVID-19 clusters were seen in various parts of the country, indicating a strong autocorrelation between the incidence rates and geographic locations (Figure 2). These included both HH clusters and LL clusters highlighting the uneven distribution of cases across Thailand.

Demography and COVID-19 incidence

The results showed that there was a spatial autocorrelation, in particular in waves 3-5, between population density, household density and urbanization on the one hand and COVID-19 incidence rate on the other (Table 3). Bivariate LISA calculations confirmed this autocorrelation showing significant clusters in the form of hotspots and coldspots as shown in Tables 4, 5, 6 and Figures 3, 4, 5.

Table 3. Bivariate analysis of demographic factors and COVID-19 incidence.

Factor	Moran's *I*	P
Population density per km^2		
Wave 1	0.227	0.011
Wave 2	0.078	0.095
Wave 3	0.563	0.001
Wave 4	0.228	0.005
Wave 5	0.224	0.007
Household density per km^2		
Wave 1	0.216	0.014
Wave 2	0.071	0.102
Wave 3	0.557	0.001
Wave 4	0.216	0.005
Wave 5	0.226	0.008
Percentage of urban population		
Wave 1	0.140	0.037
Wave 2	0.098	0.094
Wave 3	0.505	0.001
Wave 4	0.257	0.002
Wave 5	0.256	0.001

Table 4. Bivariate analysis of COVID-19 incidence rate with population density per km^2.

Correlation type	HH (no. of provinces)	HL (no. of provinces)	LL (no. of provinces)	LH (no. of provinces)
Wave				
Wave 1	3	1	5	3
Wave 2	5	0	4	3
Wave 3	8	0	11	1
Wave 4	4	0	17	5
Wave 5	3	0	16	5

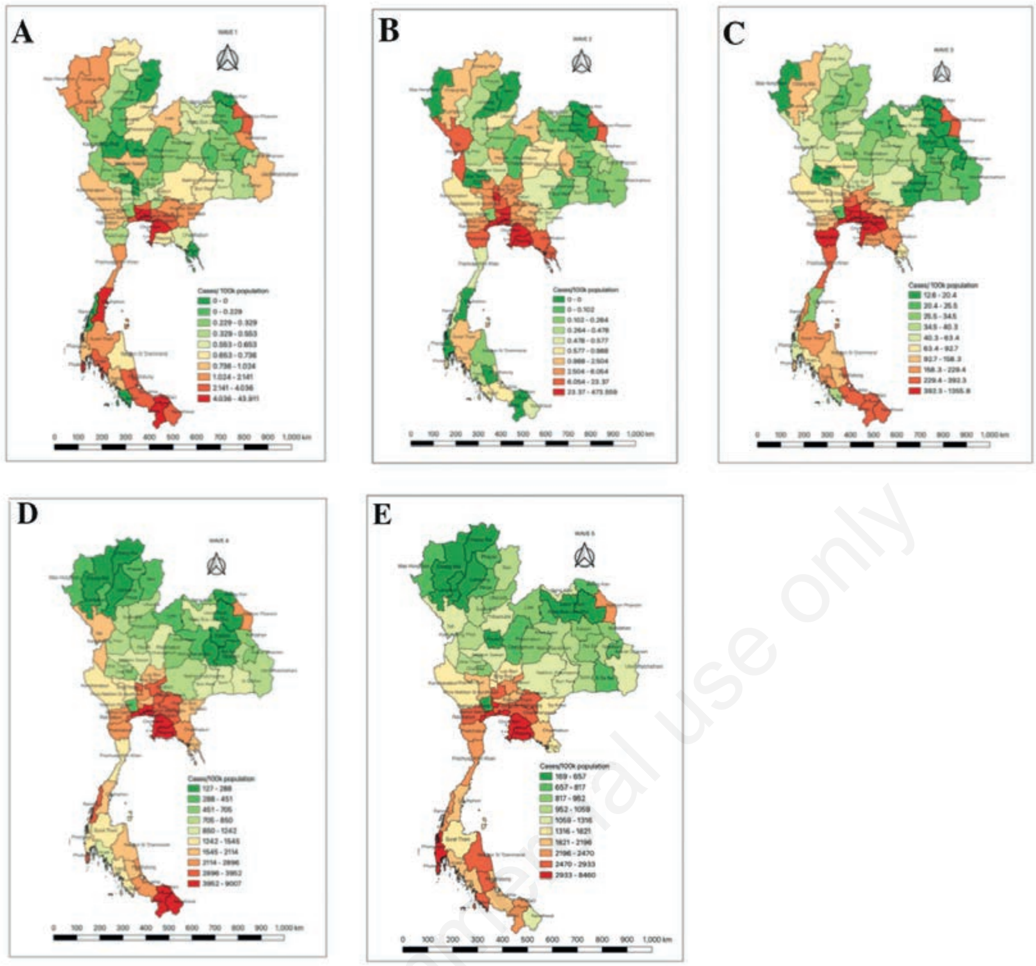

Figure 1. Incidence of the COVID-19 rate per 100,000 population in the different waves. A) Wave 1; B) Wave 2; C) Wave 3; D) Wave 4; E) Wave 5.

Table 5. Bivariate analysis of COVID-19 incidence rate with household density per km^2.

Correlation type	HH (no. of provinces)	HL (no. of provinces)	LL (no. of provinces)	LH (no. of provinces)
Wave				
Wave 1	2	0	6	4
Wave 2	5	0	4	3
Wave 3	8	0	11	1
Wave 4	3	0	17	6
Wave 5	3	0	16	5

Table 6. Bivariate Analysis of COVID-19 incidence rate with percentage of urban population.

Correlation type	HH (no. of provinces)	HL (no. of provinces)	LL (no. of provinces)	LH (no. of provinces)
Wave				
Wave 1	2	1	5	4
Wave 2	6	1	3	2
Wave 3	9	2	9	0
Wave 4	4	9	8	5
Wave 5	5	7	9	3

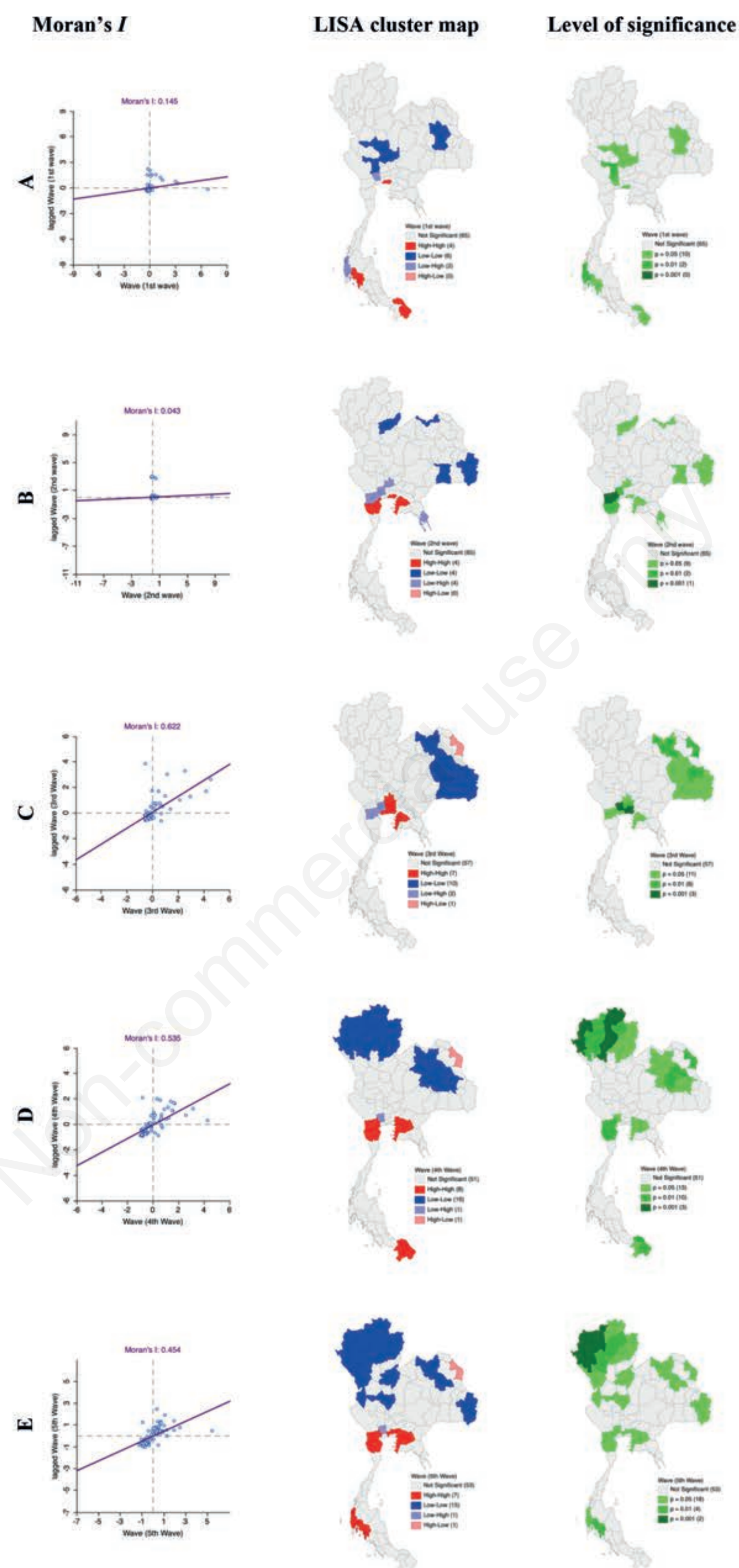

Figure 2. Univariate analysis of the COVID-19 incidence rate per 100,000 population in the different waves. A) Wave 1; B) Wave 2; C) Wave 3; D) Wave 4; E) Wave 5.

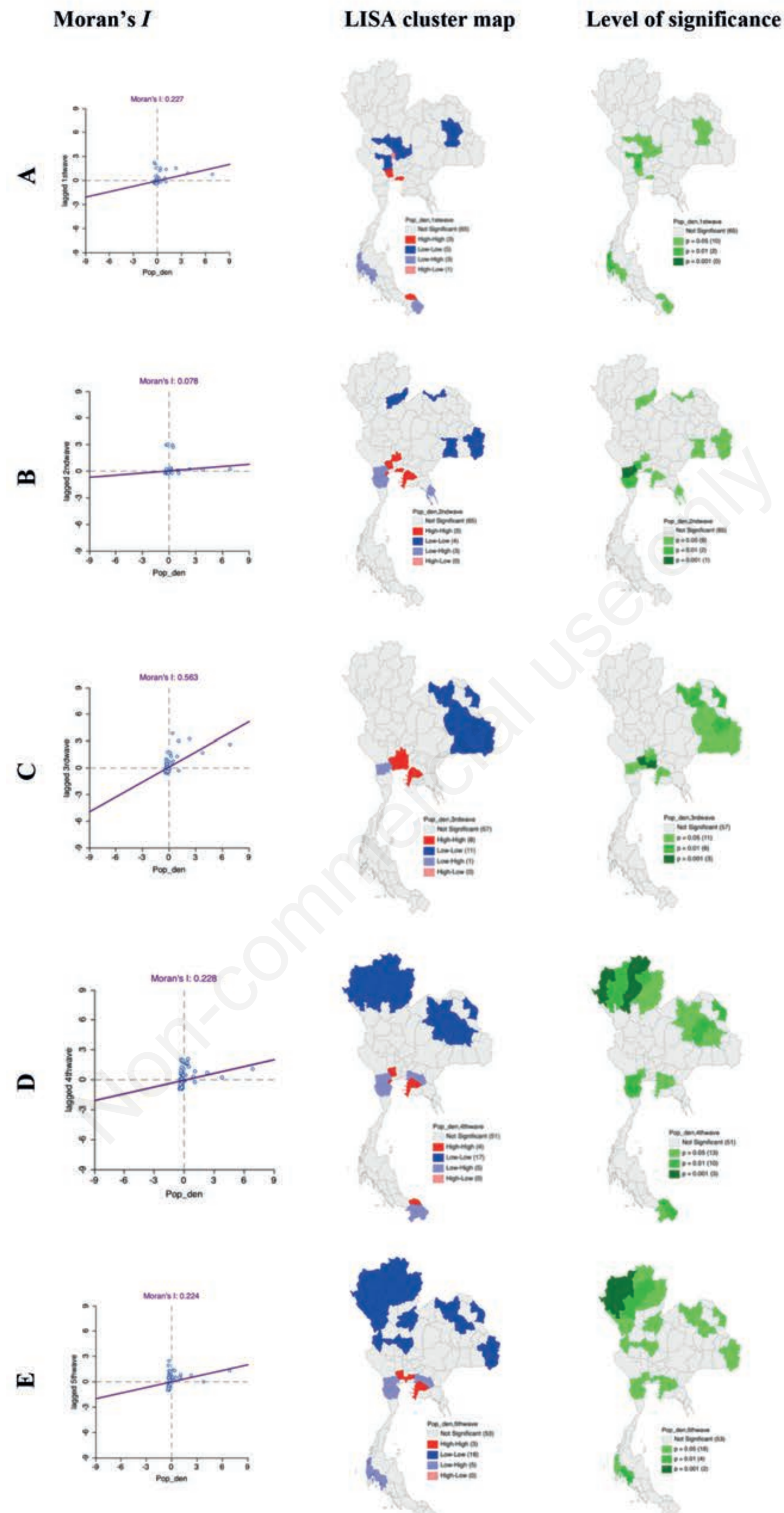

Figure 3. Bivariate analysis of the COVID-19 incidence rate and population density per km^2 in the different waves. A) Wave 1; B) Wave 2; C) Wave 3; D) Wave 4; E) Wave 5.

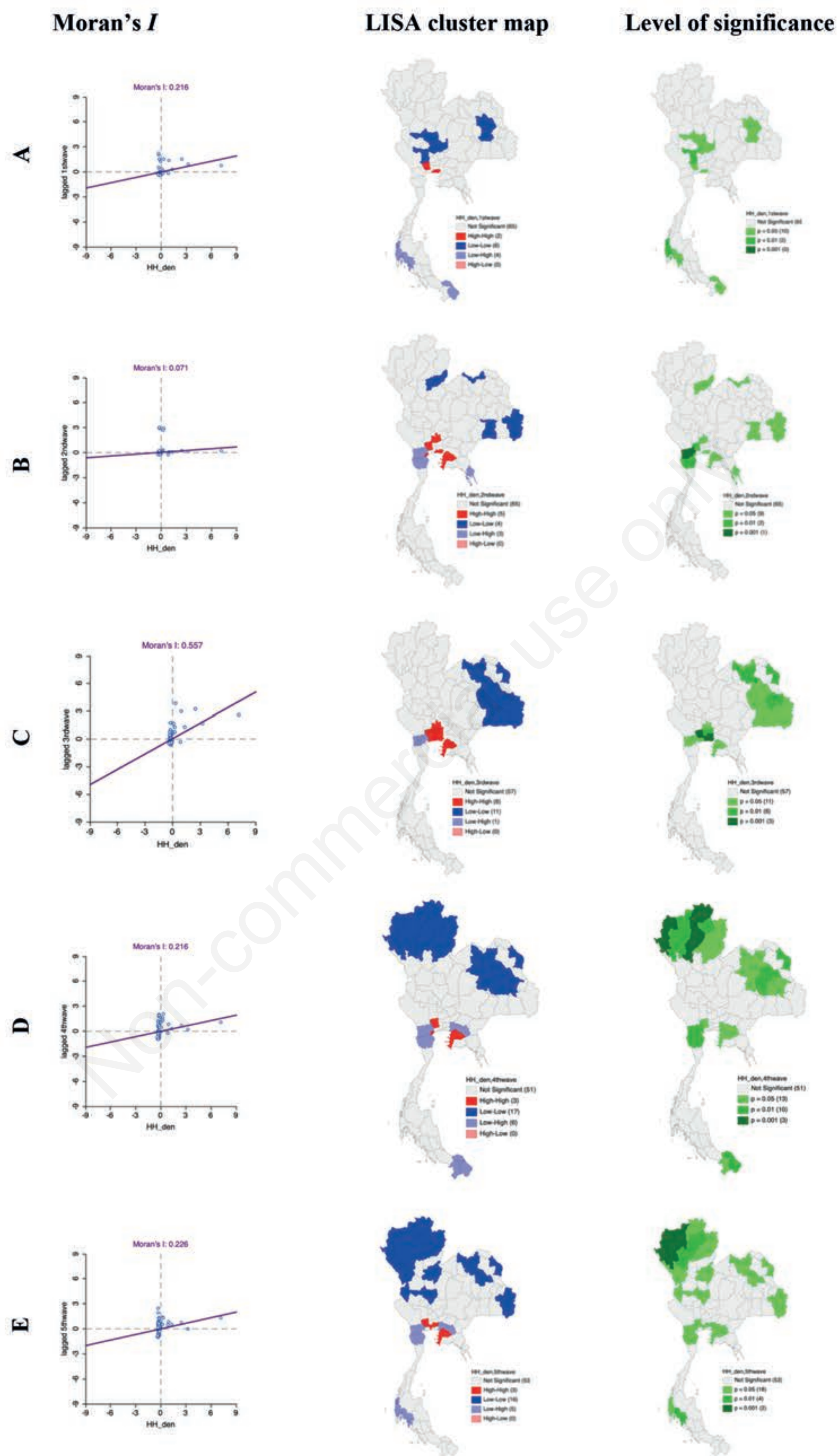

Figure 4. Bivariate analysis of the COVID-19 incidence rate and household density per km^2 in the different waves. A) Wave 1; B) Wave 2; C) Wave 3; D) Wave 4; E) Wave 5.

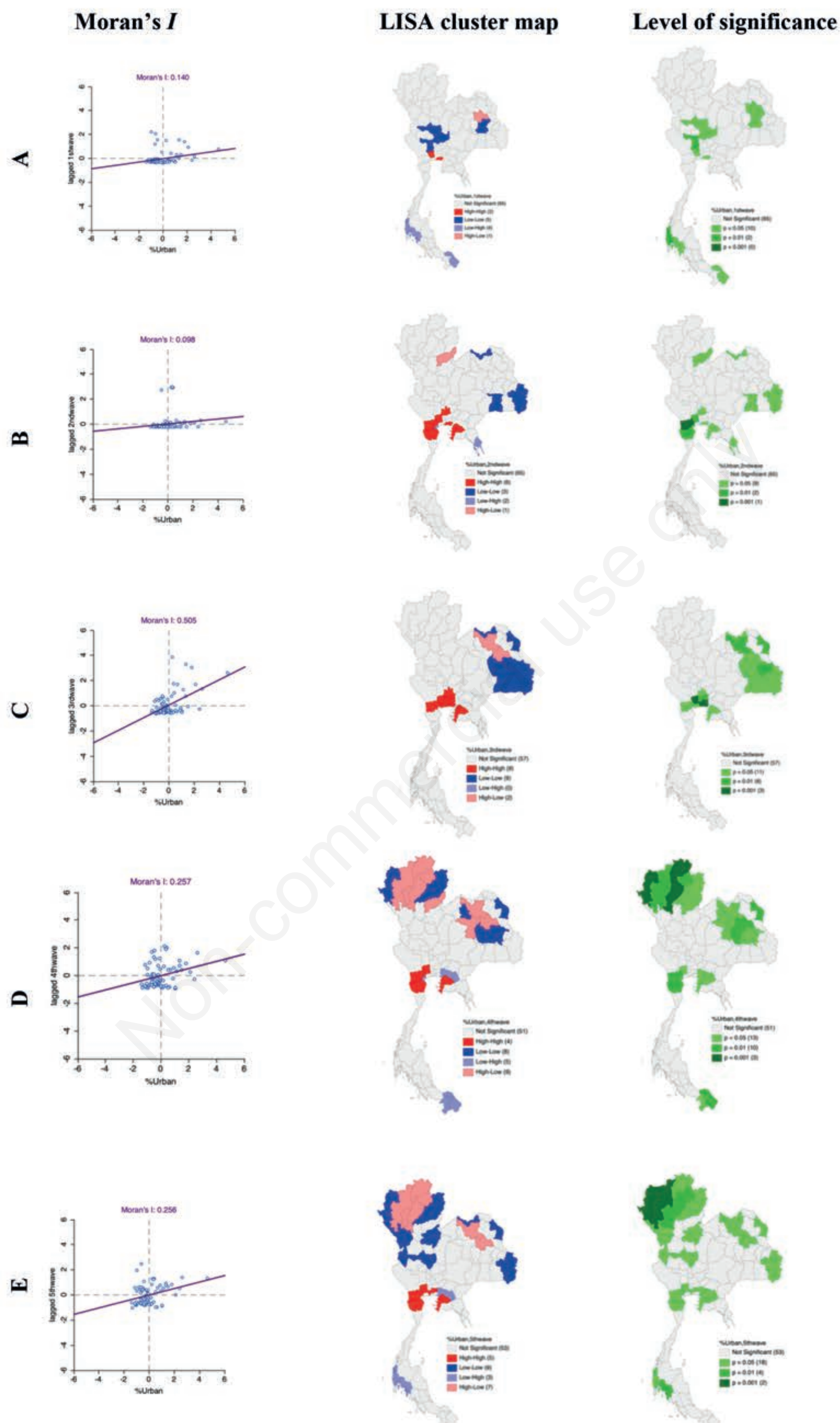

Figure 5. Bivariate analysis of the COVID-19 incidence rate and urbanization in the different waves. A) Wave 1; B) Wave 2; C) Wave 3; D) Wave 4; E) Wave 5.

Healthcare factors and COVID-19 incidence rate

There was a positive autocorrelation between the number of hospitals per km^2; of other medical establishments with beds per km^2; and of physicians per 10,000 population on the one hand, and the COVID-19 incidence rate on the other (Table 7). The results of the spatial LISA analysis confirmed this, showing significant clusters in the form of hotspots and coldspots as shown in Tables 8, 9, 10 and Figures 6, 7, 8.

The results showed positive correlations between these health care variables and COVID-19 incidence rates in waves 3-5 based on the spatial autocorrelation. The study found hotspot clusters in multiple provinces for all three variables, indicating that areas with more medical resources tend to have higher COVID-19 incidence rates. Coldspot clusters were also found in several provinces, indicating that areas with fewer medical resources have lower COVID-19 incidence rates.

Discussion

The importance of considering spatial patterns when analysing the spread of COVID-19 and the effectiveness of control measures was highlighted in this study. It was found that several provinces in Thailand experienced high COVID-19 incidence rates across the

Table 7. Bivariate analysis of healthcare factors and COVID-19 incidence.

Factor	Moran's *I*	P
Hospital density per km^2		
Wave 1	0.152	0.036
Wave 2	0.019	0.263
Wave 3	0.468	0.001
Wave 4	0.202	0.004
Wave 5	0.175	0.001
Hospitals and other medical establishments with beds per 10,000 population		
Wave 1	0.090	0.082
Wave 2	0.192	0.007
Wave 3	0.413	0.001
Wave 4	0.306	0.001
Wave 5	0.308	0.001
Physicians per 10,000 population		
Wave 1	0.108	0.059
Wave 2	0.108	0.059
Wave 3	0.543	0.001
Wave 4	0.270	0.001
Wave 5	0.259	0.002

Table 8. Bivariate analysis of COVID-19 incidence rate with hospital density per km^2.

Correlation type	HH (no. of provinces)	HL (no. of provinces)	LL (no. of provinces)	LH (no. of provinces)
Wave				
Wave 1	1	2	4	5
Wave 2	4	0	4	4
Wave 3	5	0	9	4
Wave 4	2	0	17	6
Wave 5	2	0	16	6

Table 9. Bivariate analysis of COVID-19 incidence rate with medical establishments with beds per 10,000 population.

Correlation type	HH (no. of provinces)	HL (no. of provinces)	LL (no. of provinces)	LH (no. of provinces)
Wave				
Wave 1	2	3	3	4
Wave 2	6	2	2	2
Wave 3	8	2	9	1
Wave 4	4	3	14	5
Wave 5	5	5	11	3

Table 10. Bivariate analysis of COVID-19 incidence rate with physicians per 10,000 population.

Correlation type	HH (no. of provinces)	HL (no. of provinces)	LL (no. of provinces)	LH (no. of provinces)
Wave				
Wave 1	2	1	5	4
Wave 2	6	1	3	2
Wave 3	8	0	11	1
Wave 4	5	5	12	4
Wave 5	6	6	10	2

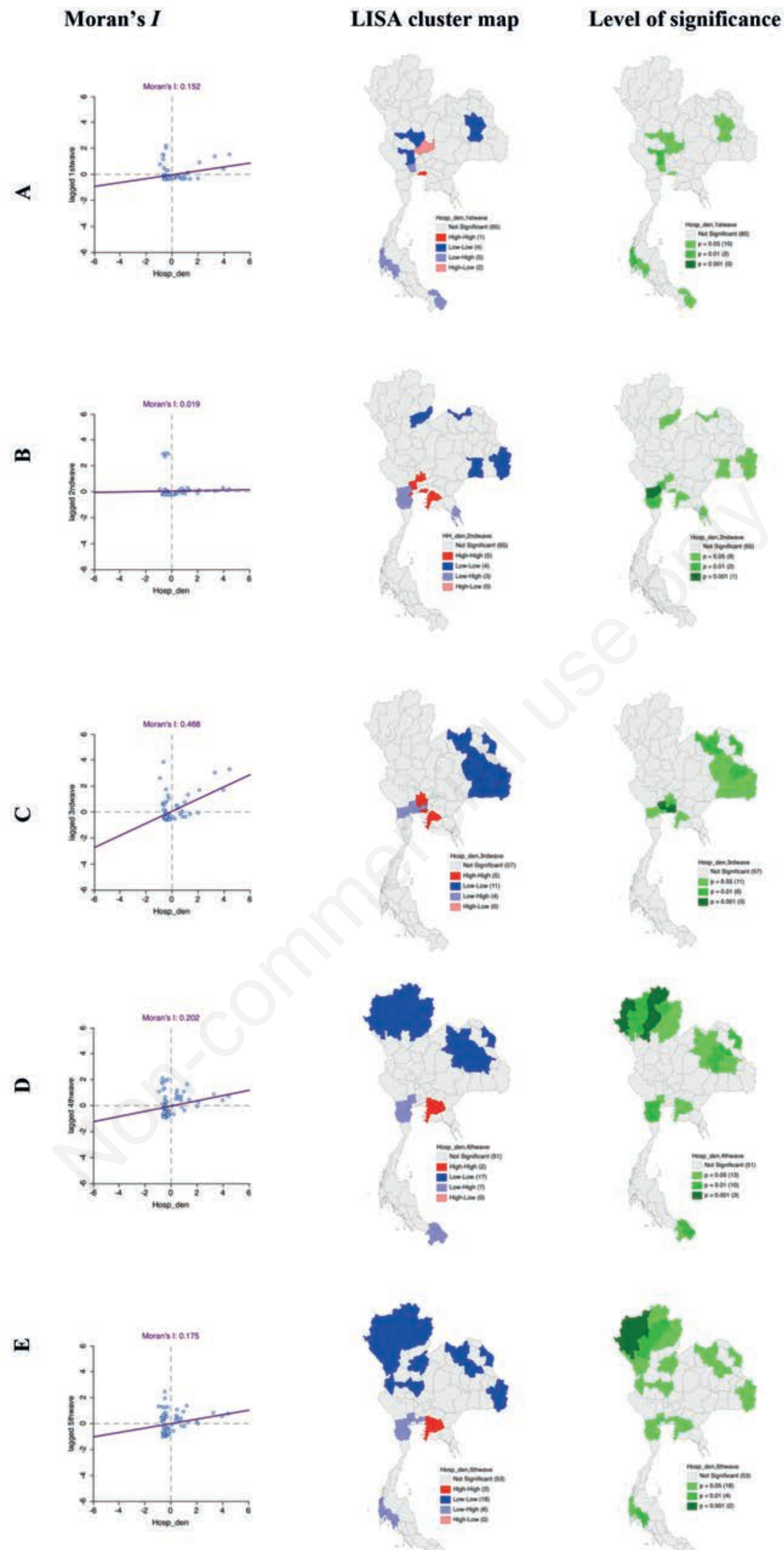

Figure 6. Bivariate analysis of the COVID-19 incidence rate and hospital density per km^2 in the different waves. A) Wave 1; B) Wave 2; C) Wave 3; D) Wave 4; E) Wave 5.

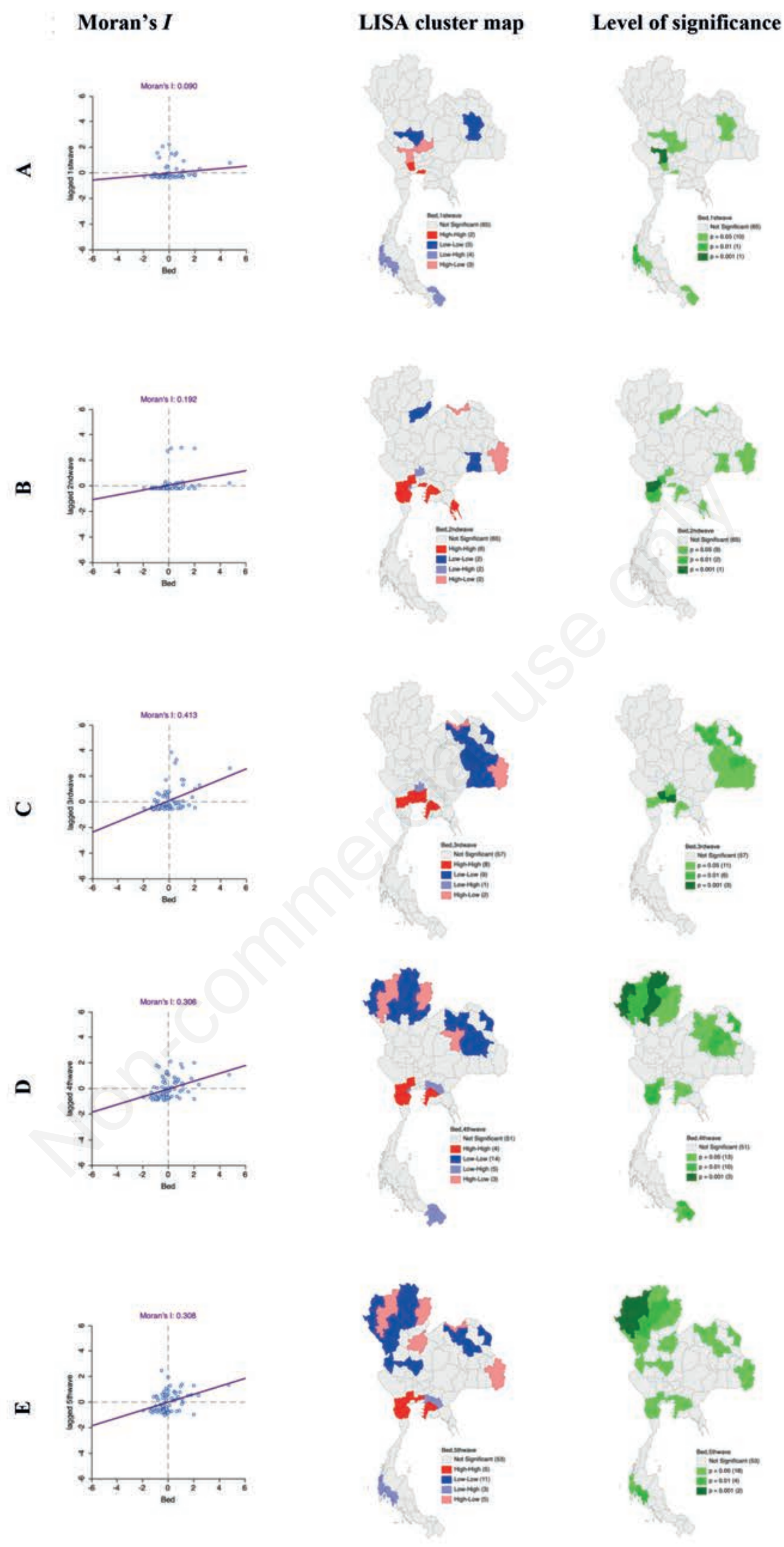

Figure 7. Bivariate analysis of the COVID-19 incidence rate and medical establishments with beds per 10,000 population in the different waves. A) Wave 1; B) Wave 2; C) Wave 3; D) Wave 4; E) Wave 5.

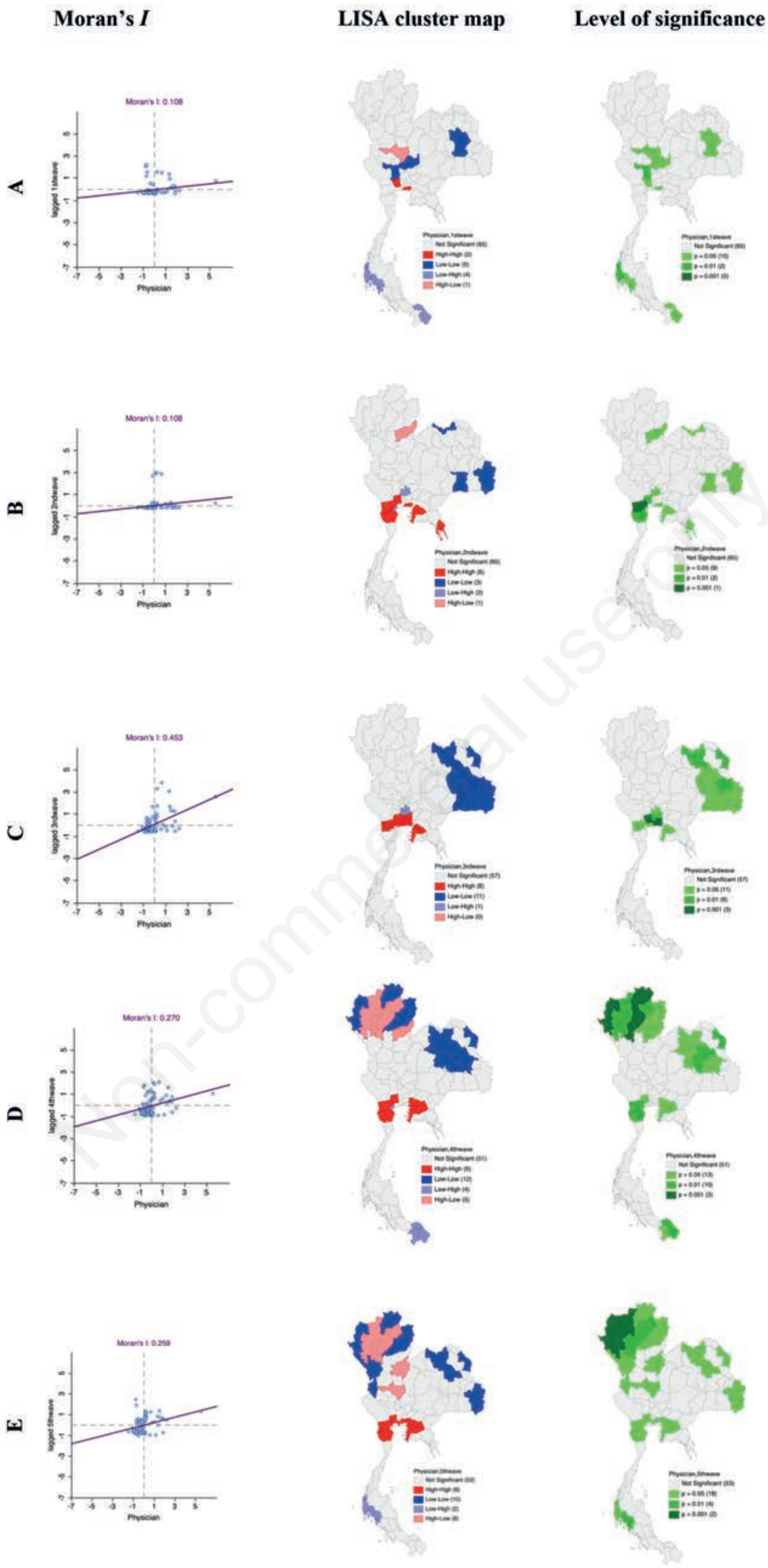

Figure 8. Bivariate analysis of the COVID-19 incidence rate and physicians per 10,000 population in the different waves. A) Wave 1; B) Wave 2; C) Wave 3; D) Wave 4; E) Wave 5.

five different waves. These cases were initially concentrated in the southern part of Thailand in Wave 1 and then shifted to the central part in subsequent waves. The results showed that the spatial autocorrelation, as indicated by Moran's *I*, was constant in waves 1 and 2 but increased in waves 3 to 5. This observed pattern suggests that the control policies implemented by the government, such as restrictive measures, conducting widespread testing of migrant workers, imposing restrictions on international travel, implementing travel restrictions for individuals coming from affected provinces as well as administering mass vaccinations may have influenced the changing spatial patterns. Similar variations have been found in other studies of COVID-19 outbreaks (Al-Kindi *et al.*, 2020; Alcântara *et al.*, 2020; Bag *et al.*, 2020; Deeb, 2021; Zhang *et al.*, 2020) emphasizing the need for timely and updated spatial analysis of epidemic diseases for accurate prediction and effective control measures. These findings suggest that spatial analysis plays a critical role in the prediction of outbreaks and development and implementation of regulations to control viral spread.

The finding that high levels of population density and household density are spatially associated with a high concentration of COVID-19 cases is supported by a majority of other studies (Al-Kindi *et al.*, 2020; Coşkun *et al.*, 2021; Dutta *et al.*, 2021; Maroko *et al.*, 2020; Sun *et al.*, 2020). The similar effect of urbanization on COVID-19 cases has also been noted by several studies (Ramírez-Aldana *et al.*, 2020; Dutta *et al.*, 2021; Sarkar *et al.*, 2021). It would be critical that planning and fulfilling measures to control the spread of COVID-19 reflect the findings that densely populated areas with high levels of urbanization seem to be at higher risk for outbreaks. Public health officials and policymakers should therefore prioritize these areas in their COVID-19 response efforts.

Some of the building blocks for healthcare system (such as manpower and hospital beds) provide health promotion to the public, prevention of uninfected population through isolation and treating infected people with proper quarantine and rehabilitation. In this study, the healthcare factors (hospital density; presence of hospitals and other medical establishments with beds; and physicians per 10,000 population) all showed a strong spatial relationship with the COVID-19 incidence rate. In other words, areas with more medical resources tend to have higher rates of cases and be surrounded by other areas with more medical resources while, areas with few medical resources, as indicated by the coldspot clusters, tend to have lower COVID-19 incidence rates. Counter-intuitively, this implies that the distribution of medical resources may have an influence on the spread of COVID-19 in a certain area. On the other hand, the lower incidence rates in areas with fewer medical resources could also be due to a lack of access to testing and healthcare or there may not be enough resources to fully protect an area from COVID-19 leading to underreporting of cases. This is supported by several studies carried out in other countries, such as Brazil, Oman, China and the United States (Alcântara *et al.* 2020; Mansour *et al.* 2021; Liu *et al.* 2021; Ribeiro *et al.* 2020; Su *et al.* 2020). It is difficult to determine whether the findings are consistent with real conditions without additional information. The relationship between medical resources and incidence rate is complex and may be influenced by several other factors, such as population density, demographic factors, access to healthcare, socioeconomic status, government response and community-level interventions to prevent viral spread.

There was a positive spatial correlation between the number of physicians and the incidence rate, with the strongest correlation found in Wave 3. This suggests that areas with higher numbers of physicians per population not only tend to have higher incidence rates, but they are also surrounded by other similar areas. The LISA analysis confirms this finding by revealing the presence of HH clusters (provinces with high numbers of both physicians and incidence rates) in several waves. The presence of these HH clusters suggests that areas with high numbers of physicians may be more susceptible to COVID-19 outbreaks. On the other hand, the LL clusters found in several waves indicate that areas with low numbers of physicians may be less affected by COVID-19. This might reflect the same situation as described above or it could be due to factors such as exposure to the virus in medical settings or a high population mobility in these areas (Ehlert, 2021; Ramírez-Aldana *et al.*, 2020; Su *et al.*, 2020; Wetchayont *et al.*, 2021). This study highlights the importance of considering the distribution of healthcare workers, particularly physicians, in the response to COVID-19. Policymakers and healthcare organizations can use these results to identify areas that need additional healthcare resources and allocate resources accordingly. This could help to minimize spread and support patients in need.

Several limitations were identified in this study. One was that it only examined six factors and did not account for other potential factors that could influence the incidence rate, such as economic status, individual behaviours, environmental factors, social and cultural practices, and public health policies. Additionally, it would be useful to examine the specific impact of different types of medical facilities *(e.g.*, general hospitals, specialized clinics, etc.) and healthcare workers (*e.g.*, doctors, nurses, etc.). In addition, we relied on secondary data that may contain inaccuracies or be limited in other ways, *e.g.*, by only covering part of the pandemic and not reflecting the current situation progress. To gain a more comprehensive understanding of the impact of demographic and healthcare factors on incidence, future research should investigate additional factors, employ more comprehensive longitudinal data and spatio-temporal analysis that can track changes over both space and time.

As the study was cross-sectional, cause-and-effect relationships between the factors examined and COVID-19 incidence could not be established, while the spatial regression analysis would have made it possible to provide more detailed information about the spatial relationship between the factors and the incidence rate. Importantly, as the study only focused on the incidence in Thailand, the results may not be generalizable to other countries with different populations, health systems, and cultural practices. Finally, this is the first assessment analysing with univariate and bivariate analysis using QGIS and GeoDa for the spatial correlation between COVID-19 incidence rate and its related factors in all 77 provinces of Thailand during the five main waves of the pandemic that clearly visualized the spatially heterogeneous autocorrelation between the demographic and healthcare factors and COVID-19 incidence rate among these provinces.

The incidence of COVID-19 varied in each of the five waves of the pandemic. The highest rates were seen in Phuket during Wave 1 and Wave 5, Samut Sakhon during Wave 2 and Wave 4 and Bangkok Metropolis during Wave 3. Several provinces in Thailand experienced high COVID-19 incidence rates across all five waves, with the cases initially concentrated in the southern part of the country in Wave 1 and shifting to the central part in subsequent waves (see online supplementary materials). The study highlights the importance of considering spatial patterns when analysing the spread and the effectiveness of control measures. The results suggest that the spatial analysis plays a frontier role in the prediction on outbreaks and development and implementation of regulations to control the spread of COVID-19. We also found that demographic factors such as population density, household density and urbanization have a strong impact on COVID-19 incidence rates, with the higher case numbers in the most highly urbanized provinces as reflected by their high densities of households and people. Moreover, the study found that availability and accessibility on medical resources, such as hospital beds, was correlated to the incidence of COVID-19 cases. Resource-limited areas with low incidence rates may suffer from limited access to testing and healthcare services leading to potential underreporting of cases and inadequate protection against the disease. The distribution of medical resources could have an impact on the spread of COVID-19 in certain areas and it is important that public health officials and policymakers prioritize these areas in their response efforts.

Conclusions

This study highlights the crucial role of considering spatial analysis, demographic factors and medical resources to better understand the spread and develop and underscores the need for a comprehensive approach that considers both demographic factors and medical resources when planning and implementing measures to control the spread of COVID-19. The study emphasizes the need for timely and updated spatial analysis of epidemic diseases for accurate prediction and effective control measures. The changing trends in the spread require regular updates to the analysis, in order to respond effectively to the evolving situation.

References

Alcântara E, Mantovani J, Rotta L, Park E, Rodrigues T, Carvalho FC, ad Filho CRS. 2020. Investigating spatiotemporal patterns of the COVID-19 in São Paulo State, Brazil. Geospat Health 15:201-9.

Al-Kindi, Khalifa M, Alkharusi A, Alshukaili D, Al Nasiri N, Al-Awadhi T, Charabi Y, El Kenawy AM. 2020. Spatiotemporal assessment of COVID-19 spread over Oman using GIS techniques. Earth Systems and Environment 4:797-811.

Anselin L. 2020. Local Spatial Autocorrelation (1). 2020. https://geodacenter.github.io/workbook/6a_local_auto/lab6a.html.

Anselin L, Bao S. 1997. Exploratory spatial data analysis linking SpaceStat and ArcView. pp. 35-59.

Anselin L, Syabri I, Kho Y. 2006. GeoDa: An introduction to spatial data analysis. Geographical Analysis 38:5-22.

Bag R, Ghosh M, Biswas B, Chatterjee M. 2020. Understanding the spatio-temporal pattern of COVID-19 outbreak in India using GIS and India's response in managing the pandemic. Regional Sci Policy Pract 12:1063-03.

Cliff AD, Ord JK. 1981. Spatial Processes: Models and Applications. Pion Limited. Vol. 13. London: Taylor & Francis Group 1981.

Coşkun H, Yıldırım N, Gündüz S. 2021. The spread of COVID-19 virus through population density and wind in Turkey cities. Science of the Total Environment 751.

Deeb OE. 2021. Spatial autocorrelation and the dynamics of the mean center of COVID-19 infections in Lebanon. Front Appl Math Stat 6:1-10.

Dutta I, Tirthankar B, Arijit D, 2021. Spatial analysis of COVID-19 incidence and its determinants using spatial modeling: a study on India. Environmental Challenges 4:100096.

Ehlert A. 2021. The socio-economic determinants of COVID-19: A spatial analysis of German county level data. Socio-Econ Plan Sci 78:101083.

Kunno J, Busaba S, Chavanant S, Budsaba W, Sathit K, Chuthamat K, 2021. Comparison of different waves during the COVID-19 pandemic: retrospective descriptive study in Thailand. Adv Prev Medi 2021:1-8.

Kwok CYT, Wong MS, Chan KL, Kwan MP, Nichol JE, Liu CH, Wong JYH, Wai AKC, Chan LWC, Xu Y, Li H, Huang J, Kan Z, 2021. Spatial analysis of the impact of urban geometry and socio-demographic characteristics on COVID-19, a study in Hong Kong. Sci Total Environ. 764:144455.

Liu Q, Sha D, Liu W, Houser P, Zhang L, Hou R, Lan H, Flynn C, Lu M, Hu T, Yang C. 2020. Spatiotemporal patterns of COVID-19 impact on human activities and environment in mainland China using nighttime light and air quality data. Remote Sensing 12:1-14.

Liu W, Wang D, Hua S, Xie C, Wang B, Qiu W, Xu T, Ye Z, Yu L, Yang M, Xiao Y, Feng X, Shi T, Li M, Chen W. 2021. Spatiotemporal analysis of COVID-19 outbreaks in Wuhan, China. Sci Rep 11:13648.

Lovett DA, Poots AJ, Clements JT, Green SA, Samarasundera E, Bell D. 2014. Using geographical information systems and cartograms as a health service quality improvement tool. Spat Spatiotemporal Epidemiol 10: 67-74.

Mansour S, Kindi AA, Al-Said A, Al-Said A, Atkinson P. 2021. Sociodemographic determinants of COVID-19 incidence rates in Oman: geospatial modelling using multiscale geographically weighted regression (MGWR). Sust Cities Soc 65:102627.

Maroko AR, Nash D, Pavilonis BT. 2020. COVID-19 and inequity: a comparative spatial analysis of New York City and Chicago hot spots. J Urban Health 97:461-70.

National-Statistical-Office. 2020. Key Statistical Data. 2020. Available from: http://statbbi.nso.go.th/staticreport/page/sector/en/01.aspx.

Pedorsa NL, de Albuquerque NLS. 2020. Spatial analysis of COVID-19 cases and intensive care beds in the state of Ceará, Brazil. Ciência & Saúde Coletiva 25:2461-68.

Ramírez-Aldana R, Gomez-Verjan JC, Bello-Chavolla OY. 2020. Spatial analysis of COVID-19 spread in Iran: insights into geographical and structural transmission determinants at a province level. PLoS Negl Trop Dis 14:e0008875.

Ribeiro HV, Sunahara AS, Sutton J, Perc M, Hanley QS, 2020. City size and the spreading of COVID-19 in Brazil. PLoS ONE 15:e0239699.

Sangkasem K, Puttanapong N. 2020. Analysis of spatial inequality using DMSP-OLS nighttime-light satellite imageries: a case study of Thailand. Regional Science Policy & Practice. John Wiley & Sons, Ltd. https://doi.org/10.1111/RSP3.12386.

Sarkar SK, Ekram KMM, Das PC. 2021. Spatial modeling of COVID-19 transmission in Bangladesh. Spatial Inf Res 29:715-26.

Sornlorm K, Roshan KM, Withaya P, Krissana A. 2022. Spatial association of land-use areas and disease occurred by pesticide poisoning in Thailand. F1000 Research 11:1386.

Steiniger S, Hunter AJS. 2013. The 2012 free and open source GIS software map - a guide to facilitate research, development, and adoption. Computers Environ Urban Systems 39:136-50.

Su D, Chen Y, He K, Zhang T, Tan M, Zhang Y, Zhang X. 2020. Influence of socio-ecological factors on COVID-19 risk: a cross-sectional study based on 178 countries/regions worldwide. MedRxiv, 1-35.

Sun F, Matthews SA, Yang TC, Hu MH. 2020. A spatial analysis of the COVID-19 period prevalence in U.S. Counties through June 28, 2020: Where Geography Matters? Ann Epidemiol 52:54-59.e1.

Wetchayont P. 2021. Investigation on the impacts of COVID-19 lockdown and influencing factors on air quality in greater Bangkok, Thailand. Adv Meteorol 2021:6697707.

Wetchayont P, Waiyasusri K. 2021. Using Moran's I for detection and monitoring of the Covid-19 spreading stage in Thailand during the third wave of the pandemic. Geogr Environ Sustain 14:155-67.

WHO. 2020. Naming the Coronavirus Disease (COVID-19) and the Virus That Causes It. 2020. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it.

WHO. 2022. WHO Coronavirus (COVID-19) Dashboard | WHO Coronavirus (COVID-19) Dashboard With Vaccination Data. 2022. https://covid19.who.int/.

WHO-Thailand. 2022a. COVID-19 Situation Update No.227, Thailand (16 March 2022).

WHO-Thailand. 2022b. COVID-19 Situation Update No.235, Thailand (11 May 2022).

Wu X, Nethery RC, Sabath BM, Braun D, Dominici F. 2020. Exposure to air pollution and COVID-19 mortality in the United States: a nationwide cross-sectional study. MedRxiv 7:2020.04.05.20054502.

You H, Wu X, Guo X. 2020. Distribution of Covid-19 morbidity rate in association with social and economic factors in Wuhan, China: implications for urban development. Int J Environ Res Public Health 17:3417.

Zhang H, Suepa T, Hong L, Nayelin P, Mot L, Chakpor A. 2021. Geospatial analysis of Covid-19 to respond to pandemic outbreaks: a case study in Bangkok Metropolitan Region, Thailand. In J Geoinformatics 17:68-80.

Zhang X, Rao H, Wu Y, Huang Y, Dai H. 2020. Comparison of spatiotemporal characteristics of the COVID-19 and SARS outbreaks in mainland China. BMC Infect Dis 20:1-7.

Online supplementary material:
Table S1. Univariate analysis of COVID-19 incidence rate per 100,000 population.
Table S2. Bivariate analysis of COVID-19 incidence rate and population density per km^2 in phases of different waves.
Table S3. Bivariate analysis of COVID-19 incidence rate with household density per km^2 in phases of different waves.
Table S4. Bivariate analysis of COVID-19 incidence rate with percentage of urban population in phases of different waves.
Table S5. Bivariate analysis of COVID-19 incidence rate with hospital density per km^2 in phases of different waves.
Table S6. Bivariate analysis of COVID-19 incidence rate with hospital and medical establishments with beds per 10,000 population in phases of different waves.
Table S7. Bivariate analysis of COVID-19 incidence rate with physician per 10,000 population in phases of different waves.