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A spatiotemporal analysis of COVID-19 transmission in Jakarta, Indonesia for pandemic decision support

Agung Syetiawan,[1] Mira Harimurti,[2,3] Yosef Prihanto[1,4,5]

[1]National Research and Innovation Agency, Jakarta-Bogor, Cibinong, West Java; [2]Geospatial Information Agency, Jakarta-Bogor, Cibinong, West Java; [3]Student in Urban and Regional Planning, Gadjah Mada University, Sleman Regency, Special Region of Yogyakarta; [4]School of Environmental Sciences, Universitas Indonesia, Depok, West Java; [5]Sensing Technology Department, Faculty of Defense Technology, Indonesian Defense University, Bogor, West Java, Indonesia

Abstract

With 25% confirmed cases of the country's total number of coronavirus disease 2019 (COVID-19) on 31 January 2021, Jakarta has the highest confirmed cases of in Indonesia. The city holds a significant role as the centre of government and national economic activity for which pandemic have had a huge impact. Spatiotemporal analysis was employed to identify the current condition of disease transmission and to provide comprehensive information on the COVID-19 outbreak in Jakarta. We applied space-time analysis to visualise the pattern of COVID-19 hotspots in each time series. We also mapped area capacity of the referral hospitals covering the entire area of Jakarta to understand the hospital service range. This research was conducted in 4 stages: i) disease mapping; ii) spatial autocorrelation analysis; iii) space-time pattern analysis; and iv) areal capacity mapping. The analysis resulted in 144 sub-districts categorised as high vulnerability. Autocorrelation studies by Moran's *I* identified cluster patterns and the emerging hotspot results indicated successful interventions as the number of hotspots fell in the first period of social restrictions. The results presented should be beneficial for policy makers.

Correspondence: Agung Syetiawan, National Research and Innovation Agency, Jakarta Bogor street Km 46, Cibinong 16911, Indonesia.
E-mail: agungsyetiawan@gmail.com

Key words: COVID-19 transmission; spatiotemporal pattern; spatial autocorrelation; emerging hotspots; Indonesia.

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Introduction

Coronavirus disease 2019 (COVID-19) is a new type of virus, discovered after its first outbreak of disease in Wuhan, China, at the end of December 2019 as reported by the Chinese Centers for Disease Control (2020). Activities in Hunan seafood and animal market were suspected as the source of the outbreak after that the local health facilities reported cases of patients with signs of pneumonia (Li *et al*., 2020; Zhu *et al*., 2020). COVID-19 is an acute human respiratory syndrome caused by a novel coronavirus-2 infection (Huang *et al*., 2020). Compared to the severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS), this disease is transmitted more rapidly (Boulos & Geraghty, 2020). In early March 2020, the World Health Organization (WHO) declared COVID-19 a global pandemic disease (Okba *et al*., 2020; WHO, 2020) with death rate estimated between 1% to 5% (Roser *et al*., 2020). This disease now affects the global population. The first two Indonesian cases were reported on 2 March 2020 (Djalante *et al*., 2020) and has continued to increase (Figure 1). This case was considered as the starting point of COVID-19 transmission for Indonesia that reported 581,550 cases on 7 December 2020, at that time making the country the 20th highest infected country in the world (Woldometer, 2020). Indonesia reported 1,007 deaths from COVID-19 on 12 May 2020, which was the 5th highest case fatality rate (CFR) in Asia (Woldometer, 2020). Experts assume that 7% of CFR in Indonesia, considered to be one of the highest CFR in the world, was due to low test rates meaning that many cases were likely not to have been detected (Barker and Souisa, 2020). As more cases became found, the CFR subsequently fell (Bergquist *et al*., 2020).

Until 31 January 2021, 269,718 cases of the total 1,078,314 confirmed cases of COVID-19 in Indonesia, including 4,267 deaths, were located in Jakarta reported by the Indonesian Board for Disaster Management (Badan Nasional Penanggulangan Bencana) (BNPB, 2020). With 267 million people, Indonesia is the 4th most populated country in the world and Jakarta, the capital city, in particular as it covers a large, urbanised area. In case of an infectious disease outbreak, the urban setting's complexity would catalyse transmission (Flies *et al*., 2019), and Jakarta plays a significant role as the centre of government and national economic activity, for which a pandemic would thus create a severe impact. With 25% confirmed COVID-19 cases of the country's total up to early 2021 in Jakarta (Halim, 2021), the disease has already had a profound impact on this strategic city. Hence, it is crucial to apply spatial analysis and modelling in an effort to understand how to contain and mitigate transmission.

Disease mapping and modelling have been widely implemented (Lawson, 2013; Liu *et al*., 2017; Pou *et al*., 2017; Hashtarkhani *et al*., 2021). This kind of statistical approach could be useful for developing an approach to minimise transmission leading to a lower number of cases as has been shown for other infectious diseases by Lee and Lawson (2014). Researchers have also proved that geographic information systems (GIS) increase understanding, visualising, and predicting disease outbreaks (Koch, 2005). Infectious diseases are usually transmitted in a pattern influenced by topographic and isotropic factors facilitating disease transmission from one place to another (Bourdin *et al*., 2020), and spatiotemporal information of COVID-19 cases is considered crucial for determining and applying treatment (Desjardins *et al*., 2020). Rapid test site selection, resource allocation and intervention must be decided early, while spatiotemporal analysis is useful for the identification of the characteristics of the changing trends of disease outbreaks (Abdrakhmanov *et al*., 2017; Mo *et al*., 2020; MohammadEbrahimi *et al*., 2021). In addition, the capacity of referral hospitals plays a major role in handling disease outbreaks (Alkuzweny *et al*., 2020). Information related to resources and spatial distribution of health facilities is very important in responding (Kazory *et al*., 2020), and knowledge regarding the spatial distribution and reach of health facilities is important for optimizing existing health services (Wang, 2011). Importantly, the ability to understand the risk spatially is considered necessary in the COVID-19 outbreak mitigation process.

Considering the need for immediate mitigation of COVID-19 transmission in Jakarta, the epicentre in Indonesia, research on this issue is crucial. We decided to analyse COVID-19's spatiotemporal transmission patterns and investigate the current condition of the disease transmission to better understand the COVID-19 outbreak and thus be able to provide vital information for developing a control strategy.

Materials and methods

Site of research

The objective was focused on 4 out of 5 cities of the Special Capital Region of Jakarta. The Archipelagic Regency (Kepulauan Seribu) was not included, as it is an isolated area with a low risk for COVID-19 exposure. From the available data, we evaluated disease transmission considering the measures taken by the government to control its outbreak. This research was conducted in four stages: i) disease mapping; ii) spatial autocorrelation analysis; iii) space-time pattern analysis; and iv) area capacity mapping.

Data

Patient-related information such as the daily number of confirmed cases of COVID-19, the spatial distribution of positive cases and the time frame of important events that occurred in the first year of the pandemic were the variables considered. An annual series (1 March 2020 to 28 February 2021) of data was used to study the COVID-19 situation. The data required for this analysis were obtained from the COVID-19 official website by the local Government of Jakarta Special Capital Region (https://corona.jakarta.go.id). The population density was classified based on the national standard (SNI 03-1733-2004) for urban housing planning. For this analysis, we used population data of 2018 and the population density of 2019 provided by the government's open data platform (https://data.jakarta.go.id).

Disease mapping

Spatial approach is one of many ways to understand phenomena and represent them in an integrated geographic information system. Spatial analysis is often implemented to understand how an infectious disease spreads (Kiani *et al*., 2021; Robertson and Nelson, 2014; Vaneckova *et al*., 2010; Weimann *et al*., 2016). This stage aimed to understand the initial outbreak situation and identify vulnerable areas with regard to COVID-19 transmission, *i.e.* answering the questions of when, where, and how the disease

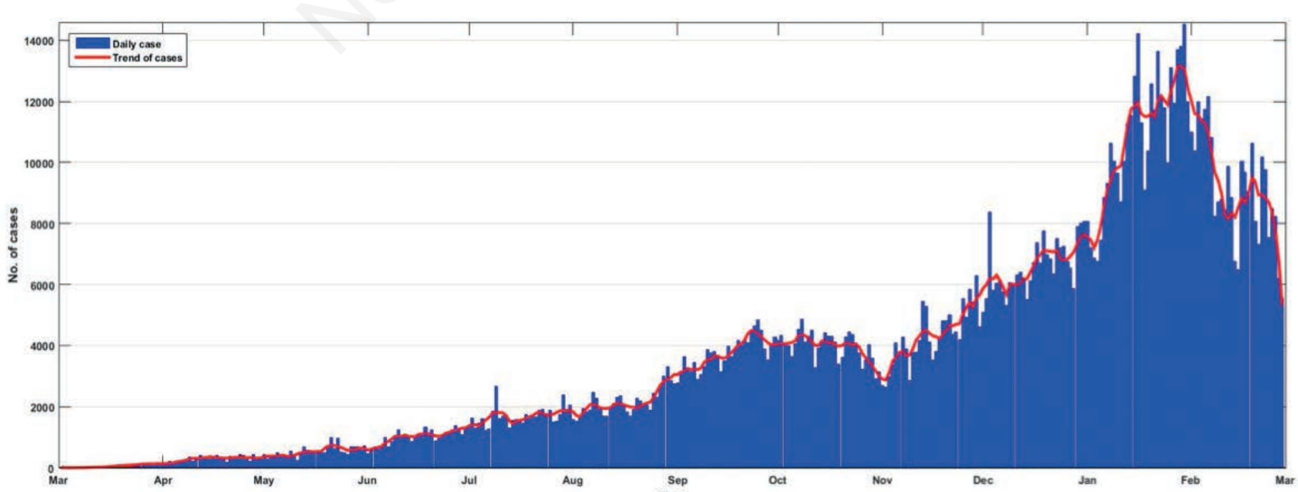

Figure 1. Daily new cases COVID-19 in Indonesia 1 March 2020 - 28 February 2021.

entered the city. The daily number of confirmed cases and their spatiotemporal distribution were grouped based on sub-district administration units.

Vulnerability is a condition of how far a disaster will affect people (Dwyer *et al*., 2004; Kumpulainen, 2006), and mapping of COVID-19 vulnerability to was conducted to identify the high-risk areas. Since aggregation of people support transmission, while elderly people (older than 50 years of age) and children (younger than 15 years of age) are at higher risk of being infected (Chen *et al*., 2020), we took into account age and density as the two variables for vulnerability area mapping. An area was considered as high risk if it had a high presence of both elderly people and children together with a high total population density. The vulnerability index was formulated using a simple method assigning a score for every variable considered. Variable age and population density were considered to have the same influence, so no weighted value was added. The index value was thus the total of the score values from the different parameters and categorised as low, moderate or high based on technical specification on vulnerability mapping for non-natural disasters developed by the Indonesian Board for Disaster Management (Badan Nasional Penanggulangan Bencana) BNPB, 2012.

Spatial autocorrelation

As it is essential to obtain information on COVID-19 transmission pattern in the different areas and find out whether or not relationships exist, spatial dependence and autocorrelation were employed to study COVID-19 transmission and concentration. A spatial autoregressive model (Bourdin *et al*., 2020) was applied to identify the factors influencing any observed event regarding concentration and transmission (autocorrelation and collocation effect) as well as any correlation between observations. Moran's *I* is a widely used method for measuring global spatial autocorrelation (Moran, 1950; Cui *et al*., 2019). Moran's *I* is also used to identify local autocorrelation or spatial correlation in every area by applying the Local Indicator of Spatial Autocorrelation (LISA) (Anselin, 1995). This study analysed the COVID-19 outbreak in Jakarta spatiotemporally using time series analysis and spatial autocorrelation. We used GeoDa software developed by Anselin *et al*. (2006) for autocorrelation analysis with the smallest administration (sub-district) unit as the analysis unit. The index was calculated by the following equation:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2 (\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij})} \quad (1)$$

where *I* is the global Moran's index; *n* the total number of spatial units; *x* an attribute of interest from a spatial unit; $\bar{x}$ the mean of *x*; and ω_{ij} the weight matrix. The higher the value of local Moran's *I*, the higher the chance that the spreading follows a specific pattern. The neighbouring relation between locations was represented by weight matrix (*W*) where every element in the matrix (ω_{ij}) shows the relation of location *i* to location *j*. Areas near the centre of the observed area were assigned higher weight values than areas farther from the centre of the area observed. LISA was created using a uniform function in the kernel adaptive method of distance weight with a neighbouring value of 8. Neighbouring relationship 8 was selected based on trial and error (experiment result) where this value produced more realistic clusters and higher significance values. To determine the statistical significance of Moran's *I*, a 999 permutation value was assigned. Random results lead to the assumption that the location of the variable value and spatial setting would not be significant.

Four types of spatial associations result from spatial autocorrelation using Local Moran's *I* exist (Anselin *et al*., 2006): i) High-High (HH): a high spatial concentration of cases and a high independent value of the neighbourhood area; ii) Low-Low (LL): a low spatial concentration of cases and a low independent value of the neighbourhood area; iii) High-Low (HL): a high spatial concentration of cases and a low independent value of the neighbourhood area; iv) Low-High (LH): a low spatial concentration of cases and a high independent value of neighbourhood area.

HH and LL spatial clusters show close areas with similar values, while HL and LH represent clusters with different values (spatial outliers). Moran's *I* indicates the spatial autocorrelation in relation to neighbouring areas. Moran's I>0 indicates a positive correlation, while a negative value points to the opposite. Values of zero or very close to zero specify random permutation.

Space-time pattern analysis

In order to evaluate the effectiveness of social restriction policies implemented in Jakarta, we employed space-time pattern analysis to identify unique patterns in datasets, including identified transmission clusters (Shekhar *et al*., 2015). The spatiotemporal hotspot trend was stored in Network Common Data Form (NetCDF) (https://www.unidata.ucar.edu/software/netcdf/), which creates a 'space-time cube' where the data are formatted into bin groups, where each bin signifies a specific time steps that together builds vertical, temporal columns for each spatial area. This approach allows the visualization and analysis of integrated spatiotemporal datasets, and we used it to define hotspots and coldspots with regard to the COVID-19 cases from both the spatial and temporal point of view, which facilitated determining the strategic measure to be implemented.

We used the daily number of confirmed cases in every sub-district in Jakarta from 25 March 2020 to 4 October 2020 for this analysis. Jakarta implemented two restriction policies, the first one on 13 April and the second on 17 September 2020, so we divided the analysis into two phases. Phase 1 signified the first social restriction and phase 2 the second. Both phases were divided into two parts (part 1 and part 2) to compare the time before and after implementation of the social restriction periods (Table 1). Space-time cube analysis needs overlapping data to provide a comparison; hence the whole period was included in part 2 of the analysis.

The time step interval per day was applied using the data for

Table 1. Space-time periods used for the analysis.

Phase (in space-time analysis)	Part 1	Part 2
Phase 1 (1st Social Restriction)	25 March - 12 April 2020	25 March - 30 April 2020
Phase 2 (2nd Social Restriction)	25 March - 16 Sept 2020	25 March - 4 Oct 2020

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the confirmed cases. Spatiotemporal pattern analysis was estimated using the hotspot analysis tool in ArcGIS Pro software (ESRI, Redlands, CA, USA). We also used Getis Gi* formula (Wang & Lam, 2020) for the emerging hotspot analysis and conceptualization of spatial relationship to carry out a hotspot pattern analysis with fixed distance.

Area capacity mapping

Information on availability on the number of beds for COVID-19 patients in the referral hospital is crucial to ensure that every confirmed patient receive the necessary care needed, especially in emergency situations. In the one-year study period of the pandemic, the government issued regulations regarding referral hospital appointment for COVID-19 mitigation. In early March, the central government appointed 8 hospitals as COVID-19 referral hospitals in Jakarta through Decree of the Minister of Health (HK.01.07/MENKES/169/2020). However, as the number of confirmed cases continued rising, the Governor of Jakarta appointed more hospitals through 3 regulations (No. 378 in 2020, No. 987 in 2020, and No. 14 in 2021).

A hospital's optimal service range can be determined using network analysis (Cho, 1998). The data required for the capacity map analysis for Jakarta consisted of hospital distribution data obtained from the government's open data platform (https://data.jakarta.go.id). The service area analysis included the calculation of a coverage area based on the time needed to reach a referral hospital, using available transportation networks. The coverage area was calculated using distance and time (Shahid *et al*., 2009; Mahmoud *et al*., 2013). We used the time aspect as input for the modelling. Based on Ristiantri *et al*. (2021), the optimum time to reach a referral hospital for COVID-19 patients should not be more than 15 minutes. Therefore, this time was used for estimating the network analysis service area. We calculated the travel time dividing the distance by the estimated speed for every road class, *i.e*. 60 km/h for highways 20 km/h for arterial, collector, local and other road classes. Footpaths and pedestrian crossings were defined as barriers. These values were determined based on Jakarta's traffic condition that is prone to traffic jams (Silalahi *et al*., 2020). The map resulting from this stage provided information that the government could use to understand the area's capability and to better contain the COVID-19 outbreak and to develop contingency plans.

Results

Disease mapping

As of February 28, the cumulative number of confirmed COVID-19 cases in Jakarta was 339,735 and 5,478 deaths. The time series of the daily case load showed a significant peak in early September 2020 and again in January 2021. The maximum number of cases was reported on 7 February 2021 with 4,213 cases. The area with the highest number of confirmed cases was Kapuk Sub-district (n=2,498), while Roa Malaka Sub-district (n=96) had the lowest confirmed cases during the entire study period. Overall, the regional distribution of confirmed cases varied significantly. More recently, after Eid Holiday, which runs between 21 and 25 May 2020, and the relaxation of the first social restriction in early June 2020, the daily number of cases started to rise. This condition worsened after the long weekend in August 2020 when about 1,000 new cases per day were reported. Although there was an extreme decrease of reported cases in February 2021, after the implementation of vaccination programme, there was no indication of a flattening curve of daily new cases in Jakarta as shown in Figure 2. Eventually, the worsening situation made the government respond and implement a second social restriction. Figure 2 shows that the trend of cases reported flattened. Both after the first social restriction on 10 April 2020 and after the second on 14 September 2020.

Figure 3 is an illustration of reported daily case situation in Jakarta at some important dates based on GIS results. In the initial phase, COVID-19 spread only in some locations with the reported number of daily cases under 10 per sub-district. The location of reported confirmed cases was initially concentrated in the Jakarta

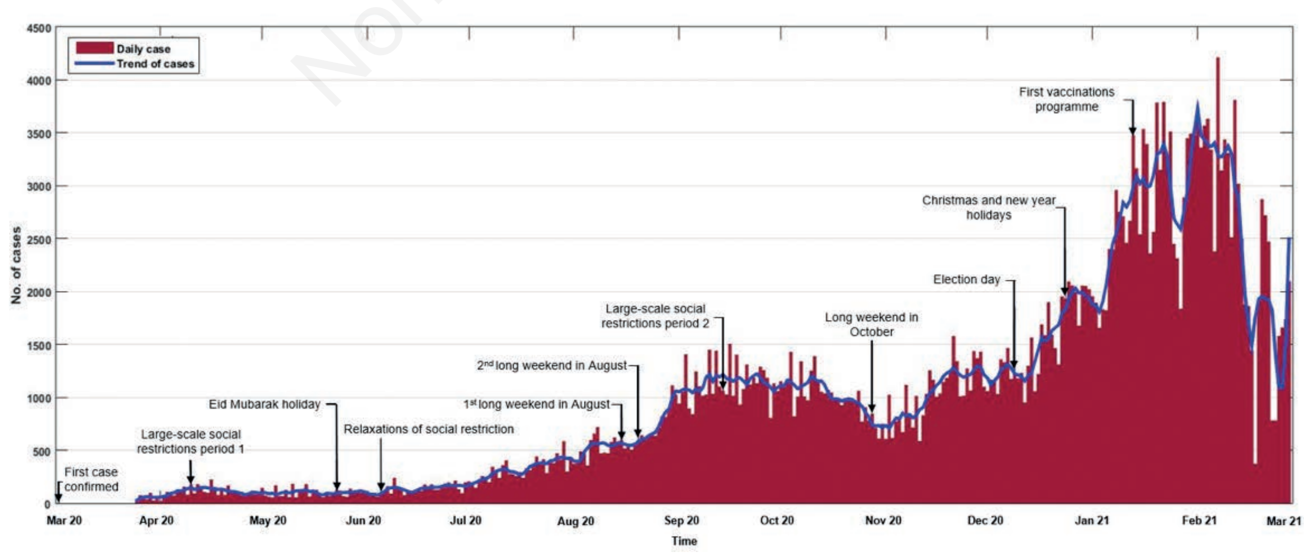

Figure 2. COVID-19 daily cases in Jakarta and important dates in the period 20 March 2020 to 21 March 2021.

Barat area, while it had reached every sub-district in Jakarta by 23 July 2020. From December 2020 to January 2021, the number of reported cases increased rapidly, with more than 50 cases reported in every sub-district. This was seen as the effect of the Christmas and New Year holidays. Starting on 2 March 2020, at least 928 people were infected every day until 28 February 2021. Figure 4 presents the vulnerability degree of the area with respect to the COVID-19 infection exposure. The vulnerability analysis result showed 144 sub-districts categorised as highly vulnerable. Higher vulnerability areas were located in the western, the centre, and the southern part of Jakarta.

Spatial autocorrelation

A long-term cluster pattern was identified based on Moran's *I* autocorrelation (Figure 5). We also found a characteristic similarity between neighbourhood locations shown by the positive autocorrelation results. GeoDa enabled us to visualise the significance detected by Local Moran's *I* statistic and LISA. The LISA cluster map (Figure 6) shows the distribution of COVID-19 hotspots and coldspots. A spatial autocorrelation cluster was visualised based on some important dates as shown in the figure.

Moran's *I* increased due to the increasing number of infected cases in every sub-district that contributed to the development of the cluster pattern. Before social restrictions were implemented, large hotspots were detected in the western and eastern parts of Jakarta on 8 April (Figure 6). The western part of Jakarta is a major city hub with the Soekarno-Hatta International Airport. As the capital city and business centre, Jakarta was first hit by COVID-19 and then became the source of transmission in Indonesia. The complexity of the metropolitan city environment with a high popula-

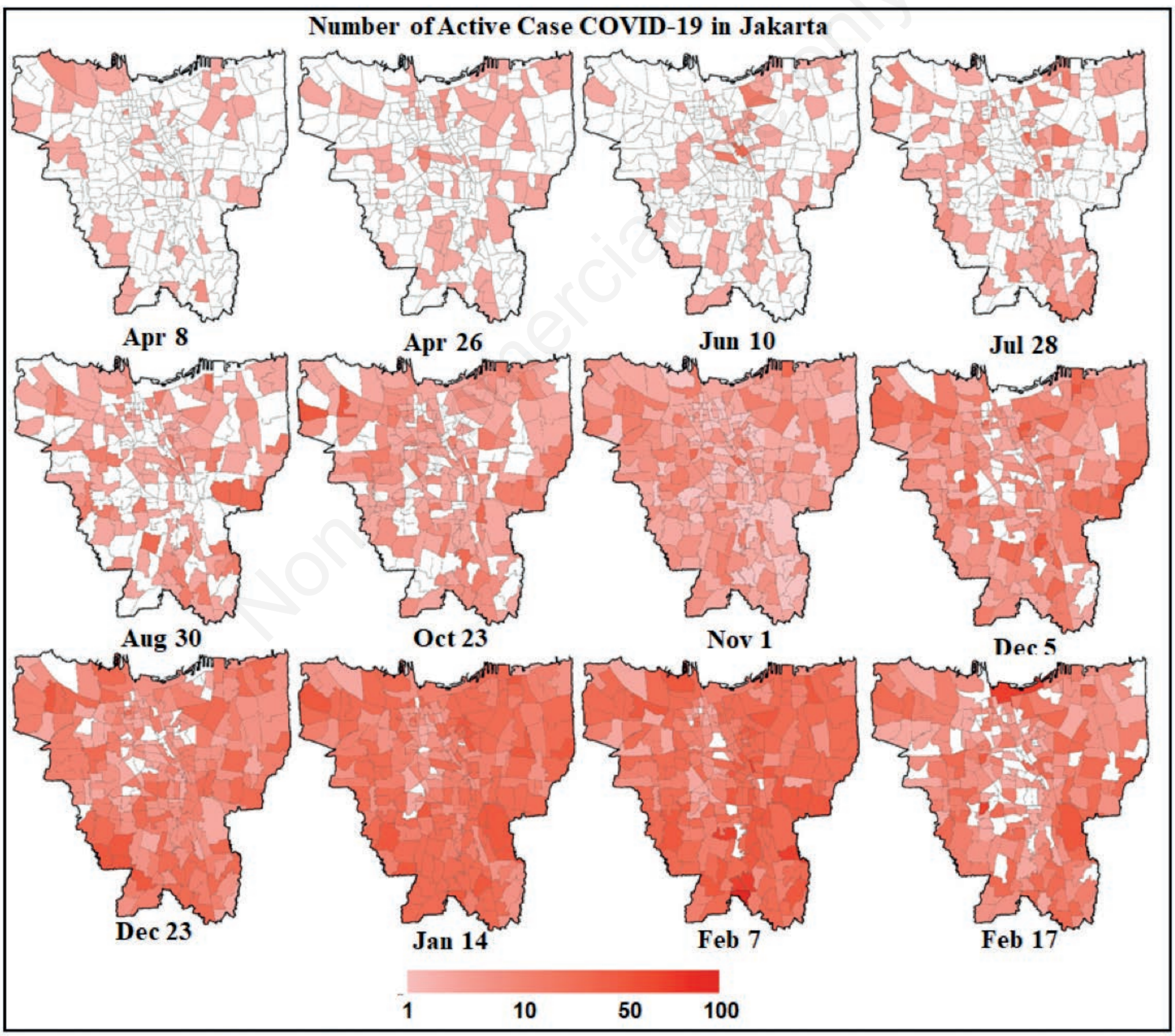

Figure 3. The number of daily COVID-19 cases in Jakarta from 8 April 2020 to 17 February 2021.

tion density, mixed land use and strong public transportation encouraged social engagement. Furthermore, the national hub status made Jakarta the leading destination for tourists and business travellers, a condition inevitably supporting the transmission of any communicable disease. To diminish the COVID-19 transmission risk, Indonesia implemented large-scale social distancing from 10 April 2020. The results were swift, with many hotspots having already decreased by 26 April (Figure 6). However, some of them remained in the central part of the city, where many areas were dominated by coldspots and outlier patterns.

Space-time pattern analysis

The spatiotemporal hotspot trend of phase 1 part 1 (before the implementation of restriction policies) included 19 days or time steps (25 March to 12 April 2020) for each spatial unit resulting in a total number of 4,959 space-time bins. The second part of phase representing the time after the social restrictions consisted of 37 time steps (25 March to 30 April 2020) resulting in a total of 9,675 space-time bins. The corresponding data for phase 2 were 176 time steps (25 March to 16 September 2020) resulting in a total of 45,936 space-time bins for the first part and 194 time steps (25 March to 4 October 2020) resulting in 50,643 bins for the latter. As seen in Figure 7, the dynamic changes moved from low numbers of COVID-19 cases in the southern parts and the centre of Jakarta, with the centre later being overwhelmed by emerging hotspots.

Figure 8 shows how the hotspots changed between phase 1 (8a) and phase 2 (8b). Before the first social restriction, new hotspot patterns spread all over Jakarta, while the first social restriction changed the patterns in the area. The number of new hotspots fell from 20 to 6. Some hotspots oscillated and their number increased strongly during the first social restriction (from 36 to 157). Furthermore, the number of areas with consecutive hotspots (areas not statistically significant until the last hotspot run) decreased from 66 to 36 and the coldspots diminished from 19 to 1. Three areas with intensifying hotspots and two historical coldspots were found in the period before the first social restriction was implemented. In this period, we found 115 areas with no pattern detected that eventually fell to 61 areas. Three new hotspots were identified before the second social restriction period was implemented but we found no new hotspots afterwards. The pattern was dominated by oscillating hotspots. We found 255 hotspots before the second social restriction was implemented, which increased to 258 afterwards. We also found an increasing number of consecutive hotspots that changed from 1 to 3.

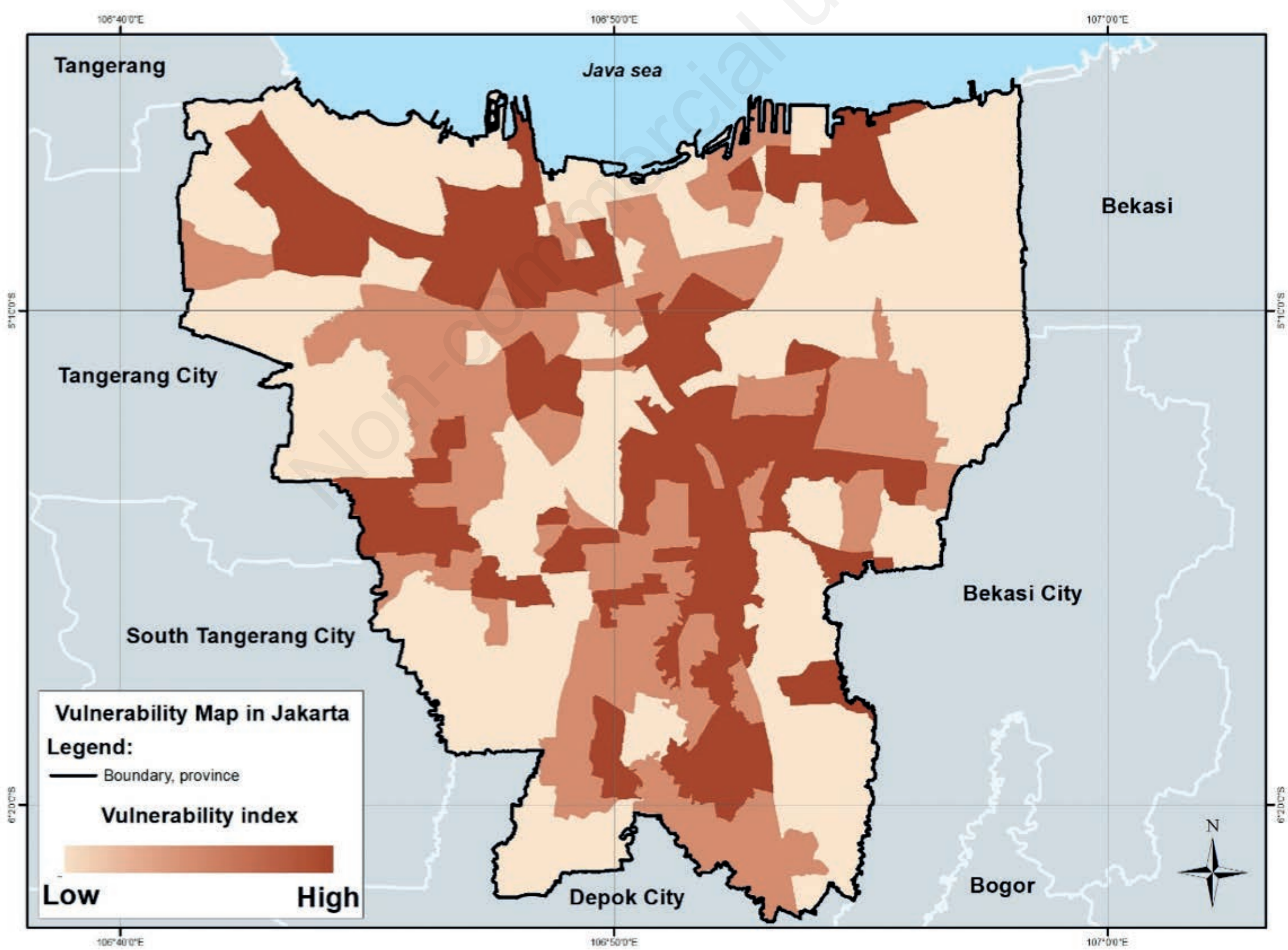

Figure 4. COVID-19 vulnerability in Jakarta.

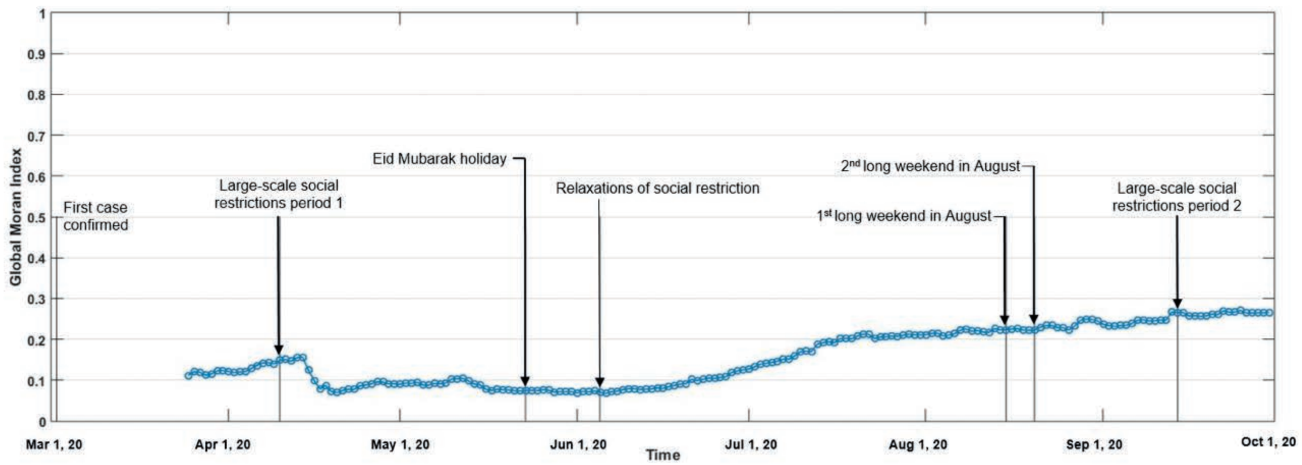

Figure 5. Timeline showing the temporal extension of the cluster detected by global Moran's *I*.

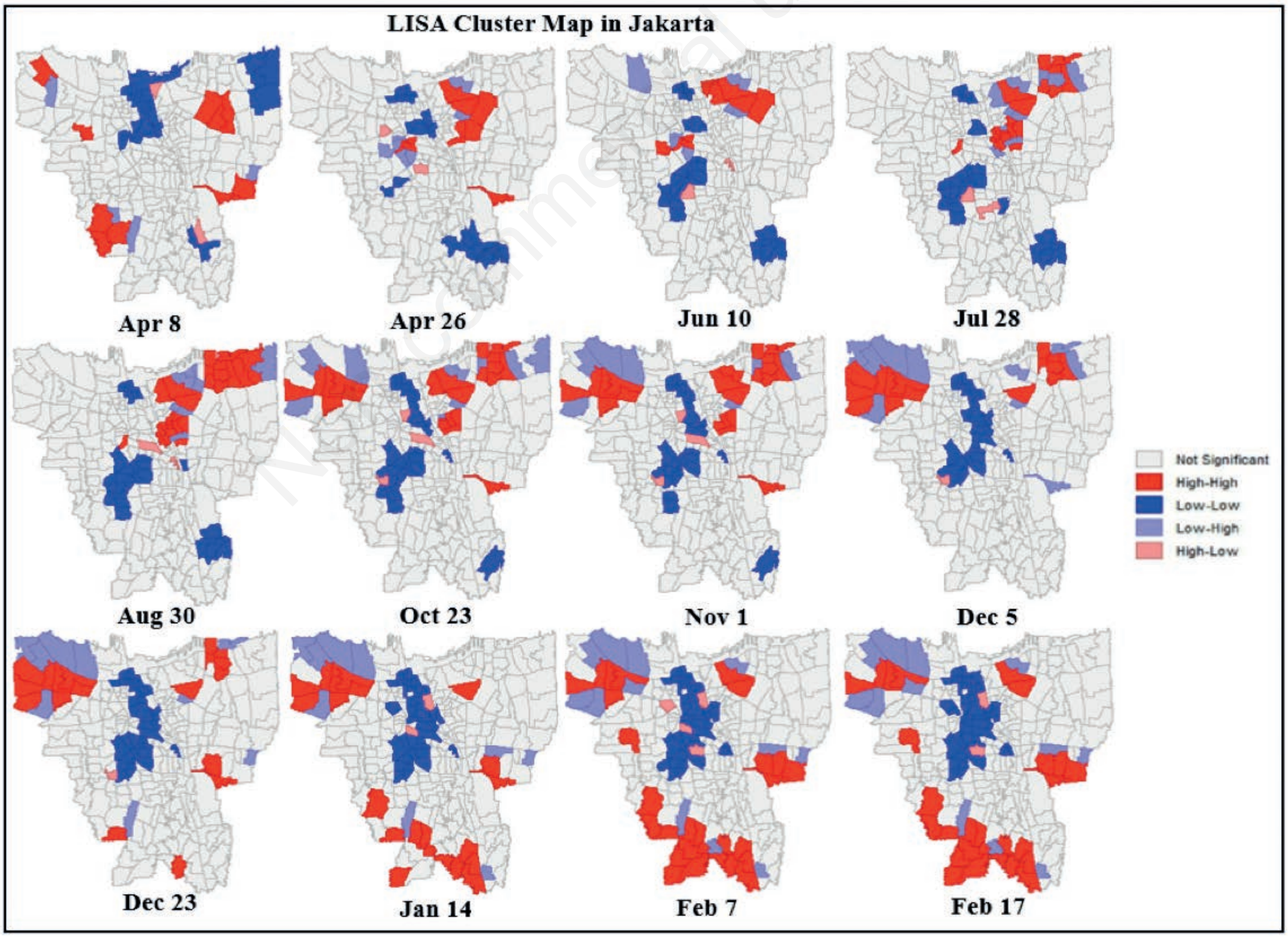

Figure 6. LISA cluster map in Jakarta. Red colour signifies High-High areas and blue colour Low-Low areas, while outlier clusters representing High-Low and Low-High areas are shown in lighter shades.

Area capacity

Figure 9 shows the distribution and coverage area of the referral hospital based on 4 referral hospital assignment regulations implemented in Jakarta and represented as time series data. As seen in the figure, some locations were not covered by referral hospital service when the first and second regulations were implemented on 10 March 2020 and 8 April 2020 respectively. However, by the current regulation implemented on 6 January 2021, the number of referral hospitals were able to cover most area of Jakarta.

The result of this stage was used to determine the coverage of services available (represented in Table 2), especially for emergency conditions. In the early stage, the referral hospitals were able to cover the area of 208 sub-districts with only 75% of the total population of those districts served. Due to the increasing number of infected cases, the government responded immediately by increasing the number of referral hospitals to 101 hospitals. This resulted in 259 sub-district areas with 99% of the population covered. The service area and population covered by the referral hospital remain the same even after the third and fourth regulations were implemented since these regulations only added three new referral hospitals at locations near other referral hospitals.

Figure 10 shows the referral hospital density based on the latest regulation on referral hospitals in Jakarta. The distribution of referral hospitals is concentrated in Jakarta Pusat City in the central part of Jakarta Province. As can be seen in Figure 10, there are at least two referral hospitals for every 3 km^2 in the high-density population areas, while, in contrast, there is only one referral hospital for every 4 km^2 in the low-density areas. However, referral hospitals in other areas were not available at all in areas, such as south and eastern Jakarta Timur, eastern Jakarta Utara and southern Jakarta Barat. Figure 10 also shows that the population is concentrated in the centre of the area. The most populated sub-district is Kalianyar (950 people/ha) within a total area of 32 ha. Areas with high population density were considered to have a higher risk of COVID-19 rapid transmission. Highly populated areas are also concentrated in the centre of the province, where the condition of referral hospital density is appropriate. High-density areas shaded in red and low density areas in green. Yellow signifies intermediate density referral hospitals.

The result is presented on the maps (Figures 2 to 10). Our results show that on 17 April 2020, *i.e.* within 49 days, COVID-19 had spread to 93.5% of Jakarta's sub-districts. This condition made the city the epicentre of the outbreak with a significant level of transmission. Holidays lead to an increasing number of daily COVID-19 cases. Based on the map of daily cases (Figure 3), high

Table 2. Regulations related to the appointment of a referral hospital.

Response by the local government	Referral hospitals (no.)	Districts covered (no.)	People served (no.)	Population covered (%)
First regulation	8	208	7,460,382	75
Second regulation	13	226	8,319,181	83
Third regulation	98	259	9,874,042	99
Fourth regulation	101	259	9,874,042	99

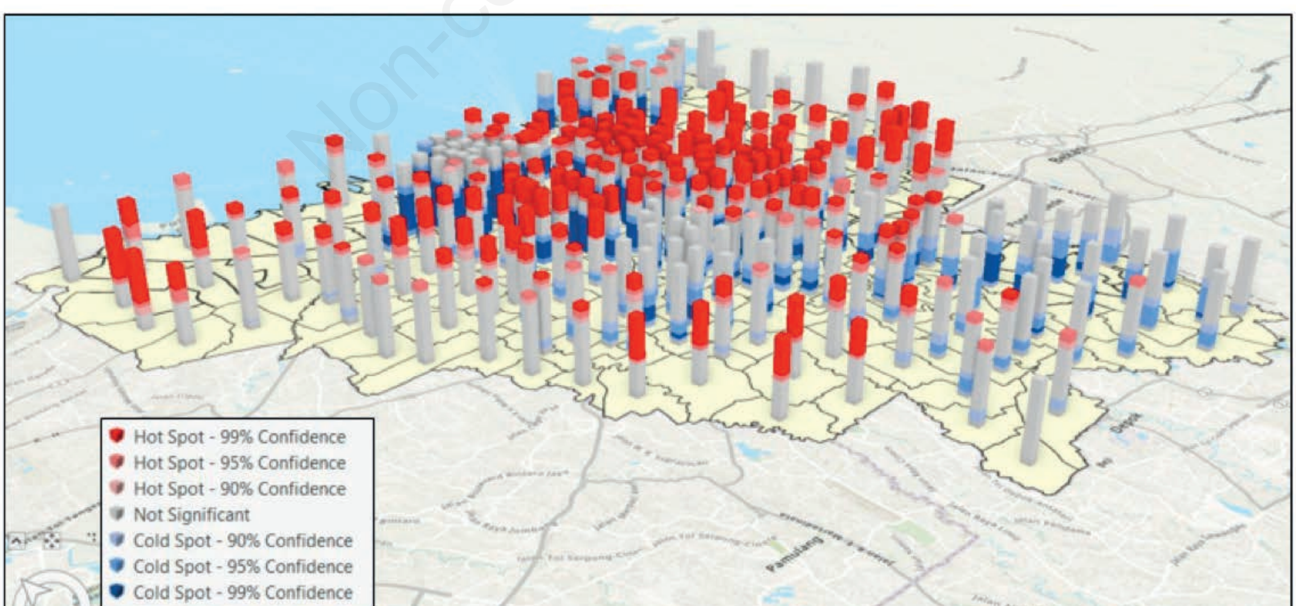

Figure 7. Three-dimensional visualization of the hotspot/coldspot dynamics in Jakarta by the space-time cube approach.

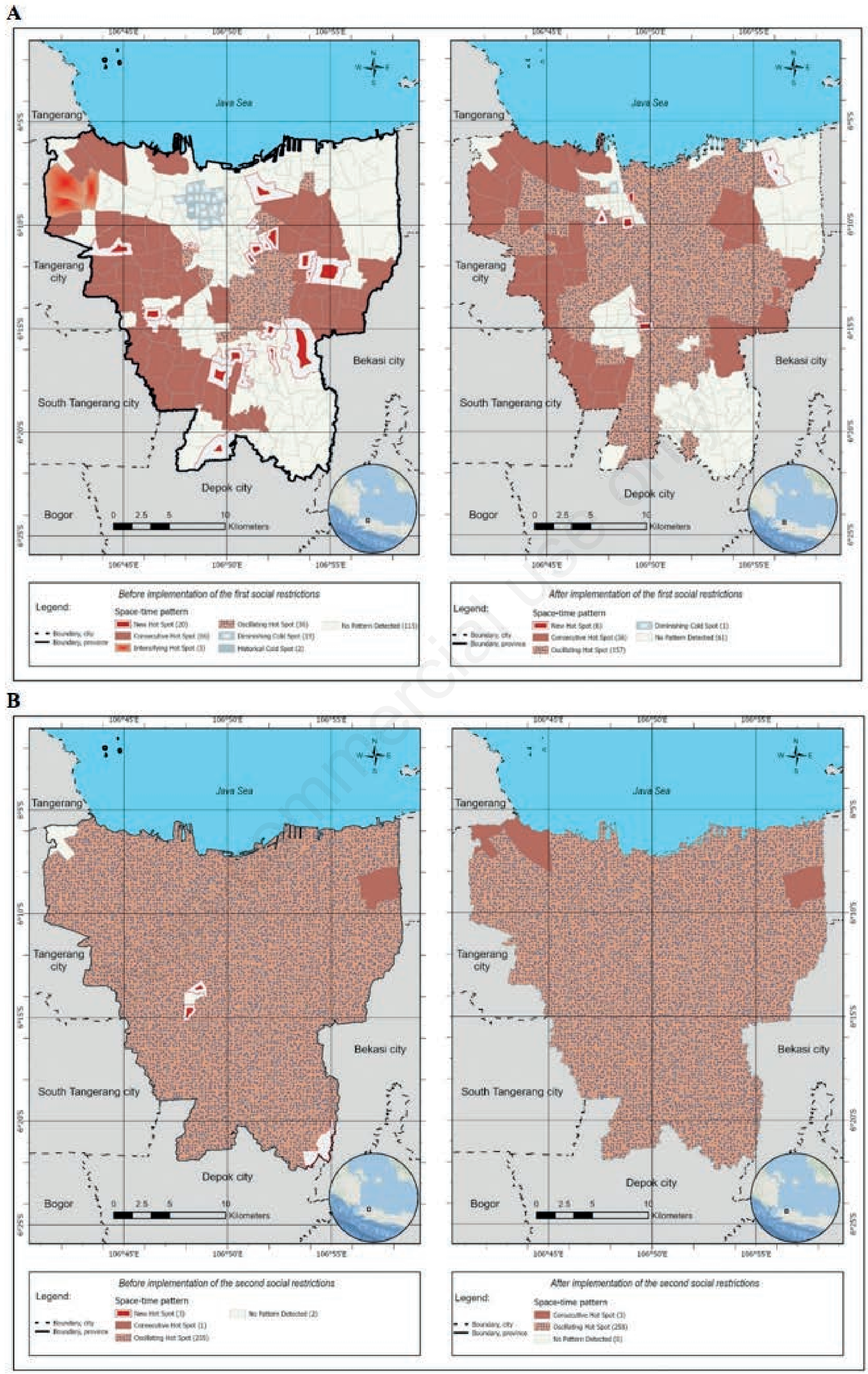

Figure 8. Emerging hotspots from the first social restriction (A) and the second social restriction (B).

numbers of infected cases were reported from low-vulnerability areas from April to October 2020. However, from November 2020 to February 2021, this condition changed to high number of infected cases dominating the high-vulnerability areas.

Discussion

Hospital accessibility plays an important role in measuring the ability of health facilities to respond the spread of COVID-19

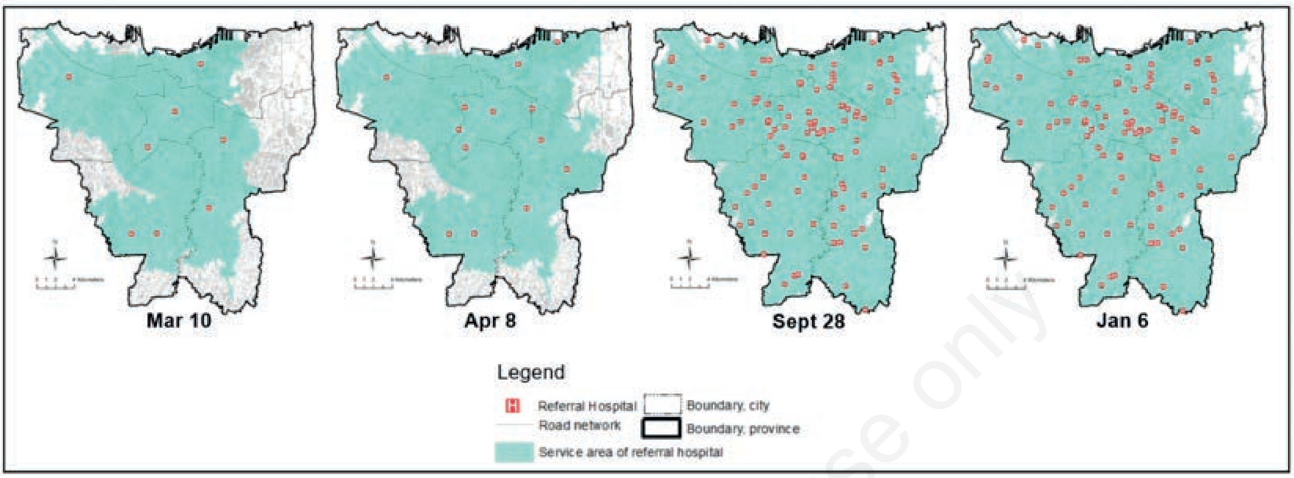

Figure 9. Time series distribution and referral hospital coverage areas.

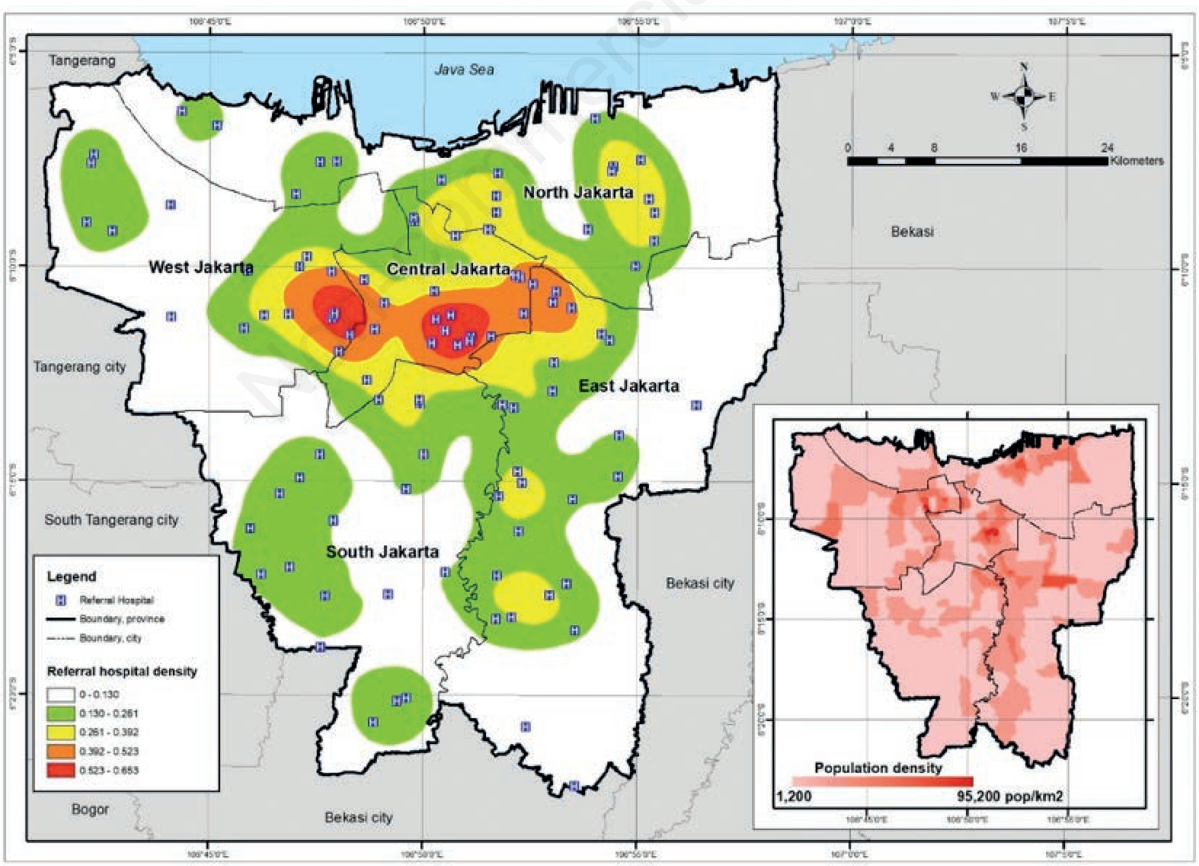

Figure 10. Referral hospital density in Jakarta.

(Kironji *et al*., 2018). Moreover, Hospital distribution is crucial because it involves the convenience of patients to get medical help (Wan *et al*., 2012). The government increased the number of referral hospitals to reduce the death rate in Jakarta. Jakarta Timur city is the area with the most referral hospitals. The increase of confirmed cases was proportional with the increase of bed occupancy, isolation room, and Intensive Care Units (ICUs) in the referral hospitals. Spatially, the final number of referral hospitals appointed by the government was capable of covering all areas in Jakarta. Overall, however, the availability of hospitals in Jakarta remained limited. The results of the density analysis of referral hospitals show that for high-density areas there are only two referral hospitals every 3 km^2.

Accessibility describes the ability of a referral hospital to provide service for patients (Levesque *et al*., 2013; Thomas & Penchansky, 1984). Based on health facilities data provided by the government, there are 153 hospitals consisting of general hospitals, hospitals for specific diseases and hospitals for mothers and children. Those hospitals are well managed by the central government, local authorities and other stakeholders. Hence, the available hospital can support the referral hospitals for treating COVID-19 patients and assist the area not covered by referral hospital services. Hence, the government needs to consider the distribution of the current referral hospital when appointing further referral hospitals.

In this study, spatial autocorrelation was conducted to investigate whether COVID-19 transmission follows a particular pattern. Figure 5 visualizes the clustered pattern, and there was a characteristic similarity between areas located closely together. Based on spatial autocorrelation analysis, there is strong clustering during the study period. In addition, we also found that the first social restriction resulted in a lower Moran's *I*. However, it started to rise again after the holidays and the relaxation of social restriction in May and June 2020. The analysis emerging hotspots supported the view that social restriction had succeeded in reducing the number of oscillating hot spots and consecutive hotspots. In addition, the intensifying hotspot area was only found before the first social restriction was implemented. After the implementation of the first social restriction, the intensifying hotspot area disappeared. The decrease in the number of consecutive hotspot areas indicates that the area with high confirmed cases was decreasing. Prior to the first social restrictions, consecutive hotspots were concentrated in most areas of Jakarta Selatan and Jakarta Timur. Both areas are densely populated. In addition, these two areas are those with the highest vulnerability (Figure 4). Social restriction turned out to be very effective in suppressing the spread of COVID-19 in Jakarta. However, the results of the space-time pattern in the second social restriction show that all areas in Jakarta had been infected with COVID-19, as evidenced by the dominance of the oscillating hotspot areas. This means that the first social restriction succeeded in slowing the trend of positive cases, but without being able to stop the transmission completely. Although the number of daily cases decreased in some parts of Jakarta, the overall number of infected areas kept rising. This dynamism can be particularly well seen in Figure 7, where the height of the columns represents time, which indicates how the COVID-19 cases first appeared in the southern parts of the city and then disappeared from there (only the column bases shaded in blue) to instead reaching peaks in the centre, with the upper halves of many columns in red. Thus, rapid response is needed to control the transmission.

The cluster map shows the high concentration of COVID-19 cases, which can be used for rapid test site selection. Hotspot areas with a high number of confirmed cases should be considered when deciding the rapid test location. Hotspot areas significantly show where the transmission level is the highest, while the coldspots show areas of lower transmission levels that are surrounded by neighbourhood areas with a lower number of confirmed cases. These hotspots and coldspots are priority areas where quarantine is contemplated to prevent further transmission of COVID-19. The result of transmission and concentration of COVID-19 was used as input information for determining the rapid test priority location, and if this done properly the transmission of COVID-19 slows and improves resource management effectiveness.

The coldspots pattern consistently identified in centre of Jakarta from the end of October 2020 to mid-February 2021 indicates the number of daily cases reported from those areas, where the vulnerability had been high but later became relatively lower. This means that a lower number of infected cases were reported from highly vulnerable areas. In contrast, the hotspot pattern was consistently identified in the southern part of Jakarta from mid-January 2021 to mid-February 2021. It means that a higher number of infected cases were reported from less vulnerable areas. Furthermore, there were effects of Christmas and New Year holidays on the rising number of daily cases resulting in the increased number and enlargement of hot spot area. The hotspot distribution was concentrated in the southern part of Jakarta.

This research provides an example of spatiotemporal analysis application in understanding a pandemic transmission pattern. This model can be adopted for other urban area as a decision-making tool for local government in developing the COVID-19 mitigation policy as follows. First, spatial autocorrelation allowed us to understand the concentration of confirmed cases spatially at different time periods. It should be useful for referral hospital decision making. Second, the cluster map can be used for rapid test site selection and priority areas where quarantine is required to prevent further transmission of COVID-19. Third, area capacity and distribution of COVID-19 cases spatially are essential for the government to develop a strategic plan on containing and mitigating the outbreak. Finally, visualizing COVID-19 case distribution with time-series data spatially should assist the government and stakeholders to better understand virus transmission patterns so that they can develop and implement significant action plans for containing the outbreak. Despite the important findings and its beneficial for pandemic decision making, we admit that simultaneous and comprehensive analysis of the time-space information was challenging. Therefore, this research is limited to spatial autocorrelation and presentation of a spatiotemporal analysis. Spatial correlation depends on what and how the influencing factors are used and analysed. In addition, limited data is a constraint to this research. In disease mapping process especially, more variables should be involved to create vulnerability maps.

Conclusions

It is important to identify key factors and relate them to patterns of confirmed cases. Implementation of spatiotemporal analysis is necessary for the understanding of all aspects of COVID-19. The government can use spatial analysis to allocate hospital resources for controlling COVID-19 outbreak in Indonesia. The results of this paper should be beneficial for policymakers since it provides evidence supporting the spatial part of the restriction policy.

References

Abdrakhmanov SK, Mukhanbetkaliyev YY, Korennoy FI, Karatayev BS, Mukhanbetkaliyeva AA, Abdrakhmanova AS, 2017. Spatio-temporal analysis and visualisation of the anthrax epidemic situation in livestock in Kazakhstan over the period 1933-2016. Geospat Health 12:316-24.

Alkuzweny M, Raj A, Mehta S, 2020. Preparing for a COVID-19 surge: ICUs. Eclinical Medicine 25. doi.org/10.1016/j.eclinm.2020.100502.

Anselin L, 1995. Local Indicators of Spatial Association - LISA. Geogr Anal 27:93-115.

Anselin L, Syabri I, Kho Y, 2006. GeoDa: an introduction to spatial data analysis. Geogr Anal 38:5-22.

Barker A, Souisa H, 2020. Coronavirus COVID-19 death rate in Indonesia is the highest in the world. News posted Mon 23 March 2020 with update the same day. Available from: https://www.abc.net.au/news/2020-03-23/why-is-indonesia-coronavirus-death-rate-highest-in-world/12079040 Accessed: 12 May 2020.

Bergquist R, Kiani B, Manda S. 2020. First year with COVID-19: assessment and prospects. Geospat Health 15:187-90.

BNPB, 2012. General Guidelines for Assessing Disaster Risk. Pub. L. No. 02.

BNPB, 2020. Hub InaCOVID-19: GIS portal task force for the acceleration of handling COVID-19 Republic of Indonesia. Available from: https://covid19.go.id Accessed: 12 May 2020.

Boulos MNK, Geraghty EM, 2020. Geographical tracking and mapping of coronavirus disease COVID□19/SARS□CoV□2 epidemic and associated events around the world: how 21 century GIS technologies are supporting the global fight against outbreaks and epidemics. Int J Health Geogr 19(8).

Bourdin S, Jeanne L, Nadou F, Noiret G, 2020. Does lockdown work? A spatial analysis of the spread and concentration of Covid-19 in Italy. Reg Stud 55:1182-93.

Chen N, Zhou M, Dong X, Qu J, Gong F, Han Y, Qiu Y, Wang J, Liu Y, Wei Y, Xia J, Yu T, Zhang X, Zhang L, 2020. Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. Chin J Epid 395:507-13.

Cho CJ, 1998. An equity-efficiency trade-off model for the optimum location of medical care facilities. Socio-Econ Plann Sci 32:99-112.

Cui Z, Lin D, Chongsuvivatwong V, Zhao J, Lin M, Ou J, Zhao J, 2019. Spatiotemporal patterns and ecological factors of tuberculosis notification: a spatial panel data analysis in Guangxi, China. PLoS One 14(5).

Desjardins MR, Hohl A, Delmelle EM, 2020. Rapid surveillance of COVID-19 in the United States using a prospective space-time scan statistic: detecting and evaluating emerging clusters. Appl Geogr 118:102202.

Djalante R, Lassa J, Setiamarga D, Sudjatma A, Indrawan M, Haryanto B, Mahfud C, Sinapoy MS, Djalante S, Rafliana I, Gunawan LA, Surtiari GAK, Warsilah H, 2020. Review and analysis of current responses to COVID-19 in Indonesia: Period of January to March 2020. Prog Disaster Sci 6:100091.

Dwyer A, Zoppou C, Nielsen O, Day S, Roberts S, 2004. Quantifying Social Vulnerability: A methodology for identifying those at risk to natural hazards. Geosci Austral 14:1-92.

Flies EJ, Mavoa S, Zosky GR, Mantzioris E, Williams C, Eri R, Brook BW, Buettel JC, 2019. Urban-associated diseases: Candidate diseases, environmental risk factors, and a path forward. Environment Int 133:105187.

Halim D, 2021. UPDATE 31 January: Distribution of 12,001 New Cases, Highest in Jakarta, West Java, and Central Java. Available from: https://nasional.kompas.com/read/2021/01/31/16461151/update-31-januari-sebaran-12001-kasus-baru-tertinggi-di-jakarta-jabar-dan?page=all Accessed: 12 March 2021.

Hashtarkhani S, Tabatabaei-Jafari H, Kiani B, Furst M, Salvador-Carulla L, Bagheri N, 2021. Use of geographical information systems in multiple sclerosis research: a systematic scoping review. Mult Scler Relat Disord 51:102909.

Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J, Gu X, Cheng Z, Yu T, Xia J, Wei Y, Wu W, Xie X, Yin W, Li H, Liu M, Xiao Y, Gao H, Guo L, Xie J, Wang G, Jiang R, Gao Z, Jin Q, Wang J, Cao B, 2020. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet 395:497-506.

Kazory A, Ronco C, McCullough PA, 2020. SARS-CoV-2 (COVID-19) and intravascular volume management strategies in the critically ill. Proc (Bayl Univ Med Cent) 33:370-5.

Kiani B, Raouf Rahmati A, Bergquist R, Hashtarkhani S, Firouraghi, et al., 2021. Spatio-temporal epidemiology of the tuberculosis incidence rate in Iran 2008 to 2018. BMC Public Health 21:1093.

Kironji AG, Hodkinson P, de Ramirez SS, Anest T, Wallis L, Razzak J, Jenson A, Hansoti B, 2018. Identifying barriers for out of hospital emergency care in low and low-middle income countries: a systematic review. BMC Health Serv Res 18:291.

Koch T, 2005. Cartographies of disease: maps, mapping, and medicine. ESRI Press redlands CA, USA, 403 pp.

Kumpulainen S, 2006. Vulnerability concepts in hazard and risk assessment. Geol Survey Finland Special Paper 42:65-74.

Lawson AB, 2018. Bayesian disease mapping: hierarchical modeling in spatial epidemiology - 3rd edn. 486 pp. Interdiciplinary Statistics Series. Chapman & Hall/CRC, Boca Raton, FL, USA.

Lee D, Lawson A, 2014. Cluster detection and risk estimation for spatio-temporal health data. arXiv:1408.1191 [stat.ME]. Available from: https://arxiv.org/abs/1408.1191 Accessed: 6 Nov. 2021.

Levesque JF, Harris MF, Russella G, 2013. Patient-centred access to health care: conceptualising access at the interface of health systems and populations. Int J Equity Health 12:18.

Li Q, Guan X, Wu P, Wang X, Zhou L, Wt L, 2020. Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. N Engl J Med 382:1199-207.

Liu Y, Watson SC, Gettings JR, Lund RB, Nordone SK, Yabsley MJ, McMahan CS, 2017. A Bayesian spatio-temporal model for forecasting Anaplasma species seroprevalence in domestic dogs within the contiguous United States. PLoS One 12(7).

Mahmoud MS, Al-Nasser FA, Al-Sunni FM, 2013. Network-based strategies for signalised traffic intersections. Indersci Publi 5(1).

Mo C, Tan D, Mai T, Bei C, Qin J, Pang W, Zhang Z, 2020. An analysis of spatiotemporal pattern for COIVD-19 in China based on space-time cube. J Med Virol 92:1587-95.

MohammadEbrahimi S, Mohammadi A, Bergquist R, Dolatkhah F, Olia M, Tavakolian A, Pishgar E, Kiani B, 2021. Epidemiological characteristics and initial spatiotemporal visualisation of COVID-19 in a major city in the Middle East. BMC Public Health 21:1373.

Okba NMA, Müller MA, Li W, Wang C, GeurtsvanKessel CH, Corman VM, Lamers MM, Sikkema RS, de Bruin E, Chandler FD, Yazdanpanah Y, Le Hingrat Q, Descamps D, Houhou-Fidouh N, Reusken CBEM, Bosch BJ, Drosten C, Koopmans MPG, Haagmans BL, 2020. SARS-CoV-2 specific antibody responses in COVID-19 patients. Emerg Infect Dis 26:1478-88.
Pou SA, Tumas N, Soria DS, Ortiz P, del Pilar Díaz M, 2017. Large-scale societal factors and non-communicable diseases: Urbanization, poverty, and mortality spatial patterns in Argentina. Appl Geogr 86:32-40.
Ristiantri YRA, Syetiawan A, Tambunan MP, Tambunan RP, 2021. Strategic planning for alternative determination of COVID-19 referral Hospital. Majalah Ilmiah Globë 23:1-12.
Robertson C, Nelson TA, 2014. An overview of spatial analysis of emerging infectious diseases. Prof Geogr 66:579-88.
Roser M, Ritchie H, Ortiz-Ospina E, Hasell J, 2020. Coronavirus pandemic (COVID-19). Available from: https://ourworldindata.org/coronavirus Accessed: 8 May 2020.
Shahid R, Bertazzon S, Knudtson ML, Ghali WA, 2009. Comparison of distance measures in spatial analytical modeling for health service planning. BMC Health Serv Res 9(200).
Shekhar S, Jiang Z, Ali RY, Eftelioglu E, Tang X, Gunturi VMV, Zhou X, 2015). Spatiotemporal Data Mining: A Computational Perspective. ISPRS Int J Geoinf 4:2306-38.
Silalahi FES, Hidayat F, Dewi RS, Purwono N, Oktaviani N, 2020. GIS-based approaches on the accessibility of referral hospital using network analysis and the spatial distribution model of the spreading case of COVID-19 in Jakarta, Indonesia. BMC Health Serv Res 20:1053.
Thomas JW, Penchansky R, 1984. Relating satisfaction with access to utilization of services. Med Care 22:553-68.
Vaneckova P, Beggs PJ, Jacobson CR, 2010. Spatial analysis of heat-related mortality among the elderly between 1993 and 2004 in Sydney, Australia. Soc Sci Med 70:293-304.
Wan N, Zou B, Sternberg T, 2012. A three-step floating catchment area method for analyzing spatial access to health services. Int J Geogr Inf Sci 26:1073-89.
Wang E, 2011. Understanding the ‘retail revolution’ in urban China: a survey of retail formats in Beijing. Service Ind J 31:169-94.
Wang Z, Lam NSN, 2020. Extending Getis-Ord statistics to account for local space-time autocorrelation in spatial panel data. Prof Geogr 72:411-20.
Weimann A, Dai D, Oni T, 2016. A cross-sectional and spatial analysis of the prevalence of multimorbidity and its association with socioeconomic disadvantage in South Africa: A comparison between 2008 and 2012. Soc Sci Med 163:144-56.
WHO, 2020. Coronavirus disease 2019 (COVID-19): situation report, 72. 13 pp. Available from: https://apps.who.int/iris/handle/10665/331685 Accessed: 6 Nov. 2021.
Worldometer, 2020. Coronavirus Update Worldwide. Available from: https://www.worldometers.info/coronavirus/#countries Accessed: 12 May 2020.
Zhu N, Zhang D, Wang W, Li X, Yang B, Song J, Zhao X, Huang B, Shi W, Lu R, Niu P, Zhan F, Ma X, Wang D, Xu W, Wu G, Gao GF, Tan W; China Novel Coronavirus Investigating and Research Team, 2020. A Novel Coronavirus from Patients with Pneumonia in China, 2019. N Engl J Med 382:727-33.