KEMAS 19 (1) (2023) 31-41

Jurnal Kesehatan Masyarakat

http://journal.unnes.ac.id/nju/index.php/kemas

The Spatial Pattern of the Spread of the COVID-19 Pandemic (Case Study: DKI Jakarta Province)

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Article Info

Article History:
Submitted December 2021
Accepted June 2023
Published July 2023

Keywords:
COVID-19, GIS, Spatial Autocorrelation, Ordinary Least Square (OLS)

DOI
https://doi.org/10.15294/kemas.v19i1.34015

Abstract

The COVID-19 pandemic has been running in Indonesia for more than two years. The first case was found in March 2020. DKI Jakarta as the capital city of the country with a high population density and an economic center that was threatened because the area has a high vulnerability to the spread of COVID-19. The number of confirmed cases that continue to soar and the spread that is difficult to be controlled have resulted in the DKI Jakarta government taking policies such as implementing large-scale social restrictions (PSBB), which aims to stop the spread of COVID-19 and to look for patterns of spread of COVID-19. This study uses a geographic information system in looking for patterns of the spread of COVID-19. The analytical method used is spatial autocorrelation, which is carried out using the Moran Index. In addition, the autocorrelation test was also carried out using a Local Indicator of Spatial Autocorrelation (LISA) with the results in the form of a cluster map and a map of significance. The Ordinary Least Squares analysis method is a regression technique that provides a global model for understanding and predicting variables in research. The correlation variables used in this research are Markets, Supermarkets, Buses, and Stations. The result of this study is the spatial autocorrelation of the pattern of spread of COVID-19 between villages and spatially the distribution pattern is clustered. In the OLS regression distribution pattern, the supermarket variable with an R-Squared value of 0.128555 or 12% affects the spread of COVID-19. Based on the calculation of R-Square, Koenker (BP) in addition to the OLS model, the assumption of homoscedasticity is not met, so the model is Ordinary Least Squares not good compared to other models in analyzing the pattern of the spread of COVID-19 in DKI Jakarta.

Introduction

Wuhan Municipal Health and Health Committee reported a pneumonia cluster of unknown etiology on December 8, 2019, in the city of Wuhan, Hubei Province, China, which was officially named by the World Health Organization (WHO) as Corona Virus Disease-2019 (COVID-19) (Mo et al., 2020). Coronavirus is a positive single-strain RNA virus, encapsulated and non-segmented (Huang et al., 2020). Coronavirus belongs to the order Nidovirales, the Coronaviridae family. The structure of coronavirus forms a cube-like structure with the S protein located on the surface of the virus (Wangping et al., 2020). COVID-19 spread quickly from Wuhan to all cities in China, including Indonesia. The first recorded case in Indonesia was found in March 2020 (Djalante et al., 2020).

The COVID-19 pandemic has been running in Indonesia for more than two years and is currently continuing. Based on data compiled by the Ministry of Health as of 31 July 2021 the Government of the Republic of Indonesia has reported 3,409,658 people confirmed positive for COVID-19 with the number of deaths reaching 94,199 people (Case Fatality Rate: 2.8%) (Ministry of Health RI, 2021). DKI Jakarta is one of the areas with the highest confirmed cases of all cases in

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pISSN 1858-1196
eISSN 2355-3596

Indonesia in the last two years. Meanwhile, DKI Jakarta as the national capital that has the largest population density in Indonesia as well as the country's economic center, makes Jakarta highly vulnerable to the spread of COVID-19.

The increase in patients confirmed positive for COVID-19 in DKI Jakarta is getting more massive day by day. This significant increase in cases is very worrying, especially for the ability of healthcare facilities. According to Ristiantri et al. (2022), most referral hospitals in DKI Jakarta have a referral hospital readiness index with moderate to low criteria. The shortage of referral hospitals with a high readiness index creates a very serious threat to handling the spread of COVID-19 in DKI Jakarta. Therefore, the regional government took several other policies such as implementing large - scale social restrictions or also known as PSBB. Furthermore, there is a new policy that has been stipulated, namely Imposing Restrictions on Community Activities or abbreviated as PPKM to stop the spread of the COVID-19 virus. To find patterns of spread of COVID-19, disease mapping is needed, one of which is by utilizing a Geographic Information System (GIS).

GIS is a system for manipulating geographic data. In simple terms, a Geographic Information System is a useful tool for presenting the topographical conditions of the earth by utilizing spatial data (Yuwono et al., 2015). GIS can be used to identify patterns of the spread of COVID-19 so that spatial connectivity can be identified in each region (Pourghasemi et al., 2020). Disease mapping and modeling have so far been implemented to map potential risks and facilitate policymakers to minimize disease transmission. In addition, disease mapping is used to study patterns of spread and the process of mitigating the spread of disease (Koch, 2005). Spatio-temporal data can be visualized and represented in outbreak information processing. One response that is often carried out is to make spatial decisions to help overcome pandemics through early detection of high-risk locations (Liu et al., 2017). Disease modeling and mapping are statistical approaches that can be utilized by policymakers in formulating actions that can be taken to reduce the spread and number of disease cases. Therefore, GIS can help local governments see the regional ability to deal with the COVID-19 outbreak spatially.

The relationship between COVID-19 outbreaks per region can be observed using autocorrelation analysis. To identify autocorrelation, 2 ways are often used. The first is the Moran Index, which is by measuring global autocorrelation. Then the second way is the Local Indicator of Spatial Association (LISA) index which measures local autocorrelation. In addition, there is also the Ordinary Least Squares (OLS) method. This method is used to minimize the number of squared errors and this method is considered the most popular for solving arithmetic averaging problems.

With indications that positive cases of COVID-19 are spatially related, this study will conduct a spatial autocorrelation analysis of confirmed cases of COVID-19 using the Moran Index and the LISA Index to determine whether there is a pattern of the spatial distribution of COVID-19 in the DKI Jakarta area. This research can later be used to provide input and suggestions to the government, especially the DKI Jakarta government in optimizing the handling of cases of the spread of COVID-19. As well as assisting the government in making policies according to COVID-19 case data.

Methods

The research was conducted in DKI Jakarta administratively located in the lowlands with an average height of 7 meters above sea level. Based on the Decree of the Governor of DKI Jakarta in 2007, the area of the Province of Daerah Khusus Ibukota Jakarta is 7,639.83 km², with a land area of 662.33 km² (including 110 islands spread across the Kepulauan Seribu) and a sea area of 6,977.5 km2. This research uses spatial-temporal analysis with several calculation approaches. The data prepared is daily case data and total positive data obtained from the DKI Jakarta government website.

Spatial autocorrelation measurements for spatial data can be calculated using Moran's Index, Geary's C, and Tango's excess. Several analyses can be performed on spatial autocorrelation by performing several calculation methods. This method applies geospatial techniques and spatial statistics to examine and detect hotspot areas for the spread of COVID-19 (Parvin et al., 2021). In addition, this method can be used to detect the onset of spatial randomness. This spatial randomness can indicate clustered patterns or trends in space (Algert et al., 2006). Spatial autocorrelation calculations based on feature locations and attribute values use the global Moran's I statistic which is calculated as (Cliff & Ord, 1981):

1. Moran's index with a non-standardized spatial weighting matrix W*

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_j-\underline{x})(x_j-\underline{x})}{S_0\sum_{i=1}^{n}(x_j-\underline{x})} \qquad (1)$$

with $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$

Wij* = element in non-standardized weights between area i and j

2. Moran's index with a standardized spatial weighting matrix W:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_j-\underline{x})(x_j-\underline{x})}{S_0\sum_{i=1}^{n}((x_j-\underline{x})^2}. \qquad (2)$$

with :
I : Moran's index
n :number of incident locations
*X*i:value on location i
*X*j:value on location j
X: the average of the number of variables or values
Wij*:element in non-standardized weights between area i and j
Wij :element in standardized weights between area i and j

The range of values of Moran's index in the case of a standardized spatial weighting matrix is -1 ≤ I ≤ 1. Values of -1 ≤ I < 0 indicate a negative spatial autocorrelation, while a value of 0 < I ≤ 1 indicates a positive spatial autocorrelation, Moran's Index value is zero indicates no group (Ijumulana et al., 2020; Moran, 1950). The research steps are outlined in the flowchart in Figure 1 so that the research can be focused and well-illustrated. The research phase began with data collection, namely information related to positive confirmed patients in the DKI Jakarta area obtained from the Jakarta provincial government website (corona.jakarta.go.id). The spatial unit used in this study was the sub-district, patient data confirmed positive was then displayed per sub-district using administrative data from the Indonesian Geospatial Information Agency. The stages of data processing are divided into two, namely spatial autocorrelation analysis and analysis of the correlation of COVID-19 cases to driving variables. Spatial autocorrelation analysis is used to determine the spatial pattern of COVID-19 outbreaks in Jakarta, whether the spread of COVID-19 is random or spatially clustered. In addition, autocorrelation analysis is used to find out which areas have high cases surrounded by high cases, and vice versa. On the other hand, correlation analysis is used to see the relationship between the addition of COVID-19 cases in Jakarta and the driving variable in the form of the number of transportation hubs and crowded centers in each urban village to determine the behavior of the area. These two analyzes are very important for the government so that the government can find out which areas are the priority for social restrictions and priority for giving vaccinations. Identification of the pattern of the spread of COVID-19 in DKI Jakarta is calculated using two methods, namely Global Moran's I and Local Moran's I. Global Moran is calculated using autocorrelation analysis in ArcGIS while Local Moran is calculated using the Local Indicator of Spatial Autocorrelation (LISA) method using the Geoda tool. Local Moran shows a positive spatial relationship based on the level of significance using the Geoda tool developed by Anselin, et al (2006) by analyzing the relationship of cases in an area to the cases around it (Anselin, 1995).

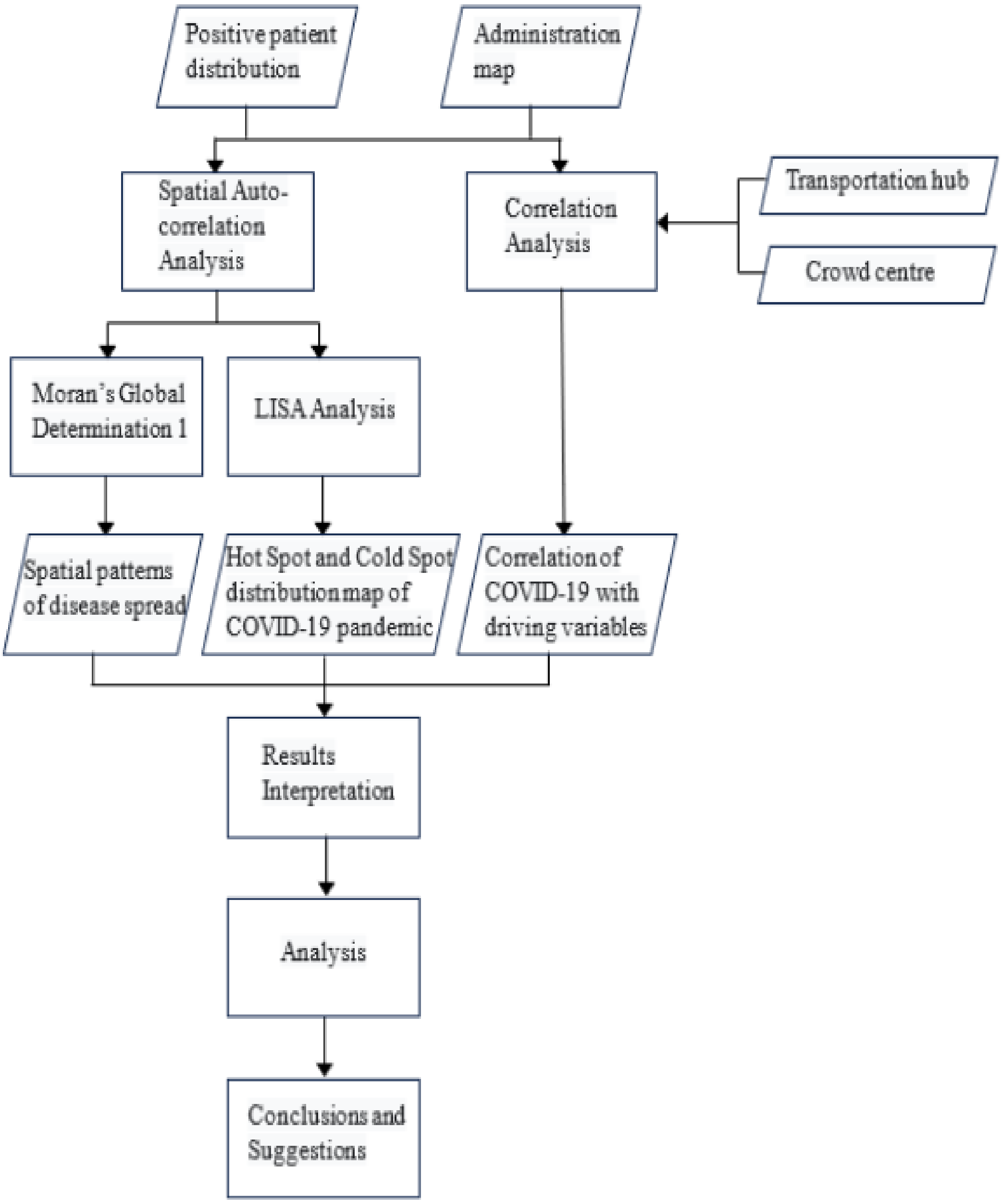


Figure 1. Research Flow Chart.

Results and Discussion

The results and discussion in this study explain the results of identifying patterns of the spread of COVID-19, the relationship of correlation analysis variables that affect distribution, explanatory variables, and Ordinary Least Squares (OLS) correlations. The same model was proposed by Raymundo et al (2021) who applied global regression models such as OLS and local regression models called multiscale geographically weighted regression (MGWR) which resulted in the finding that the higher the GINI Index (to measure income inequality), the higher the incidence disease in the city, as well as the higher the ratio of nurses per 1,000 residents in the municipality, the higher the incidence of COVID-19. While the death ratio is inversely proportional to the incidence of disease. Social inequality increases the risk of transmission in municipalities that show better social development in municipalities associated with a lower risk of disease compared to populations with increased social vulnerability having a higher risk of disease. In the study of Purwanto et al (2021), distribution patterns are interpreted based on hotspots and space-time cubes (STC) which produce Spatiotemporal Trend Hotspots, interpreted with 3D visualization in the Surabaya Raya area in 3 phases. The distribution pattern resulting from this study produced an Amoeba-shaped pattern which indicated that the spread of the Coronavirus was more widespread in urban centers than in rural areas. This pattern is different from that produced in DKI-Jakarta considering that the distribution parameters used are also different to identify distribution patterns. This distribution pattern will be analyzed based on the results of the Local Indicator of Spatial Autocorrelation (LISA) which is in line with the COVID-19 mapping carried out in central Iran by Jesri et al (2021), who succeeded in obtaining a spatial estimate of the distribution pattern in Qom Province, namely clusters of 365 populations, 75/100,000 population. The patterns formed are in the high-high category (areas with high values surrounded by high values) and low-high (areas with low values surrounded by high values) so it can be seen that distance and spatial proximity have a major role in the spread of the disease.

The methods used in previous research were also carried out in this study but used different parameters and calculation models so that identification of patterns of distribution of COVID-19 in DKI Jakarta based on analysis of spatial patterns with a moran index for the distribution of COVID-19 is recommended in previous studies as in (Jaber et al., 2022; Rodríguez et al., 2021) which produced a simple neighbor pattern to investigate the presence of spatial autocorrelation (grouping) so that one could see the relationship between variables distributed throughout the study area.

Furthermore, the identification is divided into several variables, namely the Dependent Variable and Independent Variable which consists of some data for all public facilities that allow crowds to occur in that place. Data on the factors causing this spread are data transport hubs, crowd centers such as offices, entertainment shopping centers, and others. The circulation of population movements was also carried out in Liu et al's research (2021),by collecting population travel during several periods such as the spring festival so that it provides dynamic information based on Baidu location-based services (LBS) and is statistically significant which produces Moran's I local Anselin statistics which are presented as spatial clusters. However, the pattern of movement referred to in the spread of research in DKI Jakarta is more to the distribution of transport hubs which causes the population to move to public facilities which are reported to increase the risk of spreading COVID-19.

In this study, daily total data for confirmed COVID-19 cases were used from March 25, 2020, to August 31, 2021. The total available data for confirmed COVID-19 cases was 524 days, there was 1 day of case distribution which was not available on January 31, 2021. The spatial unit used in this study is the sub-district. Pattern identification using the same method was carried out in the previous study by Kan et al. (2021), by looking at transmission patterns related to demographic patterns during the COVID-19 pandemic which were detected significantly in space-time clusters at the Large Street Block Group (LSGB) level, Hong Kong among 23 January and 14 April 2020. Two types of high-risk areas were identified at residences and several places visited by confirmed cases, and two types of cases (imported and local) need to be considered. The results show that high transportation accessibility, dense and high-rise buildings, high commercial land density, and mixed land use have a higher risk of confirmed cases. The distribution pattern seen from the demographics of this area and the pattern over time was adopted in a study in DKI Jakarta to see patterns in spatially confirmed total cases using space-time pattern analysis.

Furthermore, the results of the spatial pattern analysis based on the Moran Index show a positive spatial relationship as shown in Table 1. Based on the results of the spatial pattern analysis based on the Moran Index, a spatial relationship was obtained with a significance level of 11.89% in the spread of COVID-19 in DKI Jakarta. With an average Moran Index value of 0.118976853 which is in the range of 0 and 1, it can be concluded that the resulting autocorrelation is positive spatial autocorrelation. A positive autocorrelation indicates that adjacent locations have similar values and cases of the spread of COVID-19 in DKI Jakarta tend to be clustered. In the analysis, the provisions of neighborhood based on sub-district are used, therefore the group in question is between one sub-district and another in groups with almost the same number of cases.

The results of the Local Indicator of Spatial Autocorrelation (LISA) are divided into two results, namely the results of the Cluster Map of the Spread of COVID-19 Cases in DKI Jakarta and the Results of the Map of Significance of Patterns of Spread of COVID-19 in DKI Jakarta. Based on the thematic map analysis of the spatial distribution of output from LISA. You can see the pattern formed on the map of the DKI Jakarta area. This pattern is a grouping within the region. This grouping can be positive or negative. Cluster pattern for a pattern of spread of COVID-19. The process of identifying spatial relationships between variables uses Moran's index.

The Moran index is used to show spatial autocorrelation and spatial cluster relationships in a data set. The results of spatial autocorrelation are in the form of four types of spatial associations, including (Anselin et al., 2006): 1. high-high (HH), namely the spatial concentration of high case scores and high independent variable values from neighboring areas, 2. low-low (LL), namely in the form of spatial concentration of low case values and low independent variable values from neighboring areas, 3. High low (HL), namely in the form of spatial concentration of high case values and low independent variable values from neighboring areas, 4. low-high (LH), namely in the form of spatial concentration of low case values and high independent variable values from neighboring areas HH and LL are types for spatial clustering of the same value, while HL and LH are types of spatial clustering of different values. Based on Figure 2.a, it can be concluded that areas that are significant for the spread of COVID-19 can be seen from several date plots that have been observed on the DKI Jakarta cluster map. Analysis of the Global Moran Index was empowered to analyze the existence of spatial relationships of the spread of COVID-19 in the province of DKI Jakarta. The results of this Moran index obtained from the Geoda software show that the spatial pattern of COVID-19 distribution is clustered.

Table 1. Results of Spatial Pattern Identification of Moran's Index.

Date	Moran Index Value	Spatial Pattern
03/26/2020	0,175743	Clustered
03/27/2020	0,171075	Clustered
03/28/2002	0,152707	Clustered
03/29/2020	0,166294	Clustered
03/30/2020	0,183173	Clustered
03/31/2020	0,167766	Clustered
04/01/2020	0,166876	Clustered
04/02/2020	0,14911	Clustered
04/03/2020	0,157958	Clustered
04/04/2020	0,157958	Clustered
04/05/2020	0,158879	Clustered
04/06/2020	0,166805	Clustered
04/07/2020	0,193078	Clustered
04/08/2020	0,195587	Clustered
09/04/2020	0,200966	Clustered
10/04/2020	0,200594	Clustered
Average	0,118976853	

Source: Primary Data, 2021

DKI Jakarta has 261 sub-districts. Based on the results of the COVID-19 distribution cluster map, it can be concluded that on September 14, 2020, during the PSBB, the two spatial patterns of COVID-19 distribution were in observation areas that had a high value, which was seen in 25 sub-districts including Sunter Jaya, Sunter Agung, West Pademangan, East Pademangan, Slipi, and Petamburan. High-High Clusters (hotspots) are areas with high cases surrounded by high cases. According to (Syetiawan et al., 2022), hotspot areas with a high number of confirmed cases should be highly considered areas in determining rapid test locations.

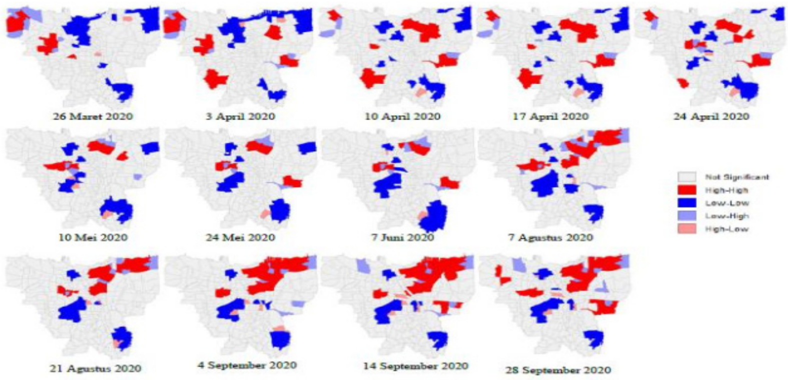
Based on Table 2, it can be concluded that in this date range, the spatial pattern of autocorrelation of the pattern of the distribution of COVID-19 in DKI Jakarta is clustered so that in general the pattern of distribution of COVID-19 undergoes a spatial grouping process in 2020 in the province of DKI Jakarta. At the end of 2020, the High-High cluster dominates the northern part of Jakarta. The area is densely populated. Similar results were also shown by Jaber et al. (2022) that High-High clusters are closely related to population density in Iraq.

The results of the LISA test on the significance of the distribution pattern of COVID-19 in DKI Jakarta provide information that there are several areas with significant values or there is spatial autocorrelation in subdistricts in DKI Jakarta. The following is the result of the significance map.

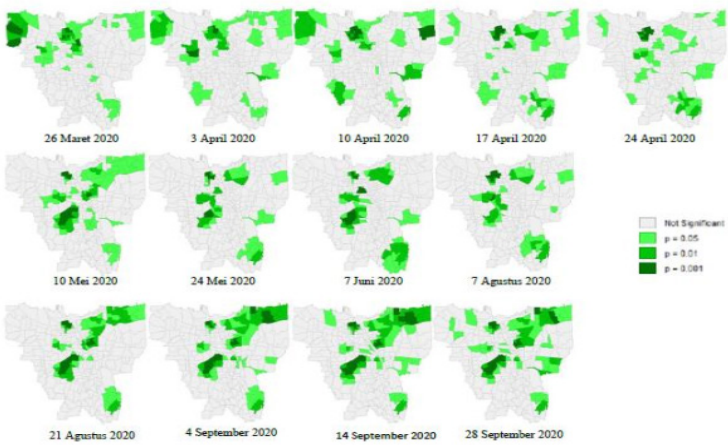
Table 2. Results Identification of Spatial Pattern of the Spread of COVID-19 in DKI Jakarta Based on the Time of Observation

Date Plot	Spatial Pattern
26 March 2020	Clustered
3 April 2020, 1 week before PSBB	Clustered
10 April (PSBB I)	Clustered
17 April 2020, 1 week after PSBB I	Clustered
24 April 2020, 2 weeks after PSBB	Clustered
10 May 2020, 2 weeks before Eid Al-Fitr	Clustered
24 May 2020, Eid Al-Fitr	Clustered
7 June, 2 weeks after Eid Al-Fitr	Clustered
7 August 2020, 2 weeks before Islamic New Year	Clustered
21 August 2020, the Islamic New Year holiday	Clustered
4 September 2020, 2 weeks after Islamic New Year	Clustered
14 September 2020, PSBB II	Clustered

Source: Primary Data, 2022



(a)



(b)

Figure 2. (a) Map of Cluster Distribution of COVID-19 in DKI Jakarta, (b) Map of Significance of DKI Jakarta

Based on Figure 2.b, the results of the LISA test on the significance of the distribution pattern of COVID-19 in DKI Jakarta, where the p-value is declared significant if the value is below 0.05 (Anselin, et al., 2006). On September 14, 2020, it shows that there are 35 sub-districts with a significance level of 0.05. Shows that the Pademangan Timur, Sunter Agung, and Kapuk Muara sub-districts are in areas with a low percentage of the spread of COVID-19 but these areas are surrounded by sub-districts that have a higher spread of COVID-19. The Significance Value of 0.01 is occupied by Menteng, Kebon Melati, and Kuningan Timur sub-districts, which means that on that date the distribution pattern was clustered. Then it can be concluded that with a significance value of 0.001, namely the Johar Baru, Karet Kuningan, and Senayan villages, the distribution is clustered.

Results of Identification of Correlation Analysis Variable Relationships Affecting the Spread of COVID-19 in DKI Jakarta. The research correlation variables used include stations, markets, supermarkets, and buses. Some of the variable layouts can be seen as follows:

1. Distribution of transportation hubsDKI Jakarta has bus terminals and bus stops which are quite spread across several urban villages. The results of the layout of data processing the distribution of terminals and bus stops. Based on Figure 3.a, it can be concluded that several sub-districts have bus terminals, including Ancol sub-district 5 bus terminals, Angke 1 bus terminal, Bendungan Ilir 9 bus terminals, Bidara Cina 6 bus terminals, Bungur 4 bus terminals and stops, Cideng 15 bus terminals bus, Ciganjur 19 bus terminals, 17 West Cilandak bus terminals, 14 East Cilandak bus terminals, Cipedak 32 bus terminals, Gambir 23 bus terminals and stops, Gunung Sahari Selatan 18 bus terminals, Gunung Sehari Utara 10 bus terminals, Jaga Karsa 51 bus terminals. Most bus terminals are dominated in the southern part of DKI Jakarta. On the other hand, DKI Jakarta has train stations spread across several sub-districts. The layout results from the processing of the distribution of train stations. Based on the layout results of Figure 3.b, it can be concluded that several urban villages have train stations, namely Bali Mester 1 train station, Ceger 6 train station, and finally Cipete Selatan 1.
2. Distribution of Shopping Centers in DKI JakartaDKI Jakarta has markets spread across several sub-districts. The layout results from the processing of market distribution in DKI Jakarta. The results of the layout in Figure 3.c can be concluded that several sub-districts have markets, including Angke sub-district has 1 market, Kali Deres 4 markets, Cengkareng Timur 2 markets, Cempaka Putih Barat 3 markets, Cengkareng Barat 5 markets. DKI Jakarta has supermarkets spread across several sub-districts. The layout results from the processing of supermarket distribution in DKI Jakarta. In Figure 3.d. It can be concluded that several urban villages have supermarkets spread across DKI Jakarta, including Bali Mester village with 1 supermarket, Bangka 2 supermarkets, and Kembangan Selatan 3 supermarkets.

Table 3. explains the explanatory of several independent variables of the spread of COVID-19 in DKI Jakarta with 13 observation times. The observation time was obtained which showed a value indicating a sufficiently influential relationship in the adjusted r-squared value in the market area, namely April 3, 2020, namely 1 week before the PSBB with a value of 0.08, September 14 when PSBB II was with a value of 0.09, and September 29, which is 2 weeks after PSBB II with a value of 0.09. The bus stop variable with the r-squared value of the time stated is in the range 0-0.09, the station area is in the range 0.09-0.1, and the supermarket is in the range 0.02-0.08, so the results of the Ordinary Least test Squares April 3, 2020, September 14, 2020, and September 29, 2020, on markets, buses, stations, and supermarkets in Table 3. It is known that several values, significant for the spread of COVID-19, affect the correlation analysis variable.

Table 3. Explanatory Variable

Variables	Adjusted R-Squared		
	03/04 /2020	14/09/ 2020	29/09/ 2020
Market	0,08	0,09	0,09
Bus	0	0,09	0
Station	0,09	0,1	0,09
Supermarket	0,08	0,02	0,08

Source: Primary Data, 2021

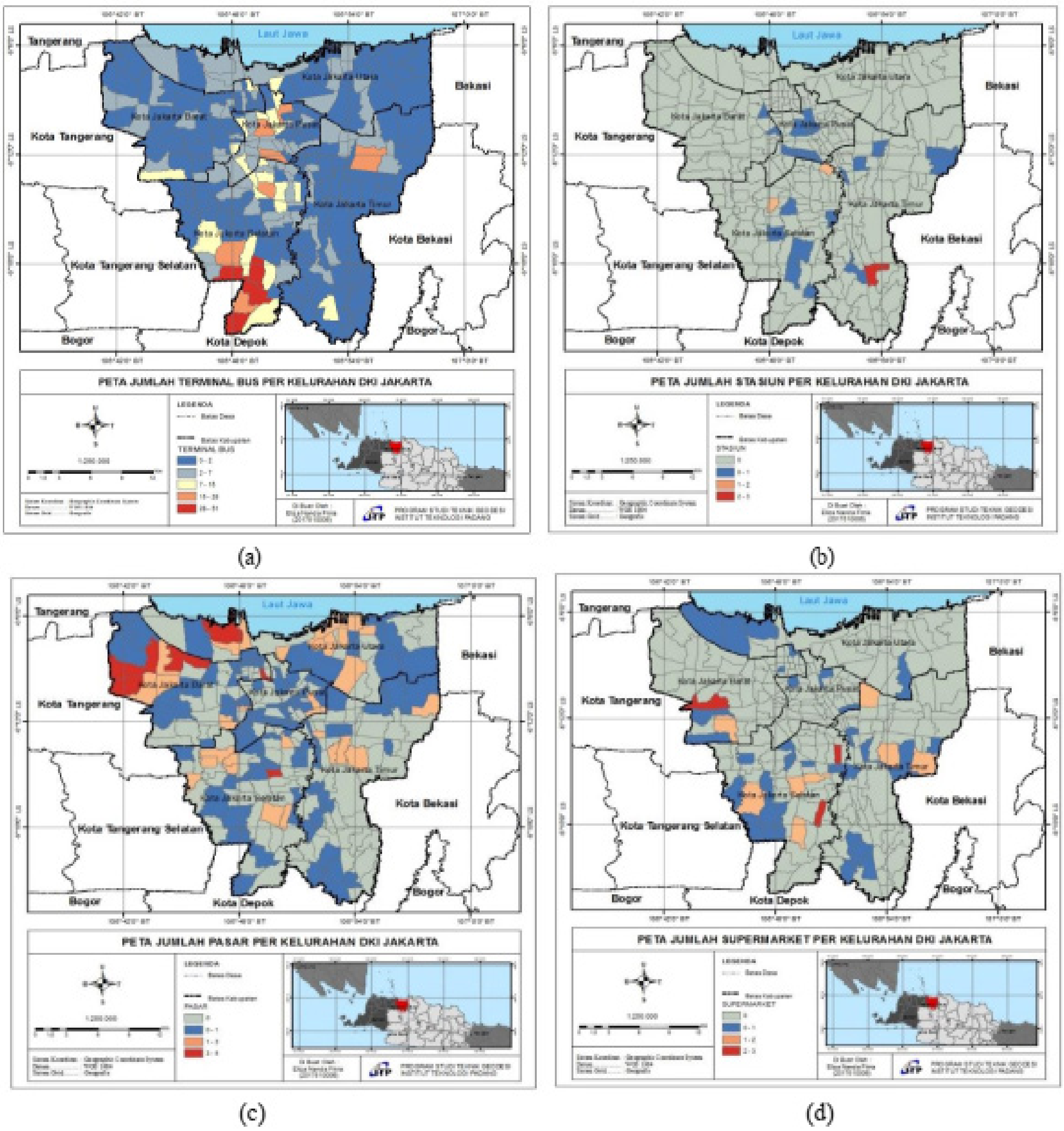


Figure 3. Transportation Hub Distribution Map: (a) Number of Bus Terminals; (b) number of Train Stations; Distribution Map of Shopping Centers: (c) Number of markets; (d) Supermarkets.

Conclusions

In carrying out the Spatial test, it can be concluded that the spatial autocorrelation of the pattern of the spread of COVID-19 is clustered. This shows that the geographical position of the region has the potential to affect the surrounding area. The results of this study also show positive spatial phenomena and autocorrelation between sub-districts in the DKI Jakarta province so that clustered distribution occurs. The variable relationship that is quite binding on the OLS regression distribution pattern is the supermarket variable with an R-Squared value of 0.128555 or 12% influencing the spread of COVID-19. Based on the calculation of R-Square, Koenker (BP) and also on the OLS model, the assumption of homoscedasticity does not meet the requirements, so the ordinary least squares model is not good compared to other models in analyzing the pattern of the spread of COVID-19 in DKI Jakarta.

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