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RESEARCH ARTICLE

Geospatial approach to accessibility of referral hospitals using geometric network analysts and spatial distribution models of Covid-19 spread cases based on GIS in Bekasi City, West Java

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Abstract Bekasi City has a high population density, as seen from its growth rate in 2020. Therefore, geospatial analysis is required to support and provide effective and efficient health services, evaluate the need for referral hospital capacity, and minimize the spread of COVID-19 cases in this city. The geospatial methods used in this study are Geometric Network Analyst and Geographic Weighted Regression (GWR), with Service Area (SA) used for analysis. The results based on the distance between the referral hospitals and settlements in Bekasi City showed that more than 2.201 million people, or 90%, have been well covered. Meanwhile, regarding travel time, 1.792 million people or 73% in eight sub-districts are in well-served areas. Conversely, referral hospitals do not cover four sub-districts, namely Bantar Gebang, Jati Sampurna, Medan Satria, and Jati Asih. The spatial modeling analysis results using GWR with spatial-temporal data recapitulation of data reports for eight months showed predictions for the spread of confirmed cases in six sub-districts, namely West Bekasi, North Bekasi, East Bekasi, Medan Satria, Mustika Jaya, and Rawalumbu. This implies that local governments need to suggest more referral hospitals serving people who live far from the existing referral hospitals.

1. Introduction

The COVID-19 pandemic is still affecting Indonesia. Since the first case was announced, the surge in positive patients has continued to increase. The government rapidly responded to the outbreak in March 2020. Bekasi was the second-largest hit city in West Java Province, with 15,109 confirmed cases and 171 deaths as of December 1, 2020 (Information & Coordination Center of West Java Province 2022). According to a 2020 population census, the city has a high population density of 2.54 million people, an increase of 208 thousand people from the 2010 Population Census. In detail, 1.28 million are males while 1.26 million are females (Central Statistic Agency of Bekasi City, 2021). The pandemic did not only claim lives, but it also had a fundamental impact on macroeconomic stability and employment opportunities in Indonesia, especially in Bekasi City, one of the areas directly adjacent to Jakarta, the State Capital. The accessibility of referral hospitals and their capacities is critical in protecting human rights and maintaining social stability (Walker et al., 2020). In 2020, some urban areas in this city had several health facilities, namely 27 hospitals, 6 maternities, 76 polyclinics, 42 public health, and 3 sub-health centers (Central Statistic Agency of Bekasi City, 2021). With a total of 3,196 bed facilities and a population of 2,859,630, the ratio of beds to the population is 1.12%. Bekasi city can only provide 1 hospital bed per 1,000 people (Central Statistic Agency of Bekasi City, 2021.

Furthermore, with the increasing number of confirmed cases as of December 1, 2020, the hospital's demand for inpatient facilities continues to increase daily. The available capacity has led to the issue of rejecting COVID-19 patients in several hospitals (Kompas, 2020). In this study, it becomes imperative to select the location and statistical analysis to determine not only the requirements and capacity of these referral hospitals but also to predict the best routes, making accessibility easier. There is also a need for recommendations of additional hospital locations and their capacities, as well as determining areas predicted to record growth cases according to statistical models. This enables the Bekasi City government to implement health protocols.

This study was carried out using COVID-19 data acquired as of December 1, 2020, and a geospatial approach, specifically network analysts (Jovanović et al., 2020; Kuupiel et al., 2020; Lakhani, 2020). Geographic information system (GIS) is an essential method due to its numerous benefits (Forkuo & Quaye-Ballard, 2013; Isa, Liman, Mohammed, Mathew, & Yayo, 2016; Rakibul, Shaharier, Torit, & Mahbub, 2022), such as spatial tracking, prediction, and segmentation, risk management for decision making, as well as spatial and network (Zhou et al., 2020). Spatial statistical modeling analysis adopted the Geographic Weighted Regression (GWR) as a simple approach or model (Fotheringham, Brunsdon, & Charlton, 2003). This study

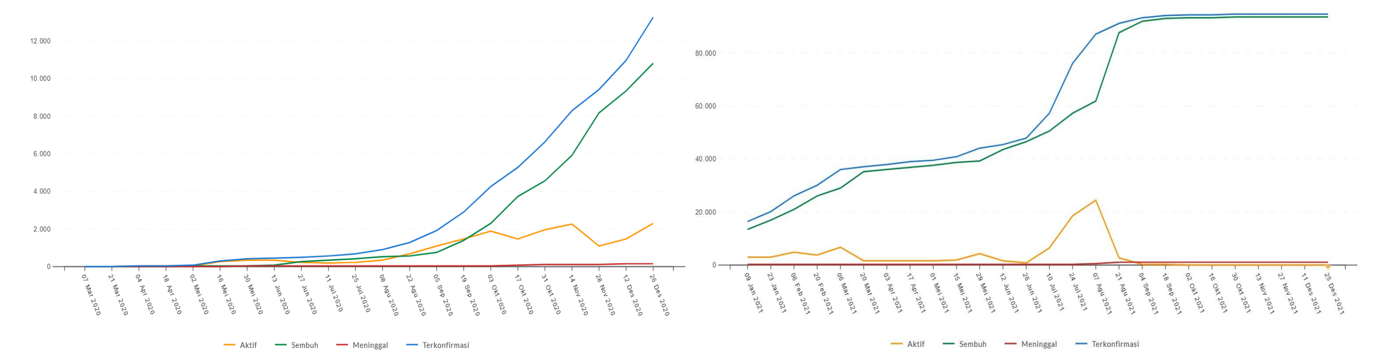


Figure 1. Cumulative Graph of COVID-19 Confirmed, Died, and Recovered Cases in Bekasi City as of (left: December 31, 2020; right: December 31, 2021) (West Java Province Information and Coordination Center, 2022)

discusses the increase in confirmed cases in Bekasi City. Its objectives are to (1) show the geospatial geographic distribution of COVID-19 as of December 1, 2020, in this region, (2) recommend the nearest health facility based on Network Analyst-Service Area, and (3) create a GWR model for the spread of COVID-19 as of December 1, 2020.

2. The Methods

Case Study Area

Bekasi City consists of 12 sub-districts and 56 urban areas, as shown in Figure 2. The census data shows that it is one of the most densely populated cities in West Java Province. According to the Central Statistics Agency, Bekasi is classified into 14 districts. The largest population is in the North, followed by the East, West, Pondok Gede, Jati Asih, Rawalumbu, South Bekasi, Mustika Jaya, Medan Satria, Pondok Melati, Jati Sampurna and Bantar Gebang with 329,949, 272,574, 269,846, 228,326, 225,680, 220,588, 211,119, 195,133, 157,676, 127,202, 106,199, and 105,376 individuals, respectively (Central Statistics Agency of Bekasi City, 2021).

Data collection

Data were collected from a series of spatial information in the form of road networks (Open Street Map), administrative boundaries (Geospatial Information Agency), referral hospital locations (National Disaster Management Agency), settlements (Ministry of Agrarian and Spatial Planning/National Land Agency), earth shape map of Bekasi City constructed using a scale of 1: 25,000 (Geospatial Information Agency), and the tabulation of population density in 2019 (Central Statistics Agency of Bekasi City).

A centroid or geometric center is a point feature that represents vector data (multi-point, line, and area features). The local government uses administrative regency centroids to ascertain that 56 rural or urban village centroid points represent COVID-19 confirmed cases in Bekasi City. This was based on observation and mapped as of December 1, 2020.

Bekasi is one of the cities in West Java where the density of geometric centers is evenly distributed due to the limited open area. This study uses the midpoint of rural or urban areas as the patient's origin based on reports concerning the number of positive cases in each region (Silalahi, Hidayat, Dewi, Purwono, & Oktaviani, 2020). Irrespective of the fact that it has limited protocols for the publication of health information and its access is restricted, the actual condition is represented by ensuring that the midpoint of the rural or

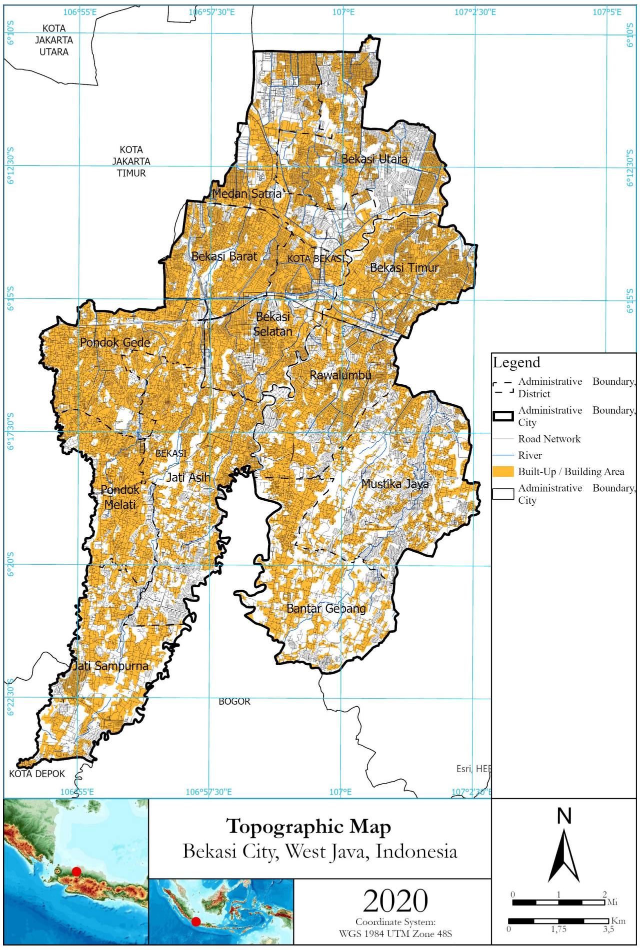


Figure 2. Topographic Map of Bekasi City in 2019 scale 1:25,000 (Source: Geospatial Information Agency – BIG)

urban areas serves as the origin of attribute data updates as of December 1, 2020. This study employed GIS software such as ArcMap 10.7.1 and ArcGIS Pro 2.6.3 with a license from the University of Indonesia. Processing extensions used in GIS software include network analyst, service-area, explanatory and geographic weighted regression, and ordinary least square.

In accordance with data obtained from the Bekasi City Health Office, which consists of recapitulated COVID-19 cases based on administrative boundaries (Table 1) and recorded incidents starting from April 7, 2020, to December 1, 2020, are presented in a graph showing the age range of each gender, as shown in Figure 3. A spatial model was

Table 1. Recapitulation of COVID-19 Cases in Bekasi City as of December 1, 2020

District	Hospitalized & Self Quarantine*	recovered*	Death*	Discarded*	Confirmed Cases*
Bantar Gebang	12	199	3	202	214
Pondok Melati	12	353	6	359	371
Jati Sampurna	20	379	3	382	402
Medan Satria	30	604	13	617	647
Jati Asih	42	675	6	681	723
Pondok Gede	18	700	14	714	732
Mustika Jaya	24	823	6	829	853
Rawalumbu	69	859	16	875	944
South Bekasi	55	1034	22	1056	1111
East Bekasi	84	1290	30	1320	1404
West Bekasi	160	1223	24	1247	1407
North Bekasi	55	1500	28	1528	1583

*Number of People
Source:Bekasi City Health Department 2020

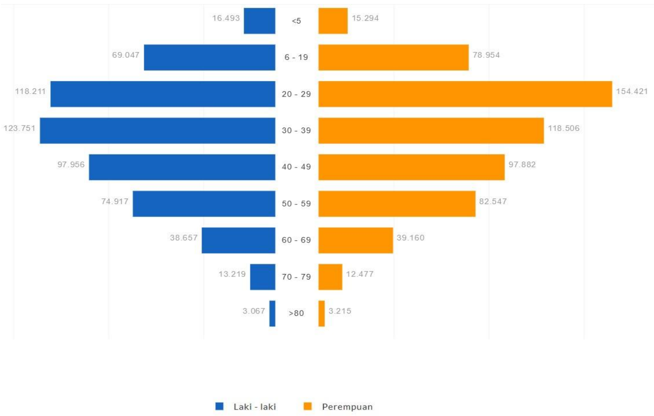


Figure 3. Graph of COVID-19 Confirmed Cases based on age range and gender (*https://pikobar.jabarprov.go.id/data*)

designed using statistical data, and it also shows the graphic trend of COVID-19 cases in Bekasi City (Figure 1).

The data obtained from local government organizations shows that the National Disaster Management Agency, Bekasi City, has 46 referral hospitals which are divided into three classes, namely (1) main, (2) additional, and (3) initial referral hospitals. The Bekasi City government initiated this class division as an early anticipation of the growth rate of COVID-19 confirmed cases, as shown in Figure 4.

Considering the data collection, analysis, output, and recommendations for COVID-19 cases in Bekasi City, the explanation of each process, as shown in Figure 5.

Network Dataset

Building a network dataset is a process that involves the creation of elements, connectivity, and assigning values to defined attributes. It is suitable for modeling transportation networks in spatially accessible areas (Jamtsho, Corner, & Dewan, 2015; Mulrooney, Beratan, McGinn, & Branch, 2017; Zannat, Adnan, & Dewan, 2020). A network dataset should be built from the one created in the previous stage to perform an analysis. According to (Silalahi et al., 2020), this includes adjusting the impedance of each segment, defining directives and one-way roads, as well as setting turning limits.

This study evaluated the road network dataset from the Geospatial Information Agency and processed it using

Figure 4. Location of the COVID-19 Referral Hospitals in Bekasi City (Source: Indonesian Ministry of Health, 2020)

ArcGIS software and add-on network analysis. Furthermore, two service area scenarios were created based on distance and time. In acquiring the Bekasi City road feature dataset, several limitations were encountered on the network elements such as one-way, link and turning impedance, underpass, and overpass. This led to certain assumptions during a service-area analysis of health facilities in the city.

Analysis of the Referral Hospital Service Area (Service-Area)

Network Analysts tend to find service areas within their locations. This includes all access roads within the specified barrier value. For example, a 10-minute service area comprises all roads that lead to a particular facility within 10 minutes facility (Nicholl, West, Goodacre, & Turner, 2007). The major drawback of this scenario is that the time required for the patient to reach the referral hospital is still unknown. Previous studies stated that it is important to incorporate actual traffic conditions into time elements. These include speed limits, traffic jams, and one-way streets (Van Wee, 2016), particularly for emergency services such as COVID-19 patients experiencing shortness of breath (Zinszer et al., 2014). A referral hospital location is defined as a facility or point of origin on the map where the service area is intended to be developed. This analysis helps to evaluate coverage and accessibility based on the seriousness of the ailment (Zannat et al., 2020). The service area is essential for evaluating health services, accessibility, and population-based health indicators for disease burden. The network-based approach was employed for service area analysis.

The accessibility evaluation is determined with two scenarios, namely 1) service areas at a distance of 5 to 10 km and 2) those based on time parameters derived from a distance (Algharib, 2011; Nicholl et al., 2007; Niedzielski & Eric Boschmann, 2014) and speed data adopted from the Indonesian Ministry of Transportation regulations (PM Transportation No. 111 2015; RI Law No. 22 2009). Based on the city area of 210.49 km^2, it was assumed that the best service area should be situated within a distance of 2 to 4 km with a driving time of 5, 10, and 15 minutes (ESRI n.d.).

Table 2 shows the speed details for various road classes in the country based on the Indonesian Ministry of Transportation Regulation and Law Number 22 of 2009. In

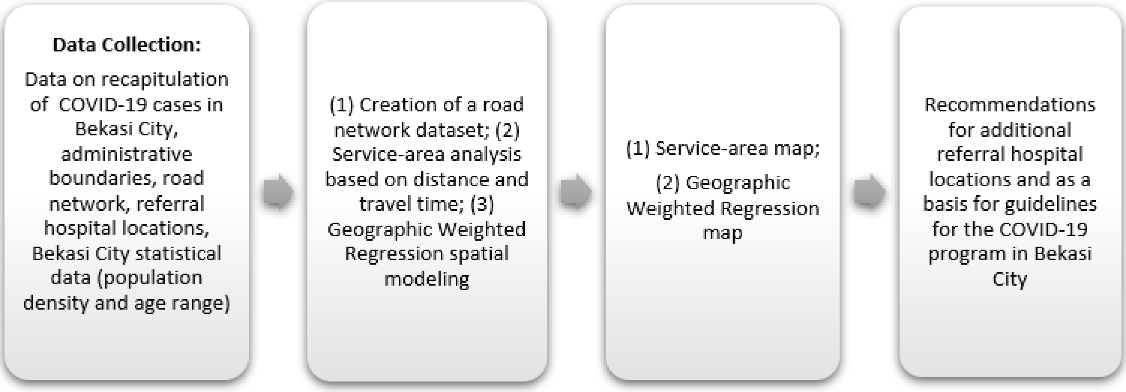


Figure 5. Research Flowchart

Table 2. Classification of roads and motorized vehicle speeds in Indonesia

OSM Road Class	Road Function Class according to Law Number 22 of 2009	Road Function Ranking	Minimum Speed (km/hour)	Maximum Speed (km/hour)
motorway	Primary Toll Road	1	60	100
motorway_link	Secondary Highway	2	40	60
primary	Primary Arterial Path	3	60	80
primary_link	Secondary Arterial Path	4	30	50
service	Secondary Arterial Path	4	30	50
secondary	Primary Collector Street	5	40	80
secondary_link	Secondary Collector Street	6	20	40
tertiary	Primary Local Road	7	20	30
trunk	Primary Local Road	7	20	30
tertiary_link	Secondary Local Road	8	10	20
trunk_link	Secondary Local Road	8	10	20
cycleway	Secondary Neighborhood Road	10	10	15
living_street	Secondary Neighborhood Road	10	10	15
residential	Secondary Neighborhood Road	10	10	15
footway	Footpath	11	0	0
path	Footpath	11	0	0
pedestrians	Footpath	11	0	0
steps	Footpath	11	0	0
track	Footpath	11	0	0
unclassified	292 Line	12	10	40

Source: (Minister of Transportation Regulation Number 111 of 2015; Indonesian Law Number 22 of 2009) addition, the ambulance vehicle acceleration parameter is assumed using the minimum speed. Table 3 shows the speed justification for each road class, and this serves as a solution to the major drawbacks of this scenario.

Geographic Weighted Regression (GWR) Spatial Modeling

Geographic Weighted Regression (GWR) is a point approach technique comprising simple (Ordinary Least Square – OLS) and weighted regression models (Charlton, Fotheringham, & Brunsdon, 2009). The spatial weighting matrix is used to determine the relationship among regions where the spread of the virus serves as a dependent variable, while age range and population density are used as the explanatory (Mansour, Al Kindi, Al-Said, Al-Said, & Atkinson, 2021; Marhamah & Jaya, 2020; Wu & Zhang, 2021; Yellow Horse, Yang, & Huyser, 2022).Each spatial object has a similar relationship between the dependent and independent variables throughout the study area, as stated in the equation 1:

$$Yi = \beta o + \beta 1\, x1i + \beta 2x2i + \cdots . \beta nxni + \varepsilon i \qquad 1$$

The prediction coefficient is constant throughout the study area (simple linear regression – OLS) as stated in the equation 2:

$$\beta' = (X^TX)^{-1}X^TY \qquad 2$$

Meanwhile, linear regression with non-stationary assumptions between objects is known as Geographic Weighted Regression, as shown in Figure 6. The spatial weighting matrix is used to determine the relationship among regions where the spread of the virus serves as a dependent variable. In contrast, age-range and population density are used as the explanatory. The position of the

Table 3. Modification Results of Motorized Vehicle Speed Justification based on Classification of Road Functions

OSM Road Class	Law Street Function Class. No.22 Year 2009	Road Function Ranking	Minimum Speed (km/hour)	Maximum Speed (km/hour)
motorway	Primary Toll Road	1	70	100
motorway_link	Secondary Highway	2	50	80
primary	Primary Arterial Path	3	70	100
primary_link	Secondary Arterial Path	4	40	70
service	Secondary Arterial Path	4	40	70
secondary	Primary Collector Street	5	50	80
secondary_link	Secondary Collector Street	6	30	60
tertiary	Primary Local Road	7	30	60
trunk	Primary Local Road	7	30	60
tertiary_link	Secondary Local Road	8	20	50
trunk_link	Secondary Local Road	8	20	50
cycleway	Secondary Neighborhood Road	10	20	50
living_street	Secondary Neighborhood Road	10	20	50
residential	Secondary Neighborhood Road	10	20	50
footway	Footpath	11	0	0
path	Footpath	11	0	0
pedestrians	Footpath	11	0	0
steps	Footpath	11	0	0
track	Footpath	11	0	0
unclassified	292 Line	12	25	40

Source: Network dataset analysis results

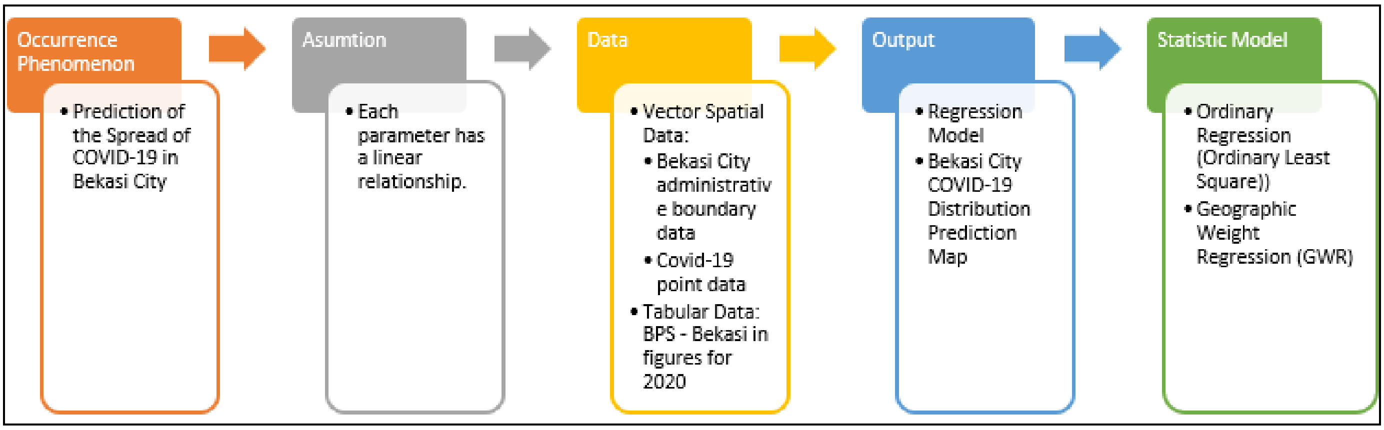


Figure 6. Spatial modeling process for the spread of COVID-19 cases in Bekasi City (Advanced Spatial Modeling Lecture Teaching Material - Manessa 2020)

object depends on the high-low correlation between the dependent and independent variables, as stated in the equation 3:

$$\beta'(i) = (X^T W(i)X)^{-1} X^T X^T W(i)Y \qquad 3$$

Where W(i) is the specific weight matrix for each location (i).

3. Result and Discussion

Referral Hospital Service Area

Identifying the movement or transportation of people, goods, migration patterns, and travel behavior is a spatial challenge. (Van Wee, 2016) stated that physical space and time are two critical dimensions that must be considered. A geospatial method was adopted to process maps, design transportation models, manage, analyze, and visualize spatial data to integrate various information sources.

Figure 7 shows the distance-based service area developed for the eight referral hospitals (Loidl et al., 2016). However, using the 2 km (dark green) scenario, it is evident that they cover half of the city. Since several regions are still not covered by one scenario, this study expands its coverage to a distance of 4 km (light green). The distance-based analysis results in Table 4 show that the referral hospitals properly serve all areas but show overlapping outcomes due to their relative nearness. The results of the distance-based area analysis show that the time requirement parameter is yet to be generated. In accordance with the objectives of this study, a time-based service area evaluation was carried out based on an earlier mentioned criteria. These are important in analyzing hospital service areas, especially how long a hospital facility takes to pick up and drop off a special patient suffering from COVID-19. This study does not include the traffic element in detail (Van Wee, 2016). In investigating time-based services, speed was added and reduced in terms of road class functions according to the Ministry of Transportation Regulation Number 111 of 2015. Figure 8 shows the second scenario, which involves the combination of time components to develop a referral hospital service area.

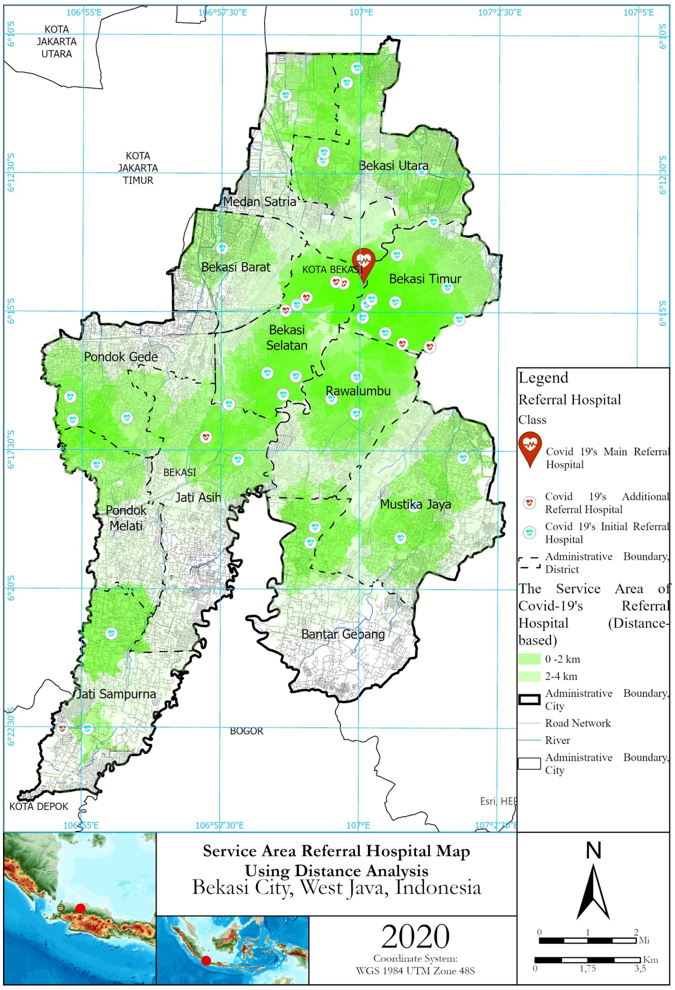


Figure 7. Service Area of Bekasi City Referral Hospitals Based on Distance of 2 and 4 km (Analysis Results, 2020)

For the second scenario, the service area of each referral hospital is divided into three categories, namely 0 to 5, 5 to 10, and 10 to 15 minutes. Figure 8 shows that all eight sub-districts are in well-served areas. Meanwhile, four of them, namely Bantar Gebang, Jati Sampurna, Medan Satria, and Jati Asih, are not covered by referral hospitals. It simply implies that local governments need to develop more of these facilities to serve people who reside far from the existing ones. This study evaluates the existing referral hospitals related to the distance and travel time from the location of the patients. The sub-districts with the service area for COVID-19 confirmed cases are shown in Table 6.

Geographic Weighted Regression Modeling Results

At the initial stage, this spatial modeling process performs Exploratory Regression (ER) to evaluate all possible combinations of explanatory variables. Additionally, it serves as an input to find the Ordinary Least Square (OLS) model that best explains the indicator variables used to determine the spatial modeling of COVID-19 spread in Bekasi City. The results of the analysis using the ArcGIS Pro software are shown in Figure 9. After obtaining the indicator variables from the ER process, the OLS evaluation procedure is carried out, and the results are shown in Figure 9.

The results of linear regression spatial modeling obtained using OLS show that the correlation of the spread of COVID-19 in this city is exceptionally high with the age range variable between U45 to 49, U55 to 59, and U65+ and that of the population density indicated by the VIF (Variance Inflation Factor) > 7.5 as well as the R-Square value and Akaike's Information Criterion (AICc) in

Table 4. Coverage of Referral Hospital Service Areas to Bekasi City Population Based on Distance

Scenario	Scenario Coverage (km2)	Bekasi City Area (Km2)	Bekasi City Population (People)	Percentage % of total population	Number of Population Facilitated by Health Services (People)
Based on a Distance of 0-2 km	120.89	210.49	2,448,830	57%	1,406,428
Based on a Distance of 2-4 km	189.2	210.49	2,448,830	90%	2,201.143

Source: Result of data processing

Table 5. Service Area Coverage of Referral Hospitals to Bekasi City Population Based on Travel Time

Scenario	Scenario Coverage (km2)	Bekasi City Area (Km2)	Bekasi City Population (People)	Percentage % of total population	Number of Population Facilitated by Health Services (People)
Based on the time of 0-5 minutes	48,39	210,49	2.448.830	23%	562.967
Based on the time of 5-10 minutes	112,68	210,49	2.448.830	54%	1.310.913
Based on the time of 10-15 minutes	154,06	210,49	2.448.830	73%	1.792.326

Source: Result of data processing

Table 6. Number of COVID-19 Confirmed Cases in Serviced and Unserved Health Facilities Areas based on the analysis results

Scenario of the Number of Confirmed Cases of COVID-19 in Bekasi City	By Distance		By Travel Time	
Subdistrict	Number of Population Facilitated by Health Services (People)	Number of Population Not Facilitated by Health Services (People)	Number of Population Facilitated by Health Services (People)	Number of Population Not Facilitated by Health Services (People)
Bantar Gebang	115	99	68	146
West Bekasi	960	447	999	408
South Bekasi	1.063	48	1,031	80
East Bekasi	1,404	0	1,397	7
North Bekasi	660	63	645	78
Jati Asih	641	82	554	169
Jati Sampurna	254	148	108	294
Medan Satria	647	0	555	92
Mustika Jaya	820	33	433	420
Pondok Gede	705	27	662	70
Pondok Melati	341	30	289	82
Rawa Lumbu	944	0	899	45

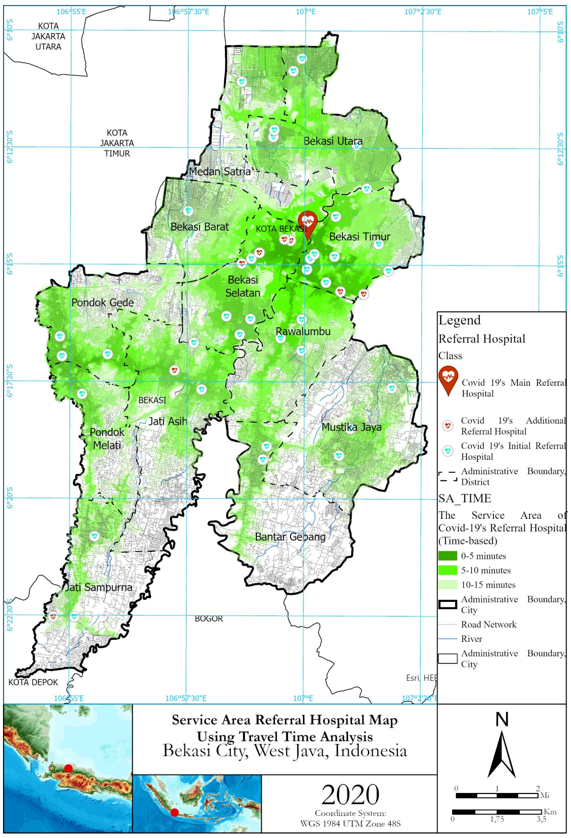


Figure 8. Service Area of Bekasi City Referral Hospitals Based on Travel Time of 5, 10, and 15 minutes (Results of Analysis, 2020).

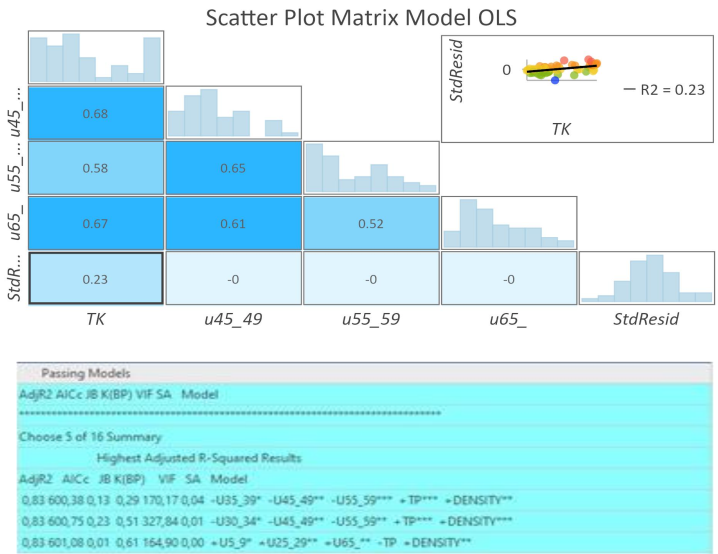
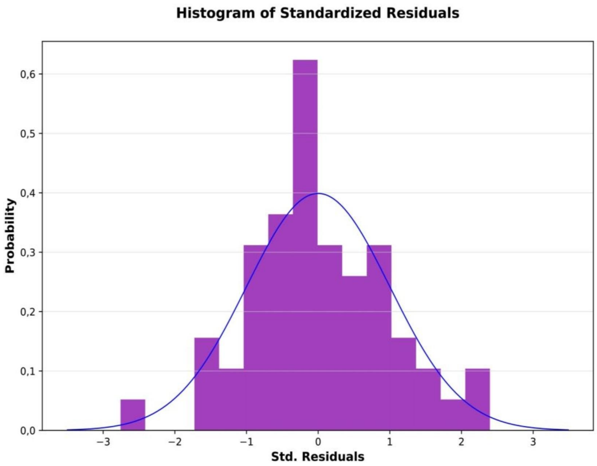


Figure 9. Results of the Bekasi City Explanatory Regression Process (Results of Analysis, 2020)

variable between U45 to 49, U55 accordance with the linear regression model, as shown in Figure 10.

Afterward, a test was carried out to determine whether the simple linear regression modeling using OLS has a spatial effect on each distance from the COVID-19 centroid. Using the dependent variable as well as age range and population density as explanatory variables similar to



OLS Diagnostics

Input Features:	CoV_C19_Bekasicity	Dependent Variable:	TK
Number of Observations:	56	Akaike's Information Criterion (AICc) [d]:	617,819422
Multiple R-Squared [d]:	0,765967	Adjusted R-Squared [d]:	0,752465
Joint F-Statistic [e]:	56,730214	Prob(>F), (3,52) degrees of freedom:	0,000000*
Joint Wald Statistic [e]:	227,331008	Prob(>chi-squared), (3) degrees of freedom:	0,000000*
Koenker (BP) Statistic [f]:	6,745593	Prob(>chi-squared), (3) degrees of freedom:	0,080464
Jarque-Bera Statistic [g]:	0,513404	Prob(>chi-squared), (2) degrees of freedom:	0,773599

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-27,389299	19,689706	-1,391047	0,170137	13,903207	-1,969999	0,054176	--------
U45_49	0,034077	0,011911	2,860971	0,006070*	0,011753	2,899573	0,005463*	3,719604
U55_59	0,013884	0,009759	1,422678	0,160803	0,010264	1,352731	0,181996	3,028094
U65_	0,045020	0,012176	3,697594	0,000527*	0,015737	2,860866	0,006071*	2,726230

Figure 10. Results of the Bekasi City Ordinary Least Square Process (Results of Analysis, 2020)

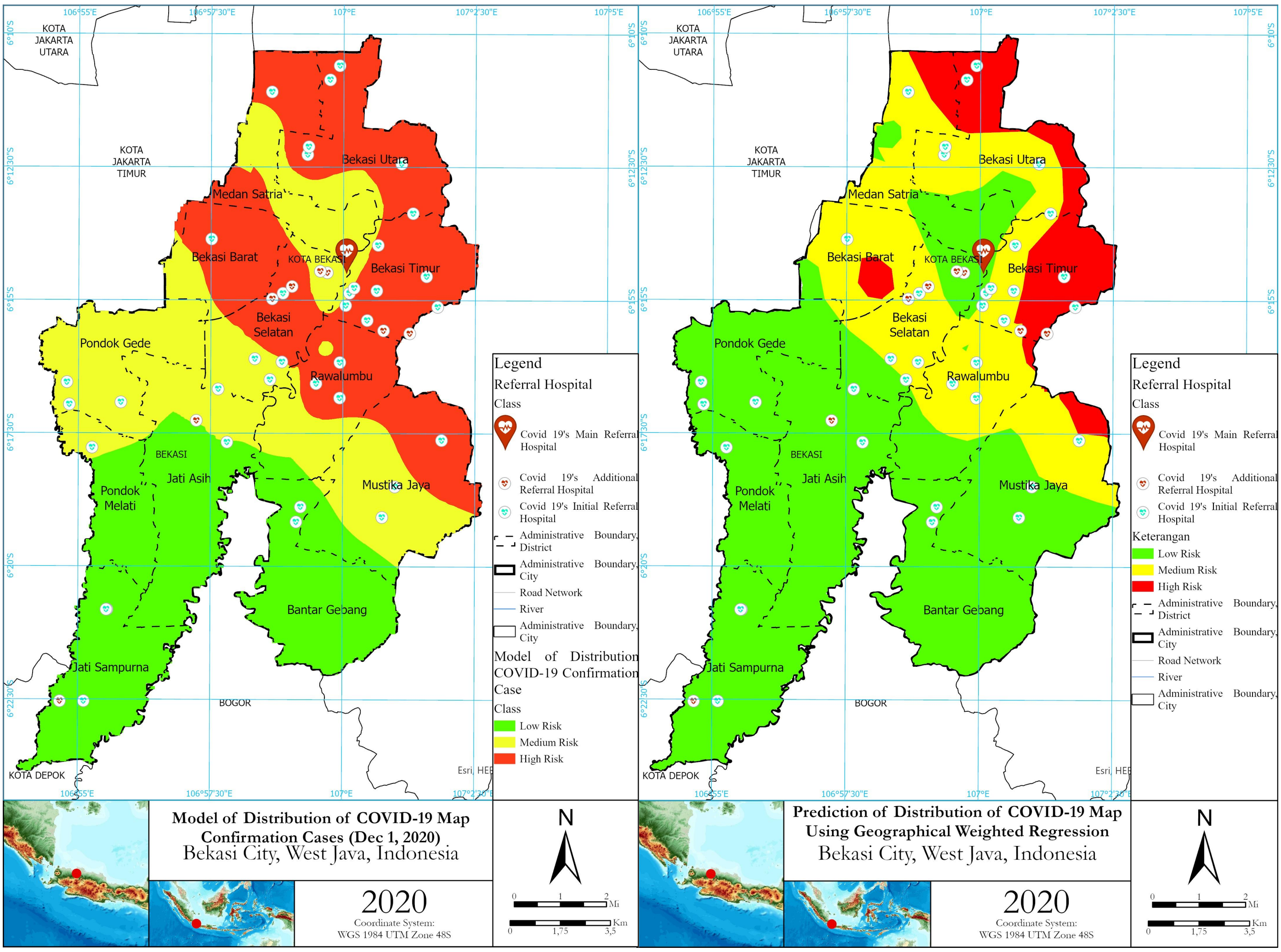


Figure 11. Comparison Distribution of COVID-19 Confirmation Cases Map and Prediction Of Distribution of COVID-19 Bekasi City (Results of Analysis, 2020)

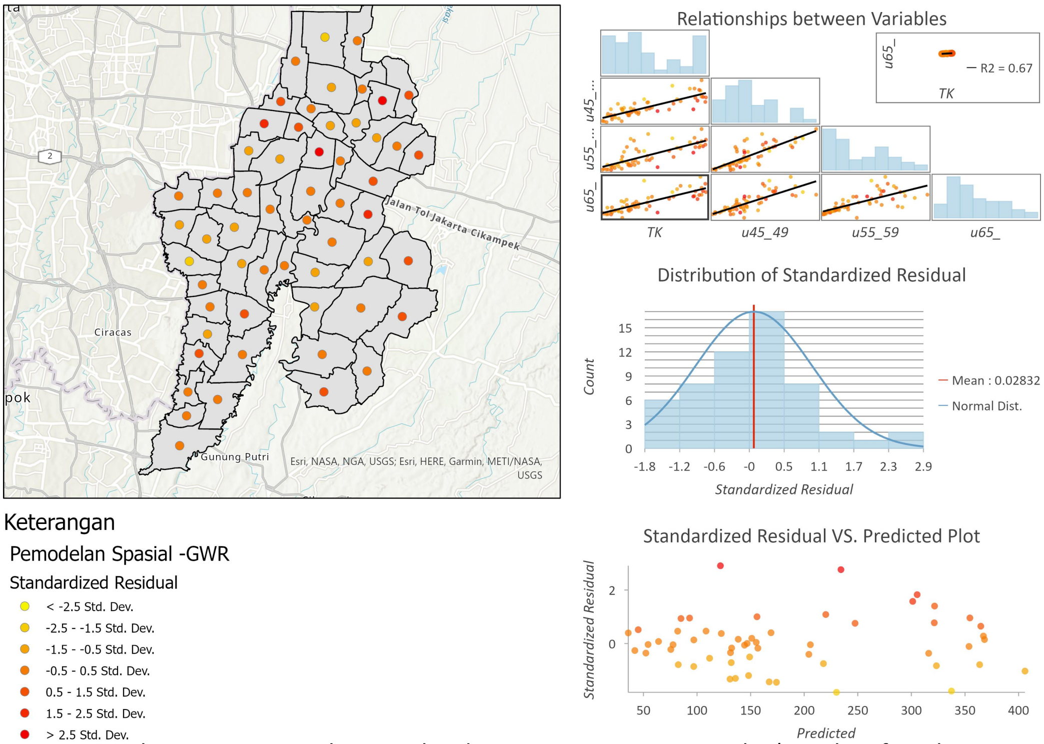


Figure 12. Bekasi City Geographic Weighted Regression Process Results (Results of Analysis, 2020)

Table 7. Predicted Data for the Distribution of Confirmation of COVID-19 in Bekasi City

No	Sub-District	Description	Area (km2)	No	Sub-District	Description	Area (km2)
1	Bantar Gebang	Low Risk	19,288	17	Rawalumbu	Low Risk	4,974
2	Bantar Gebang	Low Risk	0,913	18	West Bekasi	Medium Risk	9,988
3	West Bekasi	Low Risk	1,076	19	South Bekasi	Medium Risk	8,845
4	South Bekasi	Low Risk	6,530	20	East Bekasi	Medium Risk	4,821
5	East Bekasi	Low Risk	0,786	21	North Bekasi	Medium Risk	10,167
6	North Bekasi	Low Risk	2,066	22	Medan Satria	Medium Risk	8,124
7	Jati Asih	Low Risk	14,699	23	Mustika Jaya	Medium Risk	8,576
8	Jati Asih	Low Risk	10,784	24	Pondok Gede	Medium Risk	0,238
9	Jati Sampurna	Low Risk	18,391	25	Rawalumbu	Medium Risk	11,448
10	Medan Satria	Low Risk	6,235	26	West Bekasi	High Risk	1,399
11	Mustika Jaya	Low Risk	3,187	27	East Bekasi	High Risk	9,160
12	Mustika Jaya	Low Risk	13,427	28	North Bekasi	High Risk	7,725
13	Pondok Gede	Low Risk	16,253	29	Medan Satria	High Risk	2,520
14	Pondok Melati	Low Risk	7,805	30	Mustika Jaya	High Risk	1,398
15	Pondok Melati	Low Risk	3,847	31	Rawalumbu	High Risk	0,325
16	Rawalumbu	Low Risk	0,336				

Source: Data analysis results, 2020

the OLS analysis process (Marhamah & Jaya, 2020), it was discovered that the GWR spatial modeling is highly correlated and has an effect on the spread of COVID-19. Based on the field data analysis validation, GWR spatial modeling can be used to predict the confirmed cases in Bekasi City, as shown in Figure 11.

Based on the results of the GWR spatial modeling, the classification process was carried out in accordance with the prediction of the spread of the virus using GIS software and analysis made by the Government of Indonesia such as (1) High, (2) Moderate, (3) and Low Risk as shown in Table 7.

4. Conclusion

This study explains the geospatial-based distribution of COVID-19 and recommends alternative health facilities to support existing referral hospitals. The two methods' analysis results show slight differences between the distance and time-based service areas. The major drawback of this scenario is that the time required for the patient to reach the referral hospital is still unknown. Previous studies stated that it is essential to incorporate actual traffic conditions into time elements, such as speed limits, traffic jams, and one-way streets. It was further stated that the longer the distance to the hospital, the lower the patient's willingness to visit the facility (Van Wee, 2016).

During the pandemic, several recovered patients testified that they preferred to be treated at a nearby hospital rather than at a referral facility far from their homes. This simply indicates that people prefer health care facilities in their environment (Turnbull, Martin, Lattimer, Pope, & Culliford, 2008).

Therefore, not all in this city are covered by health services or referral hospitals based on distance and travel time. Although only a small part of relatively less than 30% was not properly served, thereby leading to the need to develop other facilities. Based on the acquired data, two sub-districts, namely North and East Bekasi, statistically have the highest population density. The results of the spatial modeling analysis obtained using GWR with a spatial -temporal recapitulation of data reports for eight months show the spread of the virus in six sub-districts, such as West, North, and East Bekasi, as well as Medan Satria, Mustika Jaya, and Rawalumbu.

The existence of certain shortcomings in the analysis was caused by several factors, including (1) limitations to the centroid or midpoint of the rural and urban areas, which may be less accurate than the home address, and (2) time-based services, due to the exclusion of traffic element in detail. However, only the speed elements according to the road class function in the Ministry of Transportation Regulation Number 111 of 2015 were included as a dataset in the Bekasi City road network. This potentially reduces the accuracy of the results because it affects the route taken, which in turn impacts the distance and travel time. Future studies are expected to analyze two methods using more detailed parameters. In this research, the presented GWR model was used to investigate the pattern of spread and direction of confirmed cases and identify risk factors over a certain period. It also described distance, and time-based service areas, including the spread model designed with the GWR analysis, which is expected to support health programs in Bekasi City to reduce risks.

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