ORIGINAL ARTICLE

A system model for real-time monitoring and geospatial data for the simulation of surveillance of COVID-19 in Makassar, Indonesia

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ABSTRACT

The rapid spread of COVID-19 requires rapid management. Prompt treatment is needed to prevent the spread of this disease, which could be minimized or isolated in one place so that it does not spread to other places. This study was conducted to discover a model of the surveillance system in real time and to analyze the change in its distribution pattern. This study was conducted in the city of Makassar, South Sulawesi, Indonesia, involving 30 volunteers. Two devices were used, the Internet reverse transcription loop-mediated isothermal amplification (iRTLAMP) and IoT button application, to provide spatial data in the form of patient points exposed to COVID-19. Furthermore, three scenarios were applied to see the pattern of data distribution. The data recorded in the cloud database were retrieved with a created application and then analyzed using Kernel Density Estimation (KDE) and Point Pattern Analysis (PPA) to observe the distribution of patterns in real time. The analysis utilizing KDE with the Gaussian kernel function as the kernel revealed significant changes in the probability distribution, which could be seen from color changes in the map. The centrographic analysis revealed that the mean and median points of the three scenarios changed in various ways within approximately 700 m to 1.7 km. Meanwhile, the radius of minimal bounding circle behaved similarly and appeared to change depending on the scenario, from a radius of 5.57 (initial) km to 6.55 km (scenario 1), 5.57 km (scenario 2) and 6.22 km (scenario 3). The standard distance also showed a change from 4.53 km to 4.60 km (scenario 1), 4.70 km (scenario 2) and 5.40 km (scenario 3). Simulations carried out using the developed system showed that the use of internet devices could help monitor people exposed to COVID-19 by changing patterns and distribution points. Therefore, decision makers could take preventive actions earlier so that this disease does not spread quickly.

Key words:
point pattern analysis; COVID-19; Sulawesi; Indonesia.

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INTRODUCTION

Covid-9 is still spreading quickly in some countries, including Indonesia. The current situation remains unstable, with the emergence of several new variants that spread more quickly and cause different symptoms in different patients.[1–4] Currently, the spread of COVID-19 can be through droplets,[5] aerosols,[6] and fomites.[7] In addition, the spread of COVID-19 is also affected by the weather,[8] temperature, humidity and population density.[9] In Indonesia, several policies were implemented by the central and local governments to prevent rapid spread, such as limiting the number of people entering public places and limiting the movement of people between regions, districts, and cities, as well as between islands.[10] However, this restriction affects many sectors, including the economy, which has a major impact on people's incomes.[11] For this reason, to prevent a more massive spread of the COVID-19 virus, a real time analysis of the spread pattern of COVID-19 is necessarily required.

In order to prevent the spread of COVID-19, cooperation with various fields other than health sciences such as information technology and geography should be made.[12] Information systems and technology are needed to provide fast access to various types of information, such as the number and location of deployment. Several systems and information technology have been developed in Indonesia, and the updating process is conducted once a day.[13–15] This information is provided by relevant authorities in order to maintain the validity of the data provided. The drawback of this method is that the spread cannot be monitored in real time, resulting in a weak anticipation of the spread of the virus. Meanwhile, the use of geography approach is required to map and analyze the spread pattern of COVID-19 within some areas by including other factors such as the characteristics of the area, the weather, population distribution and density, etc. The combination of these various fields of knowledge is expected to make a significant contribution to preventing the spread of COVID-19. The use of spatial analysis in solving problems has been carried out by many researchers.[16,17] GIS has also been widely employed for mapping and monitoring the distribution of diseases, including COVID-19.[18,19]

In general, in cases of the spread of COVID-19, GIS is used to map the number and location of the spread. GIS could be used as a tool to monitor and track the spread of COVID-19. To get real-time data as spatial data in GIS, several techniques have been used, such as using mobile phones,[20] sensor web service,[21] and data warehouse combined with Application Programming Interface (API).[22] Several methods have been used to analyze the spread of COVID-19 geospatially.[23–25] In this study, we used the data collected by IoT devices because it is easy to use and reliable[26] and analyzed the patterns of data distribution by using Point Pattern Analysis (PPA) to provide better visualization and interpretation of the data distributed by points.[27,27,28]

METHODS

Study Area

The study was conducted in the city of Makassar, located at longitude 119.423790 and latitude -5.135399. Makassar is located on the island of Sulawesi, Indonesia, and that corresponds to the Köppen climate classification category Am. Based on the population census in 2020, the total population was around 1,423,877 with a population density of 8,101/km^2 inhabiting 15 sub-districts.[29]

System design

A point collected in the location of each COVID-19 case offered two values, the position of the point itself and the value that exists at that point. The points in the form of spatial data spread over certain locations on a map are called point patterns. The analysis was conducted using the position of the points spread over several locations on the map together with the value. In the case of the spread of COVID-19, the analysis was conducted using the position of the points spread over several locations on the map with the value of the point themselves. In this study, the positions of the points on the map were obtained from two devices, namely the internet reverse transcription loop mediated isothermal amplification (iRTLAMP) and the IoT button application on Android devices as shown in Figure 1. iRTLAMP is an RT-LAMP [30] device for COVID-19 testing equipped with Internet of Things (IoT) features on the device so that it can transmit the position of the device. This device was placed at several hospitals and used to detect whether a person was exposed to COVID-19 by using the saliva sample from the person who wanted to be tested. If the device detected COVID-19, the IoT module sent the longitude and latitude of the hospital to the cloud database (Firebase) to record the position of the exposed person. The IoT Button was an Android-based IoT application that sent the location to the Firebase if the user was exposed to COVID-19 using other test methods, such as Polymerase Chain Reaction (PCR) and antigen. The main function of this application was to send input data in the form of an identification number (*NIK, Nomor Induk Kependudukan*), which is the detailed information about the patient previously entered during registration. Both platform devices collected the data for each COVID-19 infected case in the form of longitude and latitude on the map. The IoT button application should also be available in public health centers (PHC) and hospitals that carry out PCR tests or other offline COVID tests. If someone was detected with COVID using the offline method, staff from the PHC or hospital could enter patient data through the IoT button application. Both platform devices collected the data for each COVID-19 infected case in the form of longitude and latitude on the map.

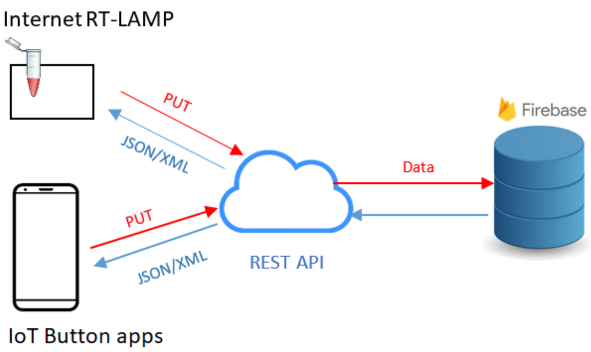

Figure 1 Storing real-time data using Iot Button apps and iRTLAMP

The next step was to retrieve data by using Python 3.9.12 [31] and export data in a CSV format. Then, the data were analyzed using Python 3.9.12 on the same computer with the data on CSV file to update spatial data in the form of points on a predetermined map, which was then analyzed using PPA[32] as shown in Figure 2. In general, the program was divided into three categories: delivery, data retrieval, and analysis.

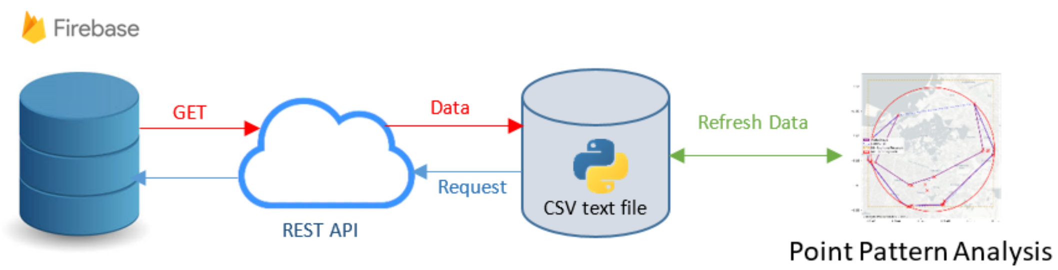

Figure 2 Obtaining real-time data form Firebase and analysis using Point Pattern Analysis

Data generation

To analyze the distribution patterns of the points, a simulation was conducted with three scenarios:

1. Scenario 1: five points were added at the edge of an existing cluster.
2. Scenario 2: five points were added at the center of an existing cluster.
3. Scenario 3: five points were added as a new cluster.

This simulation was conducted in the city of Makassar, South Sulawesi, Indonesia, involving volunteers using iRTLAMP devices and the IoT button application. Volunteers who participated in this study were not exposed to COVID-19 and only used the device and application as a simulation of the system. Thirty points were generated randomly and no existing data were used because the priority was to determine whether the delivery and analysis process in real time could function properly.

Data Analysis

Point pattern analysis was performed to observe changes in point patterns by examining the distribution of points on the map. Changes in the distribution of points on the map also caused changes in their patterns. By examining the pattern of changes from these points, it was expected that the nature of pattern changes resulting from changes in the distribution of points will be understood. In addition, by examining the existing patterns, it was expected that the spread of COVID-19 could be predicted so that prevention could be carried out in locations that may become new clusters for the spread of this disease. To determine the distribution of data, the first step was to plot the location of people exposed to COVID-19 on a map to determine the distribution of people exposed to COVID-19 in the form of points. To analyze the density of these points and classify the points in the cluster, this study performed several analyses, namely Kernel Density Estimation (KDE) analysis and centrography. KDE is a method used to estimate the probability of a density function from data. The kernel used in this study is a Gaussian Kernel expressed as follows:

$$KDE_j = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h\sqrt{2\pi}}e^{-0.5\frac{(x_j-x_i)}{h}} \quad (1)$$

where n is the number of observed data points, h is the bandwidth, x_i are observed data points, and x_j are series of data points where kernel function is calculated.

The next step was centrographic analysis. Centrographic analysis is an analytical technique that provides a summary of the point pattern such as center point, dispersion and shape of the pattern. The mean center, or average of the coordinate values, is the central tendency of the two-dimensional distribution. The purpose of this analysis was to identify the central point of the spatial distribution. The mean centers are computed as follows:

$$x_{mc} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (2)$$

$$y_{mc} = \frac{1}{n}\sum_{i=1}^{n} y_i \quad (3)$$

while the location from which the sum of all Euclidean distances to all points in a distribution is at its lowest value is known as the median center and can be expressed as:

$$\min f(x_{em}, y_{em}) = \sum_{i=1}^{n} \sqrt{(x_i - x_{em})^2 + (y_i - y_{em})^2} \quad (4)$$

In order to measure standard distance (SD) for dispersion analysis, this standard deviation formula was used:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_{mc})^2}{n} + \frac{\sum_{i=1}^{n}(y_i - y_{mc})^2}{n}} \quad (5)$$

Meanwhile, to calculate the distance between two locations with known longitude and latitude, the following haversine formula was used as follows:

$$h = \sin^2(\Delta\emptyset/2) + cos\emptyset_1 . cos\phi_2 . \sin^2(\Delta\lambda/s) \quad (6)$$

$$c = 2.\,\mathrm{atan}^{-1}(\sqrt{h}, \sqrt{(1-h})$$

$$d = R.c$$

where λ is longitude and ϕ is latitude and R is equal to 6378 km (earth's radius).

Furthermore, the minimum bounding rectangle was drawn based on the smallest rectangle that can be formed from the existing points. In other words, a minimum bounding rectangle was drawn using the outermost existing points and has to be a square. Meanwhile, the minimum bounding circle was drawn using the Skyum algorithm. [33]

RESULTS

To determine the distribution of the data, the first step was to plot the location of people exposed in the form of points. The initial point distribution was 30 points, as shown in Figure 3a, and three scenarios were used, as shown in Figures 3b, 3c, and 3d, where changes in spatial data were seen in the form of adding points that followed the three scenarios carried out in this study, which are indicated by the red circles. It can be seen from the figure that the points are scattered randomly on the map, showing the distribution locations of people who have been exposed to COVID-19. However, this visualization does not provide sufficient information to clearly show the distribution pattern because it only describes randomly scattered points.

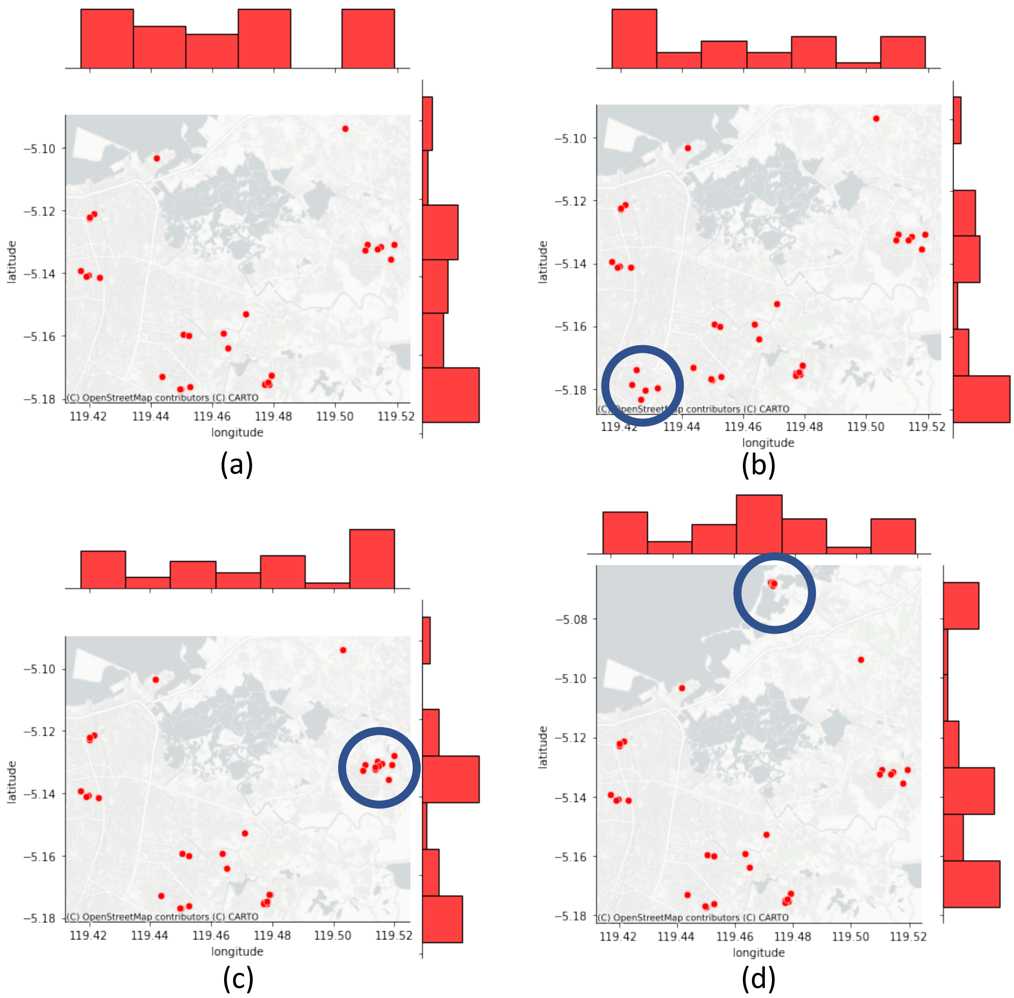

Figure 3 The distribution of people exposed to COVID-19 spread on the map in the form of points and changes in spatial data in the form of points by following (a) initial (b) Scenario 1 (c) Scenario 2 (d) Scenario 3. Changes in spatial data can be seen in the blue circle

Furthermore, KDE analysis was performed to determine the density difference in the cluster areas of the three clusters formed. In addition, the density indicated by the darker color in the center of each cluster also shows a difference. Figure 4b shows the addition of points using Scenario 1, where it can be seen that the cluster at the bottom of the map will widen, which is the impact of adding points to the cluster compared to Figure 4a, which is the initial point distribution. With the addition of a number of points in other clusters using Scenario 2, it can be seen that the density in that cluster changes, which is indicated by a darker color in the center of the cluster, as shown in Figure 4c. Meanwhile, adding points at other locations on the map creates a new cluster, namely the 4th cluster as shown in Figure 4d.

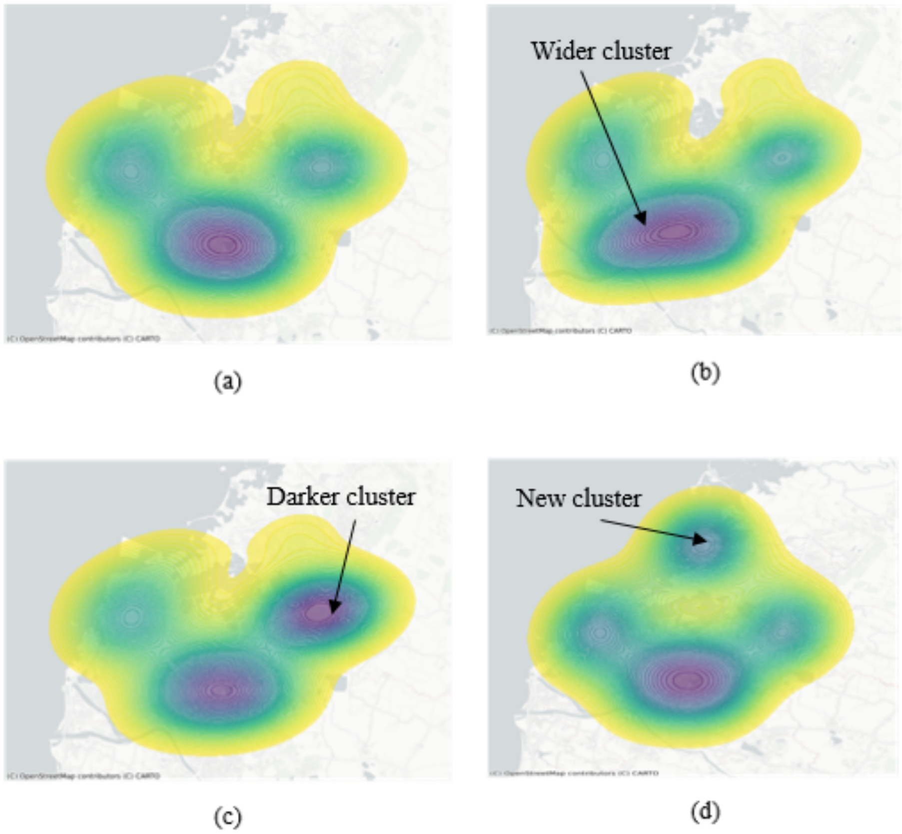

Figure 4 Changes that occur in the cluster using KDE analysis in the three scenarios; (a) initial (b) scenario 1 (c) scenario 2 (d) scenario 3.

The results of the centography are obtained by calculating the mean and median of the distribution of points, SD and calculating the minimum bounding rectangle and minimum bounding circle. From Figure 5, it can be observed that there was a shift in the mean center (black x) and median center (black dot) to the new mean (red x) and new median (green dot) when applied to the three scenarios. The mean point represents the average value of the point pattern in the distribution, and the median point represents the middle value of the existing point pattern, while ellipses visualize the dispersion and orientation of the distribution of points. Changes in the median and mean points, as well as the distance from the median and mean starting points, based on the three scenarios are shown in Tables 1 and 2.

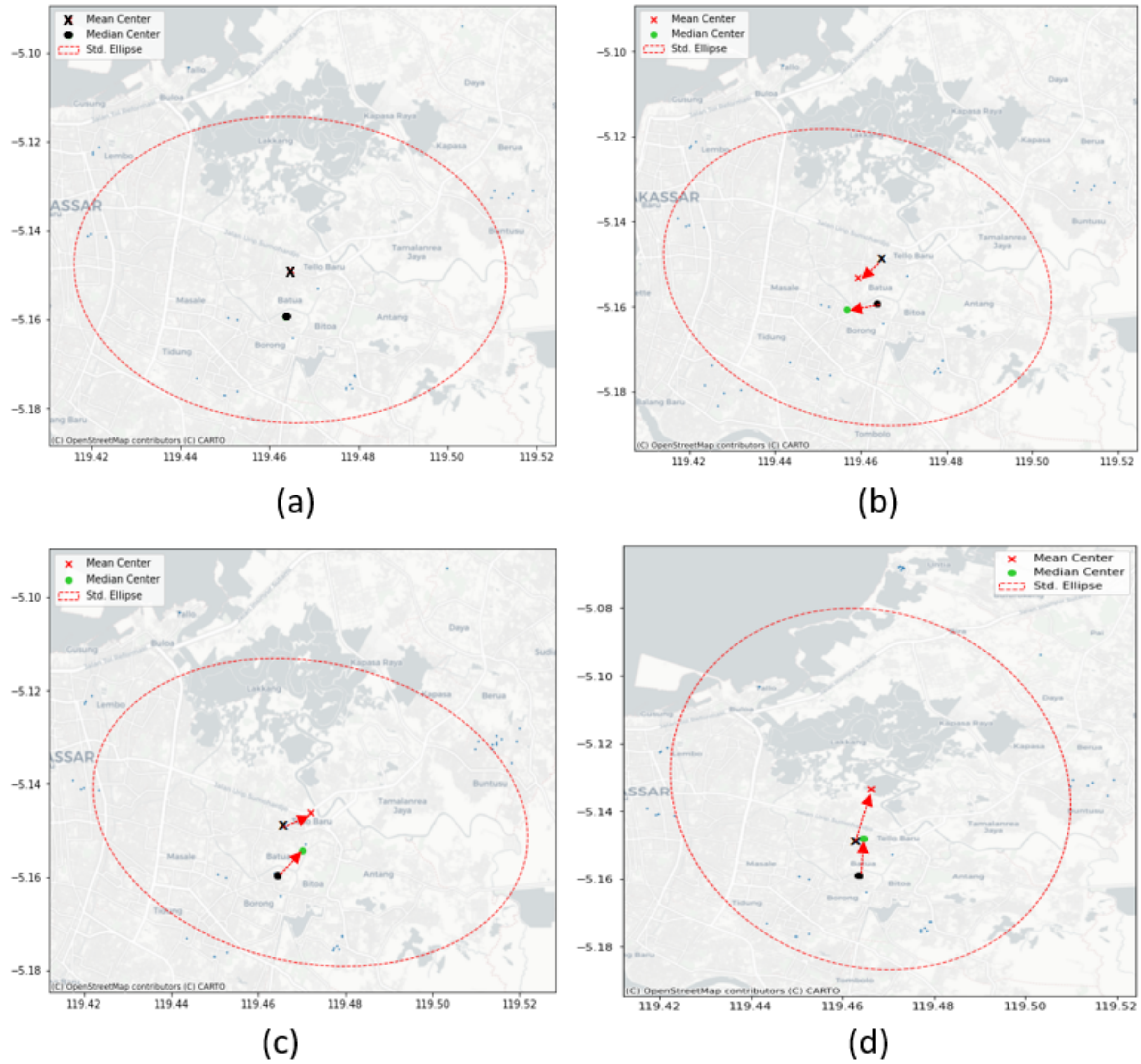

Figure 5 The initial mean center (black x) and initial median center (black dot) changes that occurred to the new mean (red x) and new median (green dot) in the clusters using centographic analysis in the three scenarios; (a) initial (b) Scenario 1 (c) Scenario 2 (d) Scenario 3.

Table 1. Longitude and latitude of mean including distance from initial point changes during simulation with three scenarios

	Location		Distance
	Longitude	Latitude	(km)
Center	119.46463257	-5.14878677	0
Scenario 1	119.45926683	-5.15312129	0.76
Scenario 2	119.47192769	-5.14612440	0.86
Scenario 3	119.46618497	-5.13351557	1.70

Table 2. Longitude and latitude of median including distance from initial point changes during simulation with three scenarios

	Location		Distance (km)
	Longitude	Latitude	
Center	119.46362200	-5.15918400	0
Scenario 1	119.45676376	-5.16075840	0.78
Scenario 2	119.47017913	-5.15436299	0.90
Scenario 3	119.46472863	-5.14818226	1.23

Furthermore, by using the visual form of the spatial distribution, several types of boundary shapes were used, namely, minimum bounding rectangles, which were made to form a boundary in the shape of a square that was the minimum square shape or the smallest square area that could be made in the existing spatial distribution. Next, we searched for the minimum bounding circle that described the minimum circle shape with a minimum area that could limit the spatial distribution. In principle, it is almost the same as minimum bounding rectangles with only a limiting shape. The convex hull shape is a line that connects the outermost points of the spatial distribution and never forms a closed pattern within the shape itself. Another shape is the alpha shape, which is a stricter version of the convex hull. It is a line that connects all the outermost points of the spatial pattern and can go back inside itself to form a tighter pattern than the convex hull. The visual form of this barrier is shown in Figure 6. The pattern of this barrier also seems to change according to the pattern of the three scenarios that have been carried out. Table 3 shows the center points of minimum bounding circle, SD, and radius of minimum bounding circle changes for three scenarios. The standard distance in the three scenarios also seemed to change indicating that these points were moving away from the center point of minimum bounding circle. This also explains why the larger the SD, the farther the points were spread from the center point of minimum bounding circle. The center point of minimum bounding circle and radius of the minimum bounding circle also seemed to change in scenarios 1 (6.559 Km) and scenario 3 (6.225 Km) due to the addition of points on the outermost. While in scenario 2, there was no change in the minimum bounding circle because the additional points were within the circle.

Table 3. Center points of minimum bounding circle, standard distance (SD) and radius minimum bounding circle (MBC) changes during simulation using three scenarios.

Scenario	Longitude	Latitude	SD (km)	radius (km)
Initial	119.469577764322787	-5.1309623877841855	4.53	5.57
Scenario 1	119.464918	-5138469	4.60	6.55
Scenario 2	119.469577764322787	-5.1309623877841855	4.70	5.57
Scenario 3	119.4638295294032	-5.122856959886026	5.40	6.22

The results of calculating the minimum rectangular boundary show that there was also a shift in the longitudes and latitudes, which resulted in a change in the size of the rectangle on the map in the three scenarios, as shown in Table 4.

Table 4. Minimum bounding rectangle (MBR) changes during simulation using three scenarios.

Scenario	Left bottom outer most		Right top outer most	
	longitude	latitude	longitude	latitude
Initial	119.417208	-5.177027	119.519174	-5.093878
Scenario 1	119.417208	-5.18342	119.519174	-5.093878
Scenario 2	119.417208	-5.177027	119.520015	-5.093878
Scenario 3	119.417208	-5.177027	119.519174	-5.067597

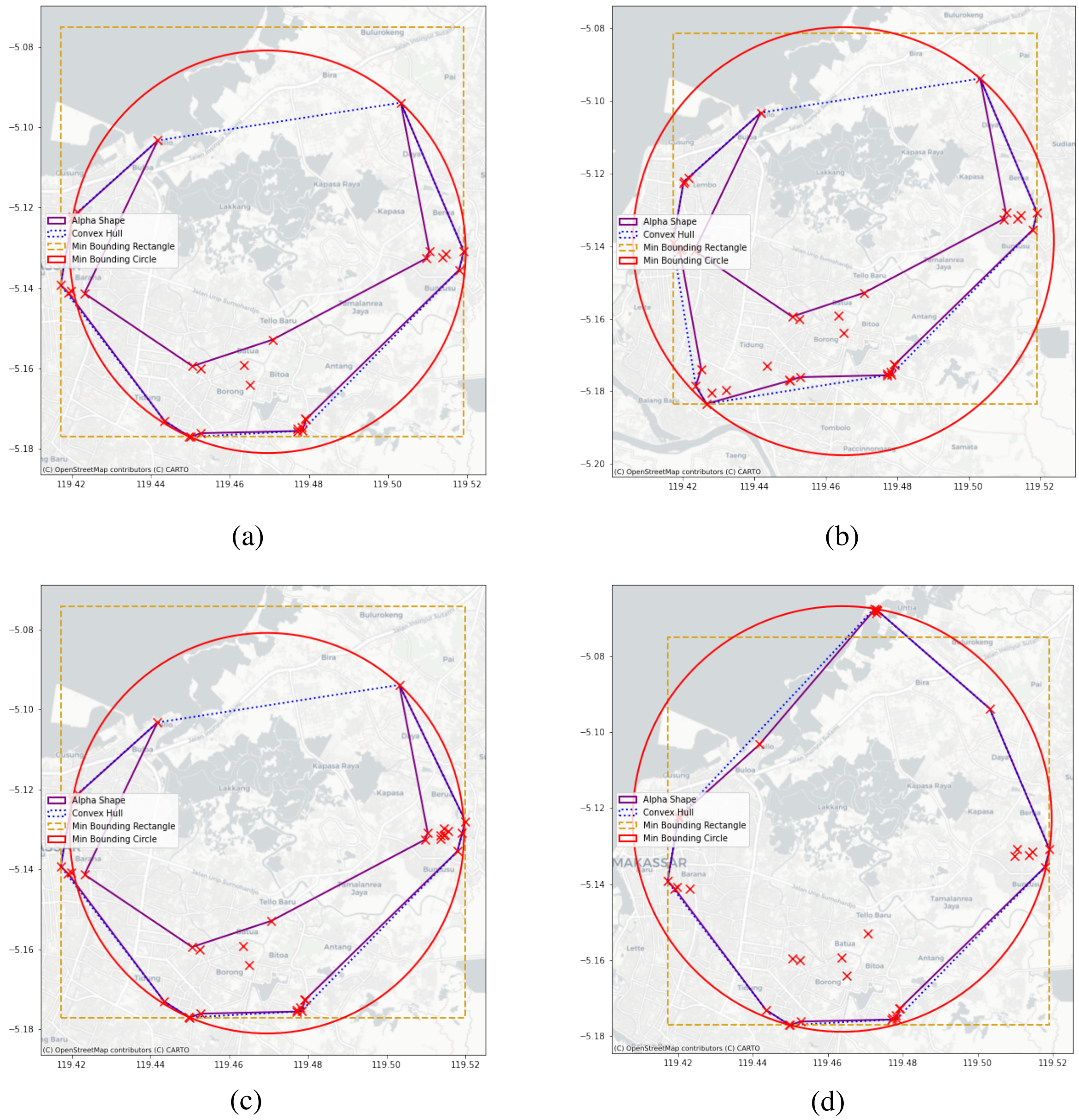

Figure 6 Extent changes during simulation with three scenarios; (a) initial (radius=5.57 Km) (b) scenario 1 (radius=6.55 Km) (c) scenario 2 (radius=5.57 Km) (d) scenario 3 (radius=6.22 Km).

DISCUSSION

Simulations carried out using the developed system showed that the use of IoT devices could help monitor people exposed to COVID-19. GIS can be used to analyze, map and visualize the spread of disease.[27,34] Analysis carried out with PPA can also show changes in the center and patterns of spread when there is an increase in the number of people exposed to an area. This surveillance was intended to minimize the spread by taking prompt and appropriate actions, such as isolating the place of spread and providing health assistance in areas where the number of people exposed is quite large. Other methods have also been used by researchers, such as the use of a regression model to observe the spread of COVID-19 by conducting cluster analysis in densely populated areas.[35] The results showed a correlation between dispersion and a dense population. In addition, mapping and spatial pattern analysis using offline data to analyze the spread pattern of COVID-19 have prevented the spread of COVID-19. The results showed that in dense areas, the spread of COVID-19 was very fast. [36,37] However, the research that we conducted provides visual information on the situation in the location in real time because it involved the health workers and community so that analysis and prevention can be carried out by decision makers quickly to prevent transmission to other locations promptly.

Some of the problems that may be encountered later in the proposed method are the high price of Internet connections for some people and the lack of familiarity of the general public with the usage of the applications created. The intensive and structured socialization of related parties and the community of this system requires further studies on the socialization of this system so that this system can be implemented properly and widely. In addition, support from policymakers at the city, provincial, and central levels is needed to encourage all circles to receive this system

CONCLUSIONS

To determine the extent of the spread of COVID-19 at a location, a real-time system that provides continuous information is needed. This has been solved by a system created using a COVID-19 detection device (iRTLAMP) and a mobile phone application (IoT button) connected in real-time to a map for monitoring and analysis purposes. Analysis using PPA showed that the pattern and extent of spread could be predicted at the location of the spread of COVID-19. Identification of the center of spread and analysis of the spread pattern of the disease, including COVID-19, are very important to prevent the spread of COVID-19. By knowing the center and the spread pattern, actions such as isolating the place of spread can be taken quickly. The sooner this information is obtained, the sooner the action can be performed. The analysis of the shift in the distribution center provides assistance to related parties to take preventive actions so that new clusters do not appear. The simulation of the monitoring system, central analysis, and distribution pattern in this study show that a real-time data delivery system and PPA could provide accurate information. With this system, it was expected that policymakers at local and national levels would obtain faster and more accurate information about the phenomenon of the spread of diseases such as COVID-19.

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REFERENCES

1. Alimohamadi Y, Sepandi M, Taghdir M, Hosamirudsari H. Determine the most common clinical symptoms in COVID-19 patients: a systematic review and meta-analysis. J Prev Med Hyg. 2020;61(3):E304–E304.
2. Whitaker M, Elliott J, Bodinier B, Barclay W, Ward H, Cooke G, et al. Variant-specific symptoms of COVID-19 in a study of 1,542,510 adults in England. Nat Commun. 2022;13(1):6856.
3. Dyer O. Covid-19: Indonesia becomes Asia's new pandemic epicentre as delta variant spreads. BMJ. 2021;374:n1815.

4. El-Shabasy RM, Nayel MA, Taher MM, Abdelmonem R, Shoueir KR, Kenawy ER. Three waves changes, new variant strains, and vaccination effect against COVID-19 pandemic. Int J Biol Macromol. 2022;204:161–8.
5. Bandari A. Sneezing plays a large role in transmission of COVID-19 by asymptomatic carriers. Scilight. 2020;2020(33):331106.
6. Wang J, Du G. COVID-19 may transmit through aerosol. Ir J Med Sci. 2020;189(4):1143–4.
7. Meister TL, Dreismeier M, Blanco EV, Brüggemann Y, Heinen N, Kampf G, et al. Low risk of SARS-CoV-2 transmission by fomites - a clinical observational study in highly infectious COVID-19 patients. J Infect Dis. 2022;jiac170.
8. Tosepu R, Gunawan J, Effendy DS, Ahmad LOAI, Lestari H, Bahar H, et al. Correlation between weather and Covid-19 pandemic in Jakarta, Indonesia. Sci. Total Environ. 2020;725:138436.
9. Jin YH, Cai L, Cheng ZS, Cheng H, Deng T, Fan YP, et al. A rapid advice guideline for the diagnosis and treatment of 2019 novel coronavirus (2019-nCoV) infected pneumonia (standard version). Mil Med Res. 2020;7(1):4.
10. Muhyiddin M, Nugroho H. A Year of Covid-19: A Long Road to Recovery and Acceleration of Indonesia's Development. JPP. 2021;5(1):1–19.
11. Olivia S, Gibson J, Nasrudin R. Indonesia in the Time of Covid-19. Bulletin of Indonesian Economic Studies. 2020;56(2):143–74.
12. Song W, Wu C. Introduction to advancements of GIS in the new IT era. Annals of GIS. 2021;27(1):1–4.
13. COVID-19 WRP. Peta Risiko [Internet]. covid19.go.id. [cited 2022 Jul 11]. Available from: https://covid19.go.id/peta-risiko
14. Info Penanggulangan COVID-19 Kota Makassar [Internet]. [cited 2022 Jul 11]. Available from: https://covid19.makassarkota.go.id/
15. Satgas Covid-19 Prov Sulsel (@satgascovid.sulsel) • Instagram photos and videos [Internet]. [cited 2023 Feb 25]. Available from: https://www.instagram.com/satgascovid.sulsel/
16. Breunig M, Bradley PE, Jahn M, Kuper P, Mazroob N, Rösch N, et al. Geospatial Data Management Research: Progress and Future Directions. ISPRS Int J Geo-Inf. 2020;9(2):95.
17. Li W, Batty M, Goodchild MF. Real-time GIS for smart cities. International Journal of Geographical Information Science. 2020;34(2):311–24.
18. Leveau CM, Aouissi HA, Kebaili FK. Spatial diffusion of COVID-19 in Algeria during the third wave. GeoJournal. 2022;1–6.
19. Rosenkrantz L, Schuurman N, Bell N, Amram O. The need for GIScience in mapping COVID-19. Health & Place. 2021;67:102389.
20. Lwin K, Hashimoto M, Murayama Y. Real-Time Geospatial Data Collection and Visualization with Smartphone. Journal of Geographic Information System. 2014;6(2):99–108.
21. Gong J, Geng J, Chen Z. Real-time GIS data model and sensor web service platform for environmental data management. Int J Health Geogr. 2015;14(1):2.
22. Chan SRS, Dilangalen DAG, Tan WM. Real-time and Secure Geospatial Data Warehouse for Intelligent Transportation Systems. In: 2020 International Conference on Information and Communication Technology Convergence (ICTC). 2020. p. 741–6.
23. Melin P, Monica JC, Sanchez D, Castillo O. Analysis of Spatial Spread Relationships of Coronavirus (COVID-

19) Pandemic in the World using Self Organizing Maps. Chaos, Solitons & Fractals. 2020;138:109917.
24. Kang D, Choi J, Kim Y, Kwon D. An analysis of the dynamic spatial spread of COVID-19 across South Korea. Sci Rep. 2022;12(1):9364.
25. Franch-Pardo I, Napoletano BM, Rosete-Verges F, Billa L. Spatial analysis and GIS in the study of COVID-19. A review. Science of The Total Environ. 2020;739:140033.
26. Chaudhry N, Yousaf MM, Khan MT. Indexing of real time geospatial data by IoT enabled devices: Opportunities, challenges and design considerations. J Ambient Intell Smart Environ. 2020;12(4):281–312.
27. Yazici M. Spatial Point Pattern Analyses and its Use in Geographical Epidemiology. BBOAJ [Internet]. 2017 May 15 [cited 2022 Jul 16];1(5). Available from: https://juniperpublishers.com/bboaj/BBOAJ.MS.ID.555573.php
28. Gatrell AC, Bailey TC, Diggle PJ, Rowlingson BS. Spatial point pattern analysis and its application in geographical epidemiology. Transaction - Institute of British Geographers. 1996;21(1):256–74.
29. Badan Pusat Statistik Kota Makassar [Internet]. [cited 2022 Jul 9]. Available from: https://makassarkota.bps.go.id/publication/2021/02/26/be312e3f776bcfd005978bda/kota-makassar-dalam-angka-2021.html
30. The Pocket Lamp - Illuminating SARS-COV-2 [Internet]. Hackster.io. [cited 2023 Mar 4]. Available from: https://www.krtkl.hackster.io/dnhkng/the-pocket-lamp-illuminating-sars-cov-2-3a1d17
31. Python Release Python 3.9.12 [Internet]. Python.org. [cited 2023 Mar 4]. Available from: https://www.python.org/downloads/release/python-3912/
32. Sergio J. Rey, Dani Arribas-Bel, Levi J. Wolf. Home — Geographic Data Science with Python [Internet]. [cited 2022 Aug 15]. Available from: https://geographicdata.science/book/intro.html
33. Skyum S. A simple algorithm for computing the smallest enclosing circle. Inform. Process. Lett. 1991 Feb 18;37(3):121–5.
34. Rezaeian M, Dunn G, Leger SS, Appleby L. Geographical epidemiology, spatial analysis and geographical information systems: a multidisciplinary glossary. J Epidemiol Community Health. 2007;61(2):98–102.
35. Kadi N, Khelfaoui M. Population density, a factor in the spread of COVID-19 in Algeria: statistic study. Bull Natl Res Cent. 2020;44(1):138.
36. Cahyadi MN, Handayani HH, Warmadewanthi I, Rokhmana CA, Sulistiawan SS, Waloedjo CS, et al. Spatiotemporal Analysis for COVID-19 Delta Variant Using GIS-Based Air Parameter and Spatial Modeling. Int. J Environ. Res. Public Health. 2022 Jan;19(3):1614.
37. Jesri N, Saghafipour A, Koohpaei A, Farzinnia B, Jooshin MK, Abolkheirian S, et al. Mapping and Spatial Pattern Analysis of COVID-19 in Central Iran Using the Local Indicators of Spatial Association (LISA). BMC Public Health. 2021;21(1):2227.