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Risk mapping and estimation of COVID-19 transmission in South Sulawesi, Indonesia by a self-identification survey

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Abstract

The rapid transmission rate of coronavirus disease 2019 (COVID-19) is multi-factorial but primarily due to population mobility and aggregation. This research aimed at estimating the rate based on risk mapping and investigation of geospatial distribution. It was divided into different phases that included data collection through a self-identification form available online; data validation of the data collected; application of spatial statistics; comparison with official numbers of positive COVID-19; and mapping of the results. The results show that self-identification based on procurement of independent personal data online had an accuracy of 89%.

Introduction

The transmission rate of corona virus disease 2019 (COVID-19) is unusually fast (Gangwar and Champati, 2021). Within one year since the first case was discovered in Wuhan, China at the end of December 2019, the infection according to the World Health Organisation (WHO) was already in 180 countries, where it had infected 270,791,973 people, and killed as many as 5,318,216 (https://COVID19.who.int/). In Indonesia, COVID-19 was first announced on 2 March 2020 and had by 15 December 2020 spread to 34 provinces infecting 4,259,644 people, out of whom 143,969 patients had died (Ministry of Health of Indonesia, 2020).

Surveillance of COVID-19 was rapidly initiated to prevent and slow down transmission. Significantly, this contributed to saving vulnerable populations from infection and helped keeping adequate health facilities available by preventing excessive burdens of hospital intake (Liu *et al.*, 2021). Contact tracing and travel history are essential preventive measures against contact with infected people in high-transmission areas. To support this general goal, we attempted to produce a reliable distribution map of COVID-19 by developing a geospatial platform with an online, self-identification form that people can fill in independently. This information can be compared with data from both provincial and district health offices.

By applying a web-based approach and a geographical information system (GIS), a large area can be mapped and show the changing patterns during this pandemic. It would not only be appropriate by contributing to limiting mobility when needed, but it would also be cost-efficient and timely (Pelucchi *et al.*, 2020). In addition, this approach should help determine epicentres, transmission points and time series of varying transmission strength so that the distribution pattern in an area can be better managed.

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Materials and methods

A spatial analysis was carried out to find the density index of the COVID-19 distribution based on incidence data sourced from the South Sulawesi Provincial Health Office (https://COVID19.sulselprov.go.id.). It was done to give the level of coronavirus transmission throughout the South Sulawesi region to be used as reference for decisions, such as to take immediate action whether or not a place needs a regional quarantine.

This research was divided into five phases that included: i) creation of a space-based COVID-19 self-identification form and using it for data collection; ii) data validation; iii) analysis of the data; iv) mapping of the results; and v) spatial analysis of the distribution of positive COVID-19 cases.

Time and place

The research was conducted between March and December 2020 in South Sulawesi Province, Indonesia, situated around lati-

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tude 4°20' S and longitude 120°15' E. The province covers an area just above 46,717 km^2 with a total population in 2020 of around 9 million people, which makes this province one one of the most densely populated areas in Indonesia.

Data collection

The primary collection included quantitative data through a survey based on self-identification forms posted online and validated (see below) by volunteers. Secondary data were collected from the South Sulawesi Provincial Health Office through its website https://COVID19.sulselprov.go.id.

Forms

Self-identification forms (Figure 1) were used to collect direct information about symptoms experienced by community residents. The data were obtained by survey123 (https://survey123.arcgis.com/share/cdeb9c57367e47df969f3fe394cbf410) available from the Environmental Systems Research Institute (ESRI), Redlands, CA, USA. The form works on smart devices, laptops or desktops capturing and saving data even when disconnected, such as when used in environments far away.

The information asked for people's symptoms; travel to suspected, high-risk transmission areas within the last 14 days; and exposure history (for example, have you been in close contact with someone tested positive for COVID-19 or have you visited any public facility related to COVID-19).

The results garnered from completed forms were used to sort the respondents into high-risk, moderate-risk, low-risk categories including a separate one including those who had visited a high-transmission area. In this way, the filled-in forms can reflect the actual condition of each community.

Inclusion-exclusion limits

Information in forms from people who did not give their cell phone numbers, name or otherwise did not finish filling them properly, was also excluded. Data generated were also not used when it was concluded that if they referred to people with symptoms different from those typical for COVID-19.

Data validation

Volunteers contacted each respondent via telephone to find out about the data provided and symptoms experienced to secure identities and confirm wich category to assign them to. Additional validation was carried out regarding low-risk data and forms that could not be validated directly by telephone. By this validation, the population could be classified into four classes, *i.e.* patients under supervision (PDP = *pasien dalam pengawasan*), if people had upper respiratory tract infection symptoms such as fever, cough, shortness of breath, sore throat *with* history of travel to suspected, high-risk transmission areas within the last 14 days, and had exposure history; people under monitoring (ODP = *orang dalam pemantauan*), if people had upper respiratory tract infection symptoms such as fever, cough, shortness of breath, sore throat *without* history of travel to suspected, high-risk transmission areas within the last 14 days, and had exposure history; people who had visited an area with known COVID-19 infections but had no any symptoms (OTG = *orang tanpa gejala*); and people not suspected for COVID 19.

Spatial statistics

We used kernel density estimation (KDE) to find the density distribution of the COVID-19 distribution based on the validated results. In this way, we could calculate the density probability as its moothly tapered towards points whose values represent the predicted density value (Seaman and Powell, 1996). The following formula determined the KDE:

$$Density = \frac{1}{(radius)^2}\sum_{i=1}^{n}\left[\frac{3}{n}\cdot pop_i\left(1-\left(\frac{dist_i}{radius}\right)^2\right)^2\right] \quad (1)$$

$$For\ dist_i < radius$$

where $i = 1 \ldots n$ is a point; pop_i the field population value at point i; and $dist_i$ the distance between point i and location x,y. We only included points within the 1-km radius of the x, y location.

Accuracy validation

We also investigated the accuracy of the data from the self-identification forms as sourced from respondents by comparing it with the available official data. An assessment of COVID-19 risk was carried out by analyzing the COVID-19 distribution in South Sulawesi Province by mapping the results of the self-identification form using the receiver operating characteristic (ROC) to plot pre-

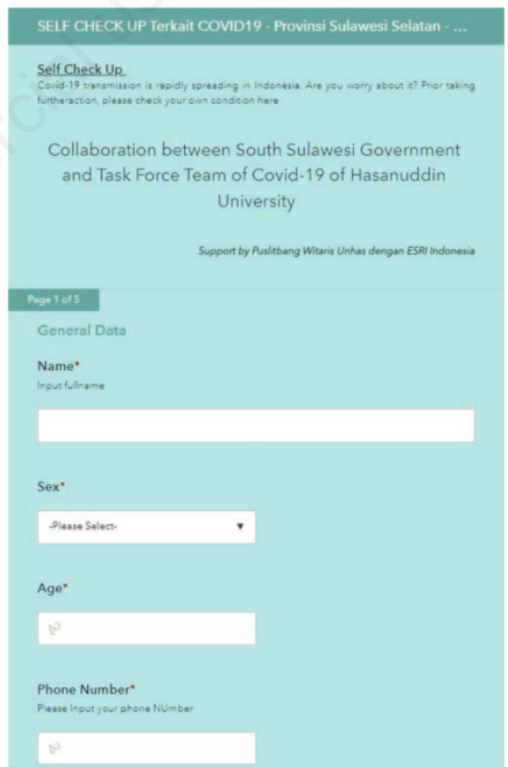

Figure 1. The self-identification forms used the ArcGIS Survey123 App.

dicted probabilities and estimate the model's accuracy. The area under the curve (AUC) measured the overall fit and comparison of model predictions (Soma and Kubota, 2018). It was done by using the map with the correct events in the field from South Sulawesi Provincial Health Office until December 2020. It was done to determine if the COVID-19 map produced could be trusted as reliable.

Results

As many as 18,888 people filled in the self-identification forms and posted the results online. Most forms were received in March 2020, after which the temporal distribution was relatively even (Figure 2). As can be seen from the spatial distribution shown in Figure 3, we did not only receive forms from South Sulawesi residents, but also from outside visitors.

There were 3 steps to find the data - First Data from Self-Identification. We received forms from 18,888 people. These were sorted into four categories: 356 with high-risk, 1967 with moderate risk; 3744 with low risk after visiting areas with COVID-19 transmission; and 12,658 with low risk. Second data from Screening first data with who had not filled in the forms properly as mentioned under the inclusion-exclusion limits, 7465 respondents were left (Figure 4). Third data from direct validation by telephone from second data, only 3692 respondents remained. By confirmation of the data filled into the self-identification form, these 3692 respondents fell into four groups as follows: PDP=71 people; ODP=305; OTG=501 people; and people not suspected for COVID-19 =2815 people (Figure 4).

Based on responding residents in South Sulawesi Province had suspected for COVID-19 infection and for whom validity had been confirmed by our volunteers and also the health centre officers, a mapping was carried out as shown in Figure 5. Although concentrated in the provincial capital Makassar, the 877 respondents with indications of exposure to the infection (PDP, ODP and OTG people) were spread across all districts and cities in the province.

Figure 6 shows the confirmed positive cases (9102) based on COVID-19 mapping from South Sulawesi Provincial Health Office. Moreover, we developed COVID-19 infection susceptibility map by using kernel density estimation from validated self-identification form, which found the highest distribution of COVID-19 (877) in South Sulawesi Province. The high susceptibility index was concentrated on the province capital, Makassar City and the two border regencies, Gowa and Maros (Figure 7).

The COVID-19 susceptibility index mapping was based on the results of self-identification after validation using official information from South Sulawesi Provincial Health Office (https://COVID19.sulselprov.go.id) providing data on COVID-19 positive cases in regencies/cities in South Sulawesi Province. From these data, it can be seen that the highest density of cases was in Makassar City. From the ROC curve, it was found that the accuracy value was 0.89 or 89% (Figure 8), therefore it could be concluded that the self-identification process for detecting positive cases had a high accuracy.

Discussion

The return of self-identification forms by as many as 18,888 people emphasizes the platform as an efficient and effective way to rapidly collect information and identify the COVID-19 conditions in the different communities (Gangwar and Ray, 2021; Langran and DeWitt, 2020; McCall, 2021). The isolation period for patients identified by active surveillance was significantly shorter, about 2-3 days less than the cases found by self-identification.

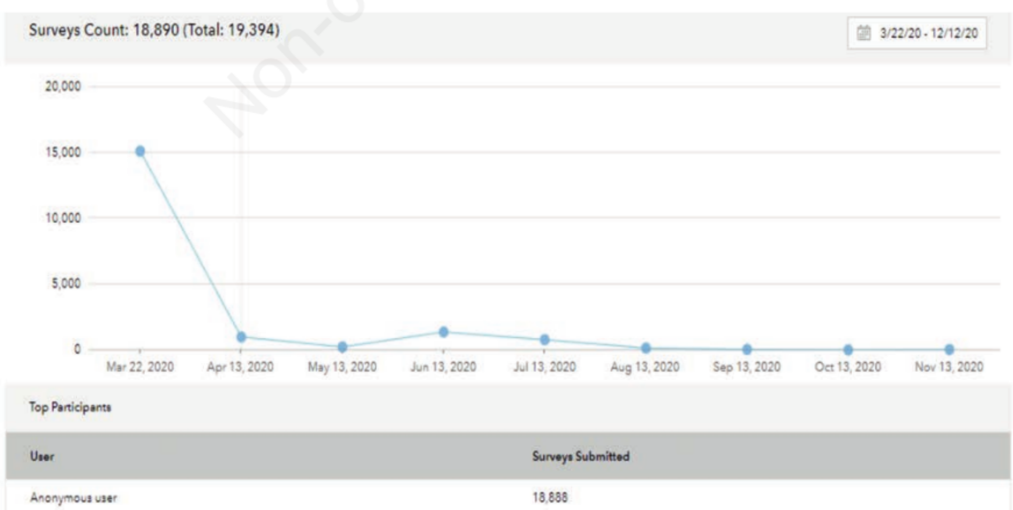

Figure 2. Distribution of incoming data forms over time.

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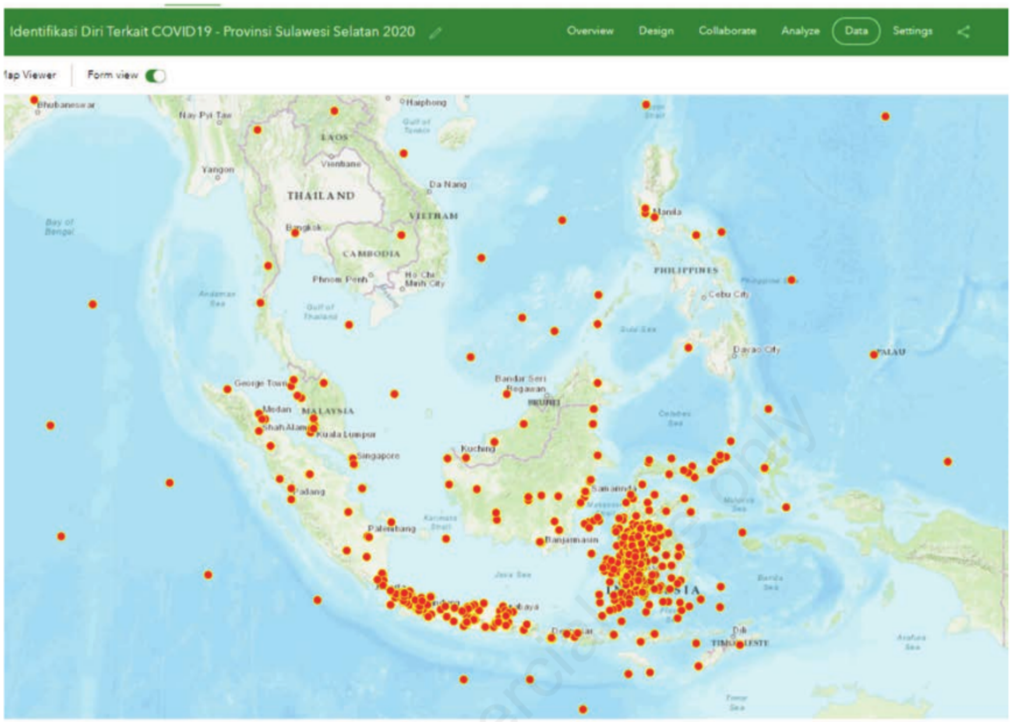

Figure 3. Spatial distribution of incoming data forms.

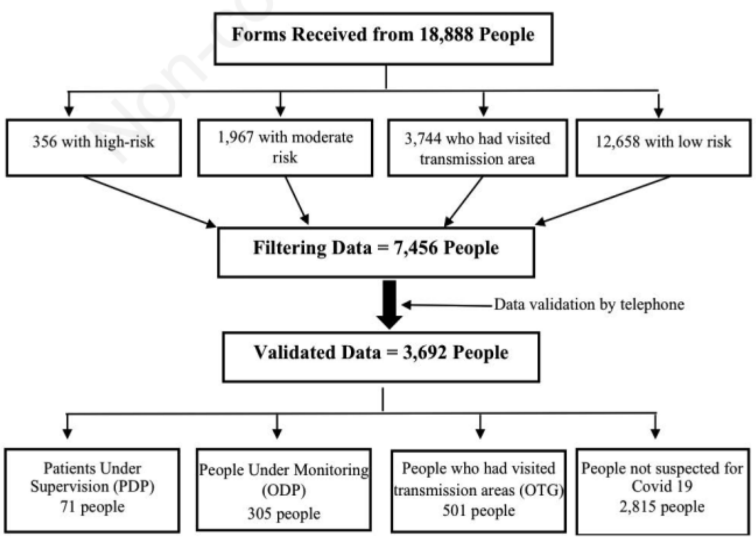

Figure 4. Distribution of respondent data from the beginning to the final validation.

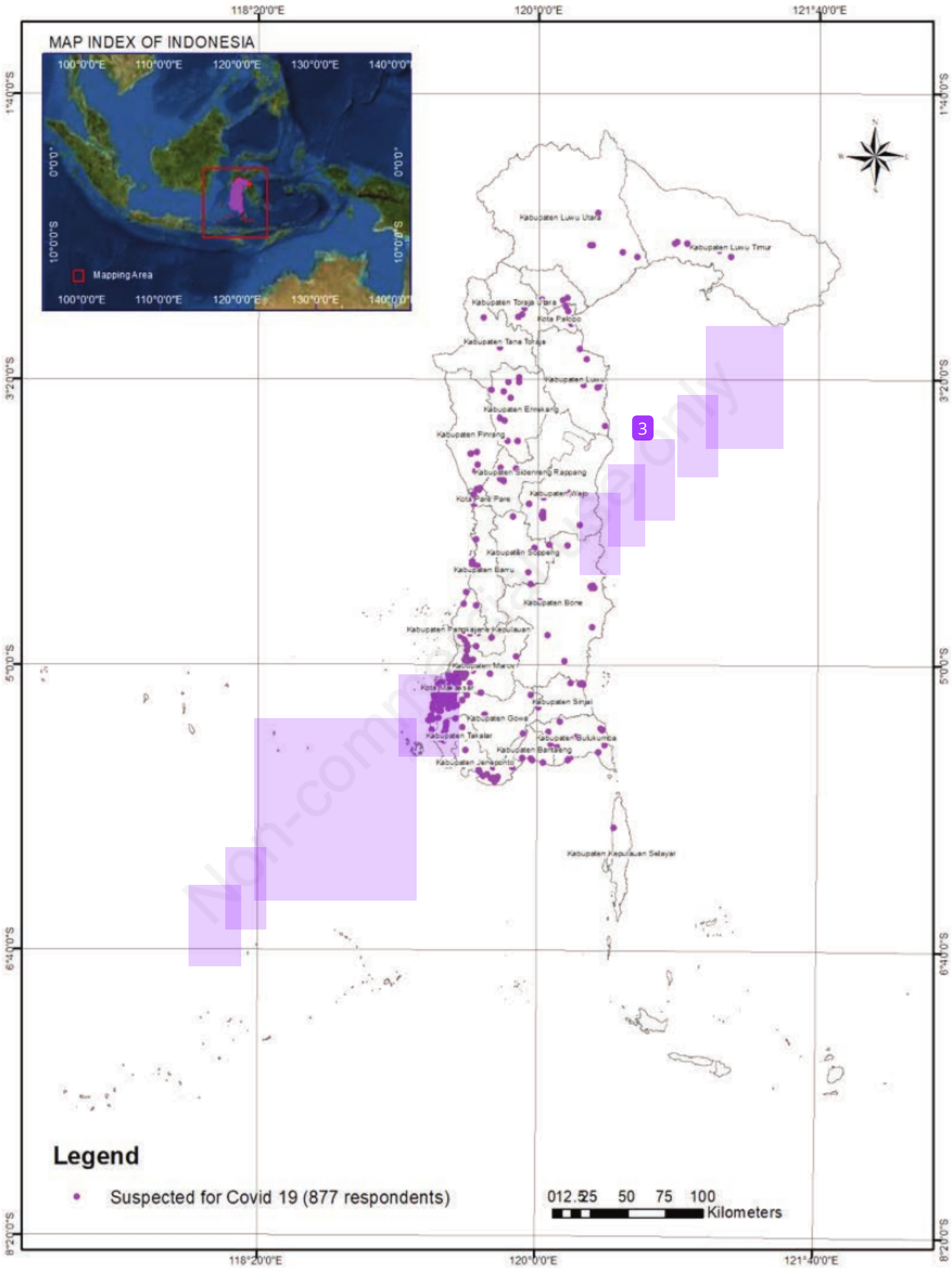

Figure 5. Distribution people in South Sulawesi Province suspected for COVID-19 based on the validation results.

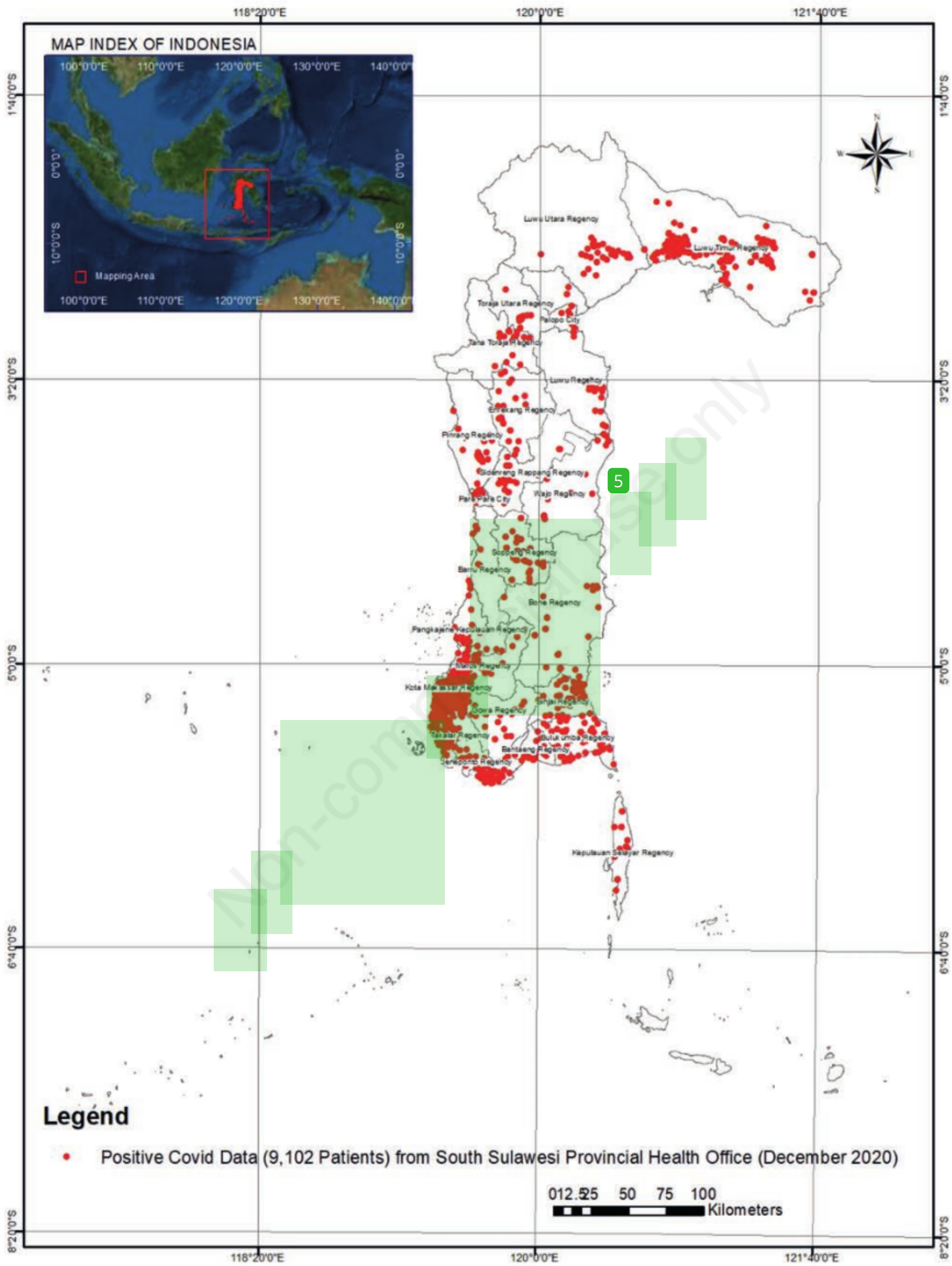

Figure 6. Map of confirmed COVID-19 case distribution in South Sulawesi Province.

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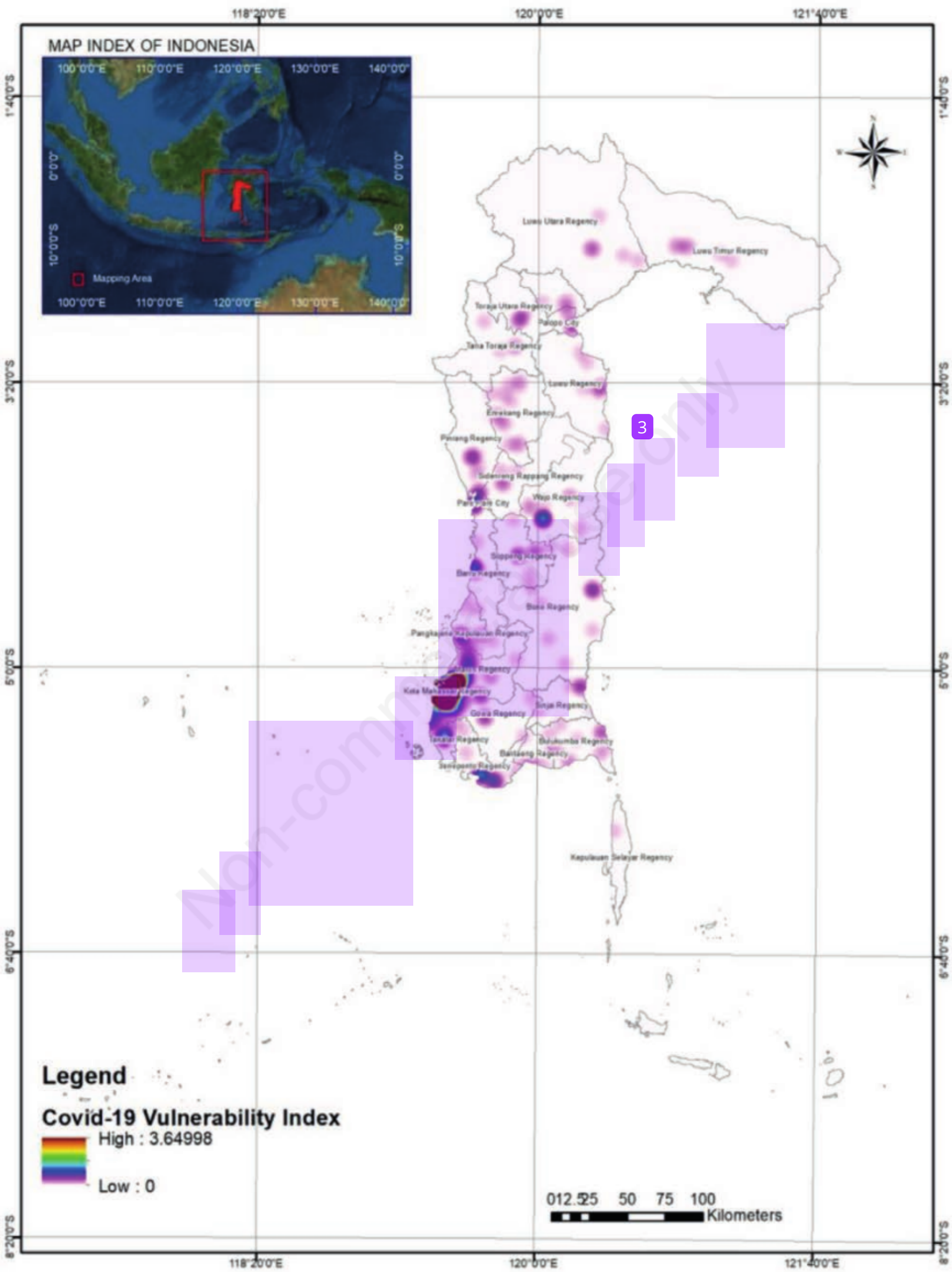

Figure 7. COVID-19 susceptibility index map based on kernel density estimation (KDE) of validated self-identification data.

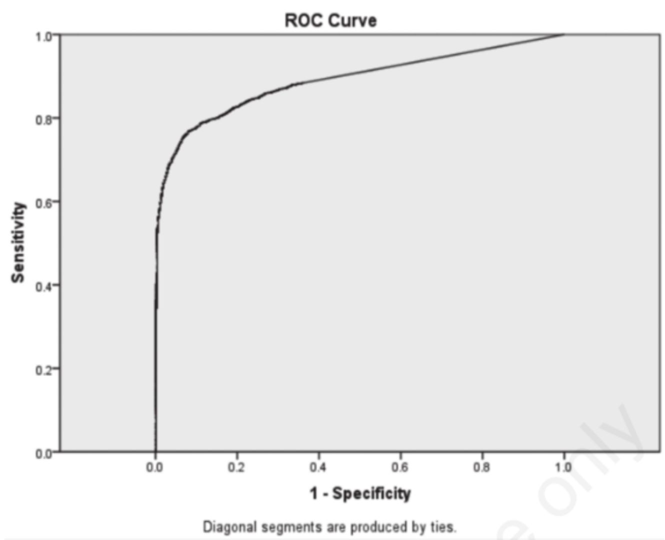

Figure 8. Graph of area under the curve (AUC) for validating the accuracy of COVID-19 vulnerability. The calculations are based on the validated self-identification data.

Based on the results of self-identification validation, it was found that the distribution of 877 respondents, for whom there were indications of COVID-19 exposure, were most common in Makassar City but also spread across all districts/cities in South Sulawesi Province. This information is strengthened through the susceptibility index map of the self-identification data (Figure 7). This geospace-based mapping makes it easier to see the COVID-19 transmission pattern and limited our planned movements as proposed by Gangwar and Ray (2021).

Spatial analysis of COVID-19 distribution aims to elucidate the level of the coronavirus transmission throughout the South Sulawesi region so that it can be used as a reference in making immediate decisions, such as whether or not a place institute a regional quarantine. The KDA approach was used because it has the advantage of transforming a collection of scattered points into a density index, in this case, that of COVID-19 susceptibility (Seaman and Powell, 1996; Setiawan *et al.*, 2016).

Surveying by self-identification provides rapid assessment of the transmission situation of SARS-CoV-2 infection in an area. The accuracy is high as evidenced by the 89% rate based on area-based risk compared to mapping of the confirmed positive cases. The limitation of this study is that self-identification simply refers to population mobility and exposure history, so it should only be used in the intial period of viral transmission growth in an area. Indeed, this rapid assessment model can be a reference for quick assessment of any infectious disease whose information increases with population mobility.

Conclusions

The study results show that positive cases of COVID-19 have spread in almost all districts/cities in South Sulawesi Province, with Makassar having the highest number of cases. The self-identification form based on a geospatial platform that can be filled in online accurately describes the state of positive COVID-19 patients in the province. Thanks to its high accuracy rate, the COVID-19 susceptibility index map based on validated self-identification data can be used as reference in handling COVID-19.

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