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Spatial distribution of COVID-19 cases, epidemic spread rate, spatial pattern, and its correlation with meteorological factors during the first to the second waves

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ABSTRACT

Currently, many countries all over the world are facing the second wave of COVID-19. Therefore, this study aims to analyze the spatial distribution of COVID-19 cases, epidemic spread rate, spatial pattern during the first to the second waves in the South Sumatra Province of Indonesia. This study used the geographical information system (GIS) software to map the spatial distribution of COVID-19 cases and epidemic spread rate. The spatial autocorrelation of the COVID-19 cases was carried out using Moran's *I*, while the Pearson correlation was used to examining the relationship between meteorological factors and the epidemic spread rate. Most infected areas and the direction of virus spread were predicted using wind rose analysis. The results revealed that the epidemic rapidly spread from August 1 to December 1, 2020. The highest epidemic spread rate was observed in the Palembang district and in its peripheral areas (dense urban areas), while the lowest spread rate was found in the eastern and southern parts of South Sumatra Province (remote areas). The spatial correlation characteristic of the epidemic distribution exhibited a negative correlation and random distribution. Air temperature, wind speed, and precipitation have contributed to a significant impact on the high epidemic spread rate in the second wave. In summary, this study offers new insight for arranging control and prevention strategies against the potential of second wave strike.

Introduction

The COVID-19 pandemic has hit almost all countries over the world and made deterioration of our health system, economy, and society [1]. Recently, the world is facing a stronger second wave of COVID-19 transmission and a new variant of COVID-19 mutation, despite several countries have been gradually recovered from the first wave, it still needs more concern about the potential of second wave strike. In Indonesia, the COVID-19 outbreak was started from a finding of 2 confirmed cases on March 2, 2020. The number of cases drastically increases to 17,025 cases on May 16, 2020, which is considered as the first wave period. In response to that, the Indonesian government sets the large-scale social restriction (LSSR) policy to suppress the number of cases. During this policy period, it has significantly reduced the daily new cases within this country. However, after the withdrawal of the policy, the daily cases begin to increase again and lead to accumulative cases reach to 271,339 cases on September 26, 2020. This strong second wave steadily increases to 643,508 cases on December 17, 2020. In the Sumatra region, the South Sumatra Province is one of the highest provinces of COVID-19 cases. The capital city of this province, Palembang, has the highest number of COVID-19 cases. The outbreak rapidly transmits across the districts only in few days.

The second wave of COVID-19 has been reported in some countries around the world. For instance, several authors have studied the second wave of COVID-19 in China [2], Italy [3], Iran [4], South Korea [5], and Vietnam [6]. Many possible factors can be listed that associate with increasing of magnitude COVID-19 cases in each country during the second wave, but a definite factor is still unknown. This is because every country has distinct policy, environmental condition, social, and cultural characteristics that may affect the COVID-19 incidences. If we looked at the previous studies during the first wave period, many studies have agreed that

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meteorological factors such as temperature [7,8], humidity [9], sunshine hour [10], precipitation [11], wind condition [12], and air quality [13] can be an important factor for the COVID-19 spread. Furthermore, the population density and geographical factors can also be related to the COVID-19 spread [14,15]. However, a new study that analyzes the spatial distribution of COVID-19 cases, epidemic spread rate, spatial pattern during the first to the second waves is still sparse. Furthermore, the relationship between meteorological factors and the epidemic spread rate is a prominent key to identifying the possible factor that leads to the stronger second wave in a particular area.

Indonesia has two seasons as dry and wet seasons. The wet season is started from October to February, during this period, we will observe a high amount of rainfall. The second wave which occurs during the wet season may give an opportunity for the virus to survive longer than usual. Temperature and wind conditions also drop during the wet season and human endurance generally decreases during the wet season thus make them susceptible to become sick. Based on these assumptions, we want to explore what possible contributors in increasing the number of COVID-19 cases during the second wave based on changes in meteorological factors. Hence, in this study, we aimed to analyze the spatial distribution of COVID-19 cases, epidemic spread rate, spatial pattern during the first to the second waves. More specifically, we investigated the association between meteorological factors and the epidemic spread rate. The output of this study suggest providing new insight for mitigating the potential of the second wave of COVID-19.

Material and methods

Study area

The South Sumatra Province is one of the mega provinces in Indonesia which locates in the southeast of the island of Sumatra (2°59′10″ South latitude and 104°45′20″ East longitude). The province has 17 administrative districts and covers around 91,592.43 km^2. Palembang is the capital city of this province which has the highest population around 1.66 million residents with a population density of 4200/km^2. The province is the 9th rank of the densely populated province in Indonesia. The total of COVID-19 cases in this province is around 24,611 cases and death cases around 1235 cases on June 3, 2020. To control the outbreak, the authority has implemented the large-scale social restriction (LSSR) policy after the first wave strike, but the current cases start to increase again after the policy is over. The study area and daily cases anomaly of COVID-19 are shown in Figs. 1 and 2.

Data collection

The cumulative number of COVID-19 cases data of the South Sumatra Province in three different dates such as August 1, September 1, and December 1, 2020 were obtained from The Department of Geospatial Palembang (http://geoportal.sumselprov.go.id/). To avoid the unreliable result of analyzing COVID-19 cases data, we provided the testing capacity information within the study area. According to the official report, the testing capacity in the study area during the first period was around 3500 tests per week, then increased to 12,810 tests during the second wave. If we compared to the WHO standard which recommended performing one test per 1000 population per week, the test capacity in the study area has been above the WHO standard.

The meteorological data such as air temperature and precipitation were obtained from the NASA website on the same dates (https://giovanni.gsfc.nasa.gov/giovanni/). For the air temperature data, we acquired from the MERRA-2 Model satellite with daily observed data at spatial resolution 0.5° × 0.625°. The precipitation data were acquired from the Global Precipitation Measurement Mission (GPM) satellite with the daily observed data at spatial resolution 0.1°. The wind condition data were obtained from the Meteorology, Climatology, and Geophysic Agency of Indonesia (https://dataonline.bmkg.go.id/home).

Spatial distribution analysis

The spatial distribution analysis was used to analyze how the distribution of total COVID-19 cases in all districts within the South Sumatra Province. Therefore, we used ArcGIS software version 10.2 to create the spatial distribution map in the study area. The spatial distribution analysis was created by entering the COVID-19 cases data into the attribute table for each districts's shapefile. The conversion from feature to raster could be used to analyze the data in more detail in the form of a raster file. Finally, the spatial distribution maps were classified into five classes of the cumulative number of COVID-19 cases such as 0, 1–50, 51–100, 101–300, and >300 persons. Furthermore, for the meteorological data, because we have already obtained the air temperature and precipitation data in raster format. The next step, we reinterpolated the pixel values using the kriging method to obtain the smoothest raster map.

Epidemic spread rate analysis

We used the total of COVID-19 cases as a variable to measure the epidemic spread rate in the study area. To avoid the bias effect due to the large coverage area, the total COVID-19 cases were divided into several number of days (<1, 1–3, 3–5, 5–7, and >7 persons/day) to determine the epidemic spread rate. The formula of epidemic spread rate was obtained from the previous study Xie et al. [16] as specified below.

$$Vi = \frac{Si}{M - Ni} \quad (1)$$

Where *Vi* indicated the epidemic spread rate in particular area *i*, *Si* indicated the total number of COVID-19 cases in particular area *i* by August 1 (for the first wave) or December 1 (for the second wave), *M* indicated August 1 or December 1, and *Ni* indicated the date of the first positive case was detected in particular area *i*.

Spatial autocorrelation analysis

The spatial autocorrelation analysis measured how one unit was in comparison with other nearby units [17]. The spatial autocorrelation was prominent because the statistics depended solely on investigations being independent of one another. If autocorrelation existed in a map, then it rejected the fact that the investigations were independent of one another. The global Moran's *I* index was used to measure the global spatial correlation [18]. The spatial autocorrelation analysis could be done using the ArcGIS software under spatial statistics and analyzing pattern tool. In the ArcGIS software, we used the default settings to run the spatial autocorrelation analysis such as conceptualization set at an inverse distance, distance method set at euclidean and distance threshold at 0.7751°.

Pearson correlation and windrose analysis

The Pearson correlation analysis was a statistical measure that used to analyze the relationship between the meteorological variables and the epidemic spread rate. To predict most infected areas and the direction of virus spread we used the wind rose analysis using the WRPLOT View software. The software used some inputs such as hourly wind direction and wind speed of the study area.

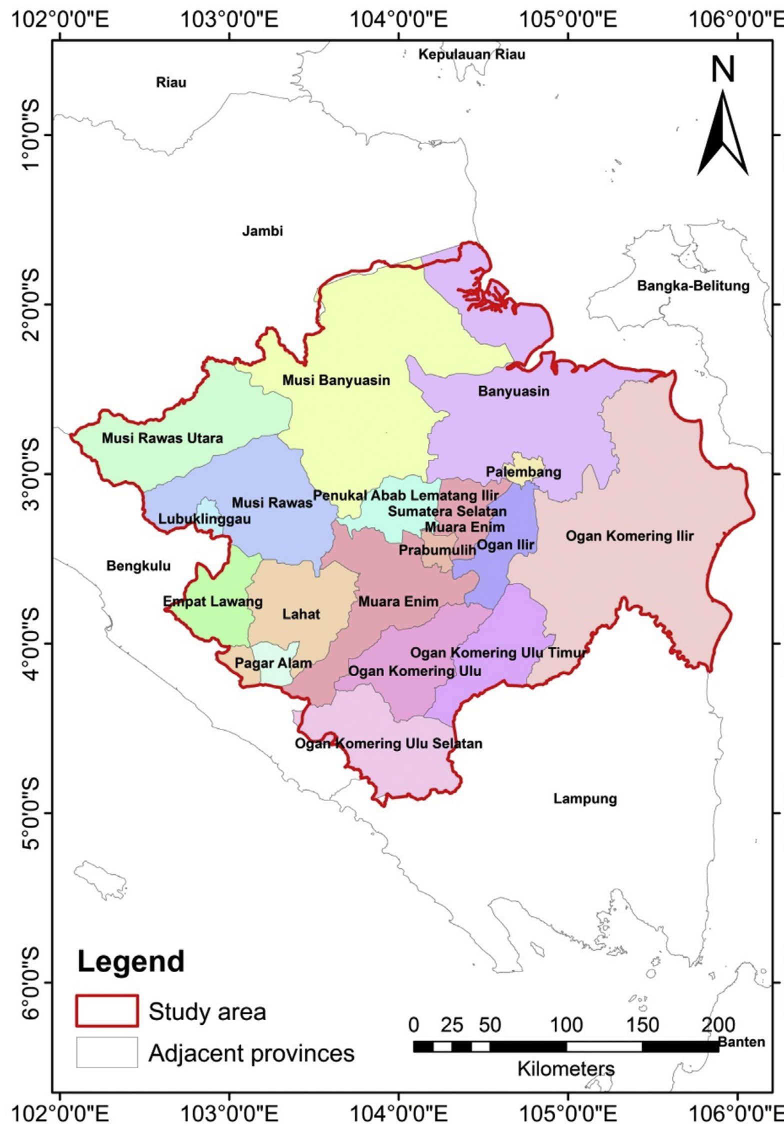

Fig. 1. Location of study area.

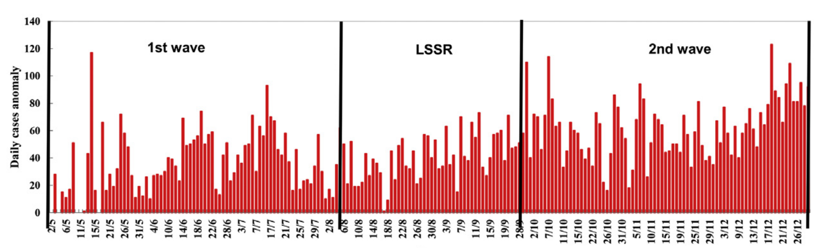

Fig. 2. Daily cases anomaly of COVID-19 in the study area.

In this study, the output from wind rose analysis was related to COVID-19 cases distribution in the study area to estimate the possible affected areas of COVID-19 impact in accordance with wind direction during the studied period.

Results

Spatial distribution of COVID-19 cases and epidemic spread rate

According to Fig. 3, the number of district units with total COVID-19 cases of more than 300 persons on August 1 was 1. Subsequently, on September 1, the number of cases of more than 50 persons was 5 and increased to 11 districts on December 1 which indicated the beginning of the second wave. Spatial distribution map showed the areas with a high number of cases (red color) scattered in several districts such as Palembang, Banyuasin, Musi Banyuasin, Prabumulih, Muara Enim, Penukal Abab, Lahat, and Lubuk Linggau. The highest total cases of COVID-19 was in Palembang district with 4150 cases, while the lowest number of cases was found in the Ogan Komering Ulu Selatan district with 29 cases.

The spatial variation of the epidemic spread rate was divided into two periods. The first wave period showed there was 1 district

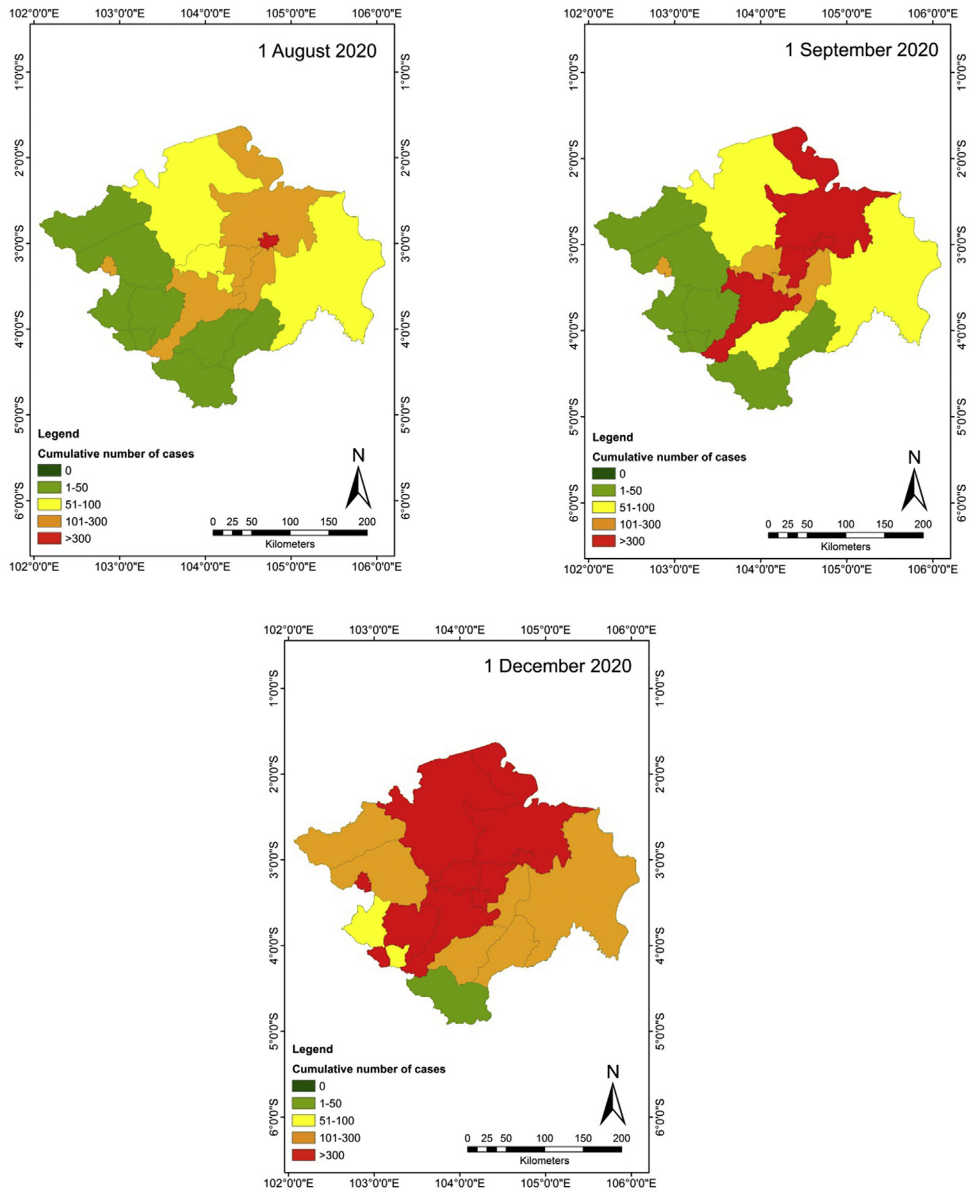

Fig. 3. Spatial distribution of the total number of COVID-19 cases in the study area from the first to the second waves.

unit with an epidemic spread rate higher than 7 persons per day, 3 districts in the range of 1–3 persons per day, and 12 districts were lower than 1 person per day. The epidemic spread rate in the second wave period was greater than the first wave, estimating an increase of 52.94%. There were 4 district units with an epidemic spread rate higher than 7 persons per day, 2 districts in the range of 3–5 persons per day, 8 districts in the range of 1–3 persons per day, and 4 districts were lower than 1 person per day. Furthermore, the average epidemic spread rate was raised from 2 persons per day (the first wave) to 5 persons per day (the second wave). As a whole, the COVID-19 spread rate increased toward the perimeter with Palembang district as the epicenter. In contrast, the lowest values were found in the east, south and southwest of the South Sumatra Province.

Spatial autocorrelation analysis

Table 1 revealed the global Moran's *I* index of the total COVID-19 cases on August 1, September 1, and December 1 were −0.01, −0.01, and −0.10, respectively, and they were not statistically significant ($P > 0.05$). These values showed a negative correlation, indicating the dissimilar values clustered together in a map. We also found that the index value first was constant and then increased at the end date of observation. The global Moran's *I* index raised by 0.09 units on December 1 compared with September 1. The global Moran's *I* index, P-value, and Z score of the epidemic spread rate during the second wave were −0.10, 0.58, and −0.54 respectively, and they were not statistically significant ($P > 0.05$). In summary, the global Moran's *I* index and P-value of the epidemic spread rate in the second wave period were greater than the first wave period. According to the global Moran's *I* index value in both periods, we obtained the spatial pattern of the epidemic spread rate was classified as a random distribution (Fig. 4).

The association between meteorological factors and COVID-19 spread

The spatial distribution of precipitation and air temperature in the study area is shown in Fig. 5. There was an increase in the amount of precipitation from the first to the second waves. The

Table 1
Global Moran's *I* index of the total cases of COVID-19 and epidemic spread rate.

Variable	1 Agst 2020	1 Sept 2020	1 Dec 2020	Spread rate (1st wave)	Spread rate (2nd wave)
Moran's *I*	−0.01	−0.01	−0.10	−0.01	−0.10
P value	0.47	0.53	0.58	0.47	0.58
Z-score	0.71	0.62	−0.54	0.71	−0.54

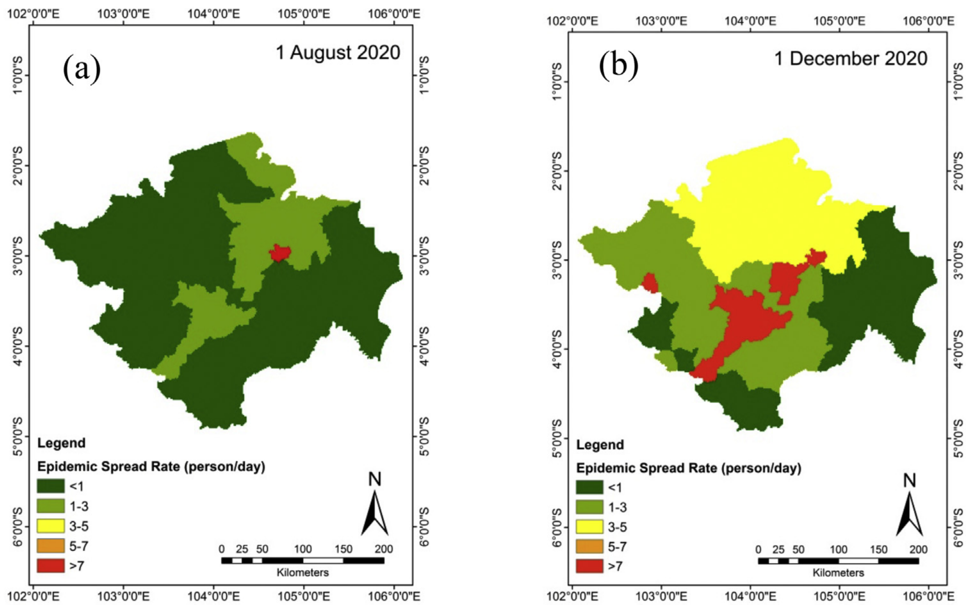

Fig. 4. Spatial distribution of the epidemic spread rate in the study area from (a) the first to (b) the second waves.

Table 2
Pearson correlation between the epidemic spread rate with the meteorological parameters during the first to the second waves.

	Meteorological parameters		
	Precipitation	Air temperature	Wind speed
Pearson's correlation, *r*	0.11	−0.26[a]	−0.30[a]
P value	0.07	0.04	0.02

[a] Correlation is significant at the 0.05 level (2-tailed).

mean value of precipitation increased from 101.2 mm (the first wave) to 338.4 mm (the second wave). It might be due to the shifting of the dry-to-wet season transition. In contrast, we found a decline in air temperature during the first to the second waves. The mean value of air temperature in the first wave recorded at 26.8 °C and then decreased to 24.6 °C in the second wave. In summary, there was a 6.4% reduction in air temperature in the study area during the period. The highest precipitation and air temperature were distributed in the northeast to southeast parts of the study area.

Furthermore, Fig. 6 showed the wind direction and speed which were described by the windrose diagrams during the first and the second wave in the study area. The wind rose diagram exhibited the wind direction blew to the east part of the study area during the first wave, while it blew to the west during the second wave. Furthermore, the strong COVID-19 spread observed in the second wave indicated that the dominant wind direction blew to the west with low wind speed in the range from 2.10 to 3.60 m/s. To analyze deeper the association between precipitation, air temperature, and wind speed with the COVID-19 spread, we have used the Pearson correlation analysis. The result of the Pearson correlation analysis could be seen in Table 2. Table 2 revealed that air temperature and wind speed had a negative significant correlation with the epidemic spread rate ($r = -0.26$, $r = -0.30$; $P < 0.05$, respectively). Furthermore, the precipitation showed a low correlation but not statistically significant with the COVID-19 epidemic spread rate.

Discussion

Our study examined the spatial distribution of the number of COVID-19 cases and epidemic spread rate in the South Sumatra Province of Indonesia. A small number of areas with more than 300 cumulative cases was discovered during the primary development stage of the epidemic (August 1) in the study area, suggesting that most infected people could not be detected because the virus was at the incubation time. The increase in the number of cases in areas (from September to December) reflected the outbreak rapidly spread around the surrounding area. This rapid spread was due to the people's strong cross-local movement. Infectious disease spread was when a pathogen moved from a host through some contagion ways to approach and attack a non-infected person [19]. Due to the major movement of the population in the Palembang district, the spatial distribution of cumulative cases that linked to the Palembang district at an early transmission of COVID-19 was scattered. This was the reason why the spatial distribution of cumulative cases in the study area was random. Subsequently, with the implementation of social restrictions carried out by the government, the cumulative cases were more clustered. Between September and December, the kind of aggregation in the spatial distribution of COVID-19 cases was 101–300 cases and was scattered in a ring around the Palembang district. This was because the COVID-19 outbreak was concentrated in this district. Thus, this ring area was a prominent factor for the control and prevention of the outbreak.

Moreover, the COVID-19 epidemic spread rate was estimated to decrease toward the perimeter with the area of Palembang as the

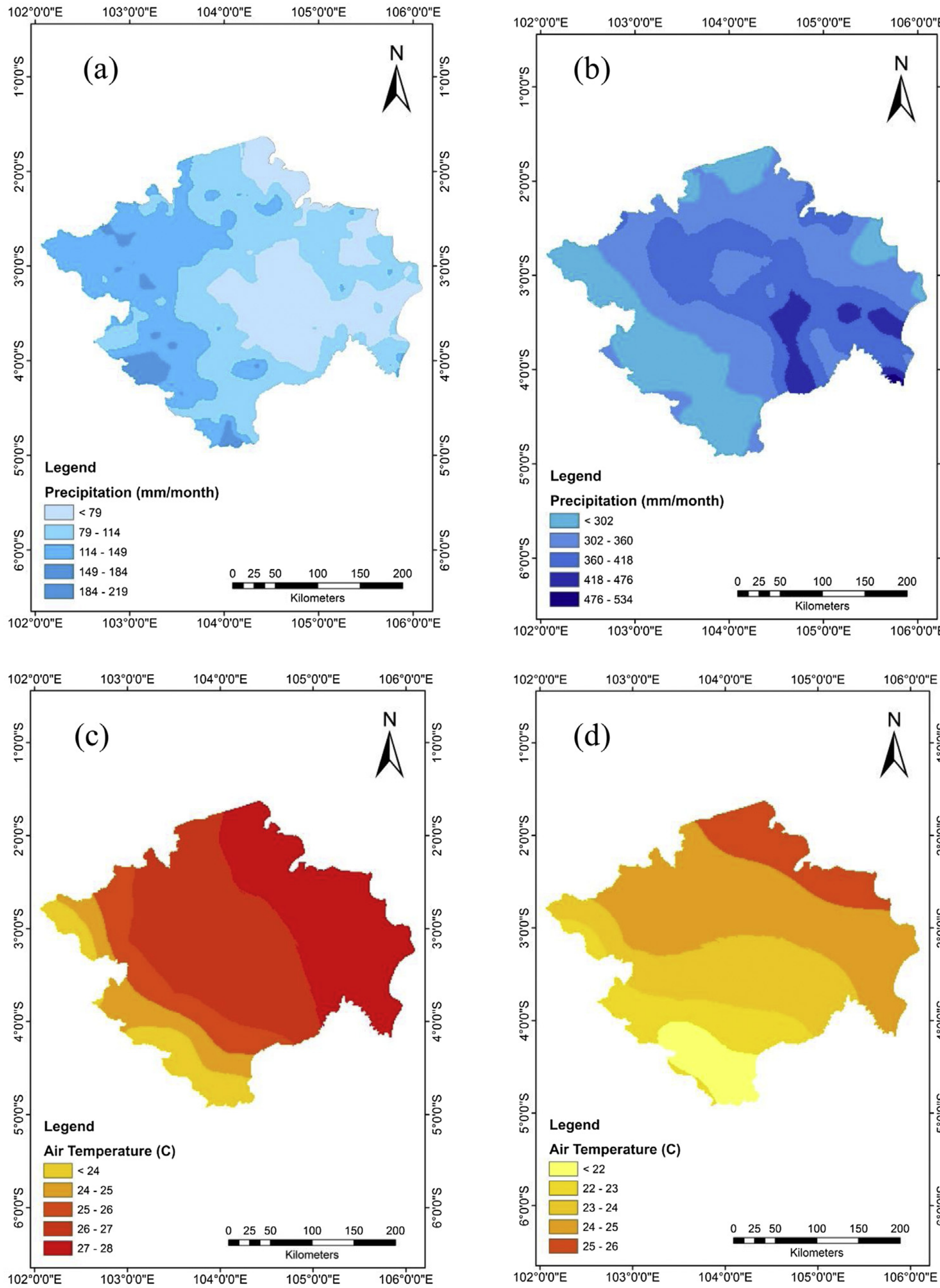

Fig. 5. Spatial distribution of the precipitation and air temperature in the study area, (a) the precipitation in the first wave, (b) the precipitation in the second wave, (c) the air temperature in the first wave, and (d) the air temperature in the second wave.

epicenter, with the high number of cases was found in the dense urban areas. In contrast, the rural areas tended to record lower cases that commonly distributed in the east, south, and southwest of the South Sumatra Province. This is the reason why the spatial pattern in the study period was characterized by the decentralized expansion trend. This result was consistent with another study in the mainland of China by Xie et al. [16] who obtained that the epidemic spread rate reduced toward the perimeter with the Wuhan city as the center of the epidemic. If we looked at the global Moran's *I* index, the clustering degree of the second wave was greater than the first wave. Although in this study we obtained a slight increase and low association of Moran's correlation. But the other studies also showed similar results For instance, Han et al. [20] have found the trend change characteristics of Moran's *I* index slightly raised from 0.007 to 0.013 in Beijing, China. Another study by Wang et al. [21] also revealed the trend of Moran's *I* index values in 31 provincial-level areas of China slightly increased from 0.01 to 0.17. Based on this comparison, we estimated that the average of the Moran's *I* index of the number of COVID-19 cases just slightly increased all over the world.

In this study, we also investigated the association between meteorological factors and COVID-19 epidemic spread rate using the Pearson correlation test. According to previous studies, the environmental and meteorological parameters could indicate patterns in the expansion of infectious diseases on a large scale such as close contact due to people's movement might greatly govern the transmission of infectious diseases [22]. During the development of COVID-19 in the South Sumatra Province, there was an association between air temperature, wind speed, precipitation, and the epidemic spread rate. But, the association between meteorologi-

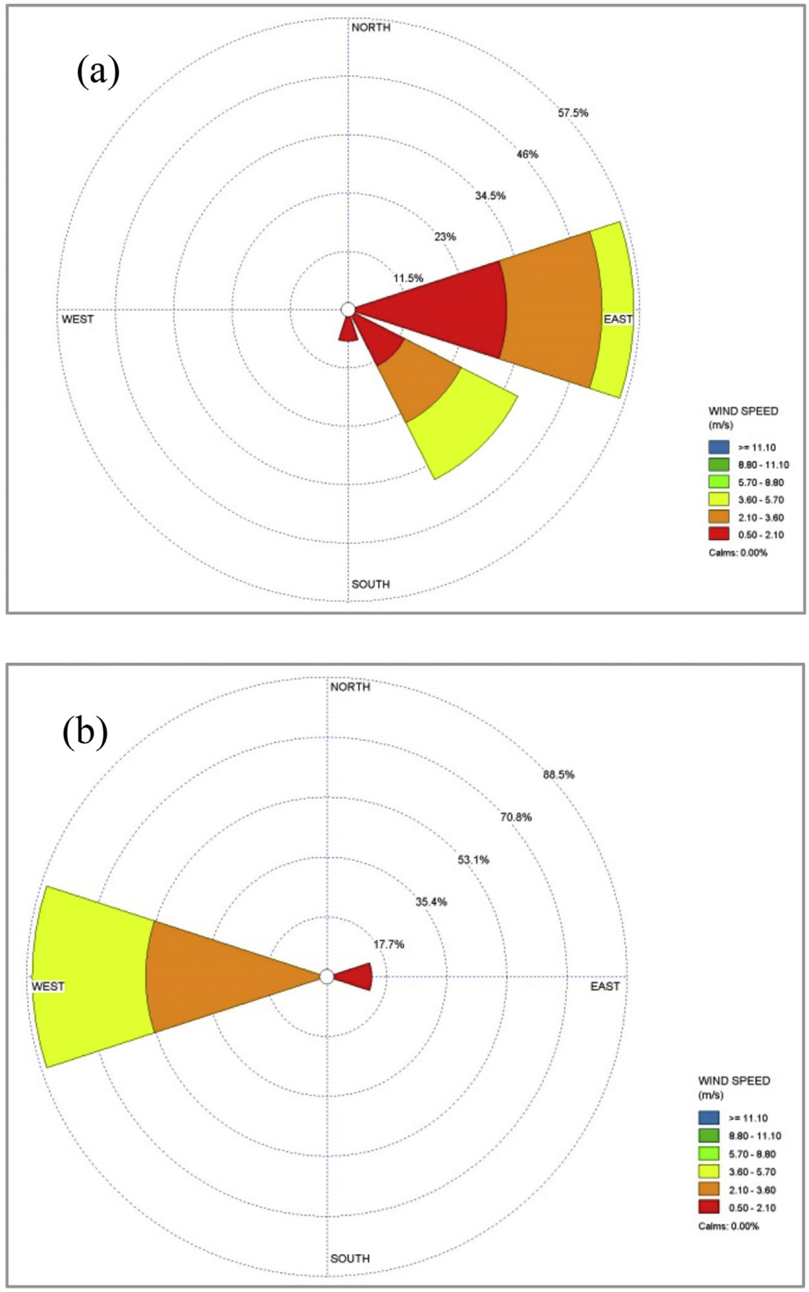

Fig. 6. Wind rose diagram and its response with COVID-19 cases distribution in the study area during (a) the first and (b) the second waves.

cal factors and pandemic development might alter in the different studied periods. The negative correlation between the epidemic spread rate with air temperature and wind speed, and the positive correlation between the epidemic spread rate and precipitation (Table 2), suggesting that air temperature, wind speed, and precipitation in the study area aggravated the spread of COVID-19 during the second wave period. However, several cases might have transmitted to remote areas due to the adversity in discovering new cases and the delay in preventing and controlling policies. This situation might have reduced the correlation between the epidemic spread rate and meteorological factors in the study period. In the second period, with the further expansion of COVID-19, the effect of air temperature and precipitation exacerbated again (Fig. 5). In addition, the population density and movement of people in public places also could intensify the number of cases in certain areas [20]. Here, the control and prevention policies were mainly needed.

The evidence of a correlation between air temperature and COVID-19 incidences has been widely reported by previous studies. A previous study in Jakarta, Indonesia has obtained a significant correlation between air temperature and COVID-19 cases [23]. Average air temperature also had asignificant correlation with the COVID-19 outbreak in New York, USA [24]. In general, the temperature had a significant variation of seasonal behavior of respiratory diseases [25]. In China, the meteorological data were important parameters to be associated with COVID-19 diffusion. The higher temperature condition would tend to suppress the virus [26].

Furthermore, the meteorological factors could be related to environmental stability and the viability of the virus. The wind speed was one of the important parameters associated with the

COVID-19 cases. The wind speed in the study area during the study period was categorized as low level and had a negative correlation with the epidemic spread rate. This result was in line with the previous studies. In Italy, several cities with high wind speed tended to have a lower number of COVID-19 cases [3]. High wind speed could improve the diffusion of COVID-19 and decrease the risk of the COVID-19 spread around the cities. However, in the low wind speed areas, the number of COVID-19 cases was more found. Our previous study [12] and the other study by Sahin [27] revealed low wind speed was significantly associated with the virus stayed longer in a particular location and easily infected more people in a certain area.

The precipitation values in the study area showed an escalation from the first to the second wave period (Fig. 5(a), (b)). Although we obtained a low positive correlation between the precipitation and the epidemic spread rate (Table 2), we believed both variables were closely related to each other. The high amount of precipitation usually associated with low air temperature and wind speed. As a whole, our main findings predicted that meteorological factors such as air temperature, precipitation, and wind speed had a direct role in the stronger second wave of COVID-19 in the study area. This study had some limitations such as many possible factors were needed to be analyzed before we decided on the best strategy against the second wave of COVID-19 such as virus mutation, vaccination, people immunity, treatment, and lockdown policy type for future works.

Conclusions

Based on the epidemic spread rate analysis, the epidemic rapidly spread to most districts from August 1 to December 1. The epidemic spread rate rose sharply from September 1 to December 1. The highest epidemic spread rate was found in the Palembang district and its surrounding districts, which was characterized by a dense population. While the rural areas located in the eastern and southern region tended to show a slow epidemic spread. The spatial correlation characteristic of COVID-19 cases in the study area demonstrated a random distribution. The spatial correlation characteristic that was measured by the global Moran's I index found there was an increase of around 0.09 units on the second wave compared with the first wave, meaning that the clustering degree was higher than the first wave, and the spatial distribution of the COVID-19 cases was characterized by the decentralized expansion trend. Furthermore, the meteorological factors had a significant correlation with the COVID-19 epidemic spread rate which could be associated with the stronger second wave in the study area. The increase in the COVID-19 epidemic spread rate possibly occurred when temperature and wind speed values decreased, while the amount of rainfall increased. In addition, the most infected areas were found fit in with wind direction blew. As a whole, our results could be suggested to arrange the best strategy and control the second wave of COVID-19 spread.

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Competing interests

None declared.

Ethical approval

Not required.

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