Socio-spatial aspects contributing to the spread of COVID-19 in Yogyakarta Province (Indonesia)

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In the early pandemic, the positive cases of COVID-19 predominately occurred in the big cities in Indonesia. However, the virus spread rapidly and extensively across the cities and districts. This shows that the COVID-19 pandemic is limited to urban areas and has spread widely to more remote area This study aims to investigate the correlation between socio-economic characteristics against the spread of confirmed COVID-19 cases. In this study, we collected data from residents with confirmed positive for COVID-19 and their socio-economic profiles in 78 subdistricts in the Special Region of Yogyakarta province, Indonesia. The collected data were statistically analyzed in three sequential steps, including a correlation test, classic assumption test (e. g., normality test, homoscedasticity test, and non-multicollinearity test), and multiple regression test to determine the correlation between the COVID-19-infected population and the socio-economic data in each subdistrict (as dependent variables). The results demonstrated that regions with more urban character, particularly socio-economic, were more susceptible to COVID-19 infection during the first year of the pandemic. However, the socio-spatial aspects such as population density as one of the requirements for the "compact cities" and the proportion of built-up land area were not contributing factors to the viral transmission. Socio-spatial aspects may influence the risk of virus transmission, but not as significantly as social factors and human behavior in an area. Therefore, efforts to prevent the spread of the COVID-19 virus must be more focused on social factors and human behavior.

Keywords: COVID-19, socio-spatial aspect, socio-economic aspect, transmission, Yogyakarta — Indonesia.

1. Introduction

The coronavirus 2019 (COVID-19) disease pandemic has spread to more than 190 countries (WHO, 2021) from November 2019 to March 2020. Indonesia's first free fall was in the country's capital, Jakarta, on March 3, 2020. The first and second cases occurred due to the capital's interaction with foreign nationals. The number of infected people has been increasing dramatically over time. Within one year, 1,511,712 positive cases were reported throughout 36 provinces and affected 514 districts and cities in Indonesia (Fig. 1).

Since the beginning of the pandemic, Jakarta has remained the main epicenter of the COVID-19 spread. Additionally, the region with a large population (such as in Java

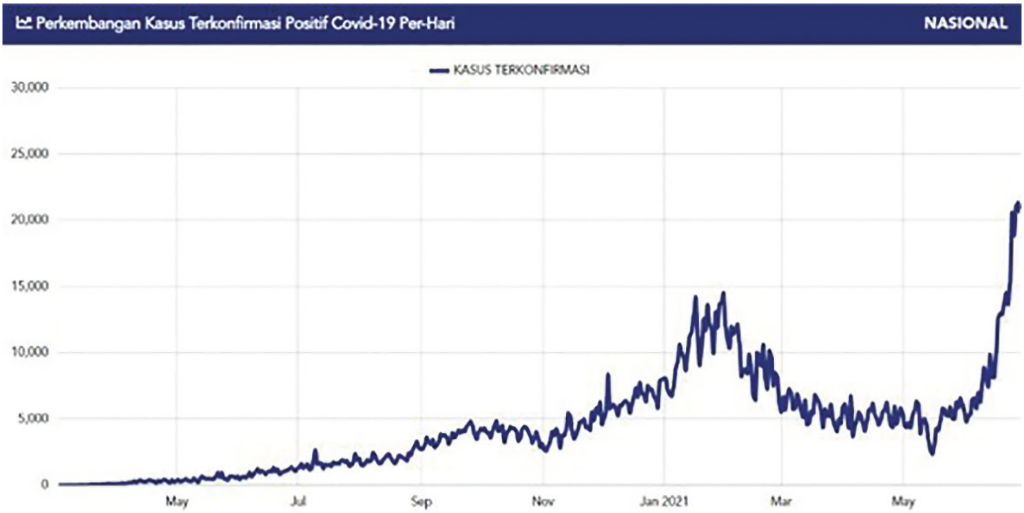

Fig. 1. Growth of COVID-19 in Indonesia as of June 26, 2021
Compiled by: Official Site of COVID-19 Handling Indonesia . Available at: https://covid19.go.id/id. [Accessed 28.02.2021].

Fig. 2. Scattering Pattern of COVID-19 in Indonesia as of December 10, 2020
Compiled by: Official Site of COVID-19 Handling Indonesia. Available at: https://covid19.go.id/id. [Accessed 28.02.2021].

Islands and other major cities) becomes the next epicenter (Fig. 2). It is suggested that the spreading pattern of COVID-19 mainly lies in densely populated cities.

Population density is predicted to be an important factor in the virus spread. It is a fundamental issue in urban design and regional planning because of the coagulation of one of the factors driven by the idea of a compact city for sustainability. The editorial of Botterman (2020) discussed "Corona and Compact City Architecture". A. Sharifi and A. R. Khavarian-Garmsir (Sharifi and Khavarian-Garmsir, 2020) argued that densely populated areas would become hotspots for the rapid spread of the disease.

Nevertheless, several studies conducted in countries such as the United States, Netherlands, Italy, and China discovered a negative correlation between density and COVID-19. Therefore, further study is still required, such as on a more mesoscale region or by noting the difference between gross and net density. Other spatial aspects, such as distance to a main urban center, infrastructure density, and intensity of economic activity, should also be addressed to understand the relationship between COVID-19 and socio-spatial comprehensively.

2. Literature review

Studies performed by (Galanakis, 2020; Wang et al., 2020; Tosepu et al., 2020; Capraro and Barcelo, 2020; Shereen et al., 2020; Byass, 2020; Coccia, 2020; Sun et al., 2020) discovered several factors which influenced the spread of COVID-19, such as meteorological, population density and mobility, and healthcare service and facility. They claimed to do the first study by confirming geographic density and population density on the daily COVID-19 measures of China under the strict lockdown policies.

According to public health experts, there are two factors, micro and macro factors, contributing to the spread of COVID-19. Variables related to droplets and aerosol and close contact among persons are classified as a micro factor, which significantly increases the people-to-people transmission (Manigandan et al., 2020). Other micro factors are allergic immune responses to particular foods, accessibility to health facilities and services, and the prevalence of an invading disease in communities (Randolph and Barreiro, 2020).

Environmental conditions are one of the macro factors affecting COVID-19 spread. Pramanik with the authors (Pramanik et al., 2020) found that temperature seasonality (29.2 % ± 0.9 %) was the highest contribution to COVID-19 transmission in the humid continental region. In comparison, the diurnal temperature range (26.8 % ± 0.4 %) and temperature seasonality (14.6 % ± 0.8 %) had the highest impacts in the subarctic region. Rashed with the authors (Rashed et al., 2020) investigated the correlation between the spread and decay stages of COVID-19 with ambient conditions and population density in 16 prefectures in Japan. They revealed that the population density was predominant factor to deployment rates. In contrast, absolute humidity and higher temperatures led to shorter inequality. K. Biswas with the authors (Biswas et al., 2020) simulated a susceptible — infected — removed model on a Euclidean network by plotting the number of cases against the distance from the epicenter for both China and Italy, demonstrated that the spatial dependence, such as the density of population and travel patterns, played a crucial role in COVID-19 transmission.

Y. Qiu with the authors (Qiu et al., 2020) examined the role of various socio-economic factors in mediating local and cross-city transmission (considering both within and between intercity transmission) based on the data in China between January 19 and February 15, 2020. The result showed that all population flow from the source of the outbreak led to a higher risk to the destination than other factors, such as geographic distance and similarity in economic conditions. Furthermore, K. Allel with the authors (Allel et al., 2020) found that the early implementation of effective and incremental measures was crucial to control the spread of COVID-19 in the early weeks of the pandemic.

For the Indonesian context, a large number of residents in an area is not the main factor in determining the virus transmission in Jakarta but also the interaction between individuals within the community. The mobility within and outside the city contributed to a higher number of positive confirmed cases (Ghiffari, 2020).

Hypothetically, the relationship between the rate of virus spread and the various factors, such as environmental, socio-economic, and socio-spatial factors, can be formulated as follows:

$$Spread = \frac{\left(Interaction \times Env.\ \ Factor\right)}{Immunity \times Measure}\ . \qquad (1)$$

Explanation: Interaction = f (Socio-spatial character, socioeconomic-related population spatial behavior).

Regarding the socio-economic aspect, population behavior describes migratory patterns in the population living inside and outside the area. This character includes gender, education level, occupation, and income level. Conversely, socio-spatial character includes population density; access level to service, which for instance, is indicated by infrastructure density. Therefore, possible mobility and social-economic interaction levels were facilitated by an urban spatial structure such as land use pattern.

Moreover, S. Hamidi with the authors (Hamidi et al., 2020) on over 900 US metropolitan countries did not find a strong positive correlation between COVID-19 infection and mortality rates and population density. W. R. Boterman (Boterman, 2020) also discovered that population density was not associated with infection rates. However, the Netherlands is highly urbanized and densely populated. Conversely, some studies have shown significant relationships between density and the spread of the virus. Y. Qiu with the authors (Qiu et al., 2020) indicated that specific socio-economics and environmental characteristics on transmission rates had an impact on two stages of the epidemic in China, January 19 to February 1 (first phase) and February 2 to February 29 (second phase). Their study revealed that the population density did not significantly correlate with the transmission rate of COVID-19 in the first phase. However, in the second phase, it had a significant negative effect. They recommended public health measures and sharing of intercity resources, which could reduce social interactions and build a substantial correlation in the second phase.

On the contrary, H. Ren with the authors (Ren et al., 2020) discovered that COVID-19 infection in Beijing and Guangzhou likely occurred in high-population density areas. A. Cartenì with the authors (Cartenì et al., 2020) conducted similar research in Italian regions and found that areas with high population density experienced high transmission. Furthermore, twenty Chinese provinces/municipalities also reported a positive relationship between density and spread rates (Lin et al., 2020). C. Connolly with the authors (Connolly et al., 2020) also argued that population density contributed to the spread of various infectious diseases. Conversely, low-density, peri-urban, and suburban areas that have limited access to resources also have a bigger chance of being exposed to new types of viruses and diseases that can be transmitted through human–wildlife interactions (Connolly et al., 2020; Sharifi and Khavarian-Garmsir, 2020).

Other variables that were discussed in the literature are connectivity and the size of the city. Several studies in Wuhan noticed that connectivity is the main factor affecting the disease spread in early outbreaks (Lin et al., 2020; Xie and Zhu, 2020; Wu and

McGoogan, 2020). Similarly, S. Hamidi with the authors (Hamidi et al., 2020) recognized that connectivity is a risk factor for COVID-19 in the United States. Based on A. Stier with the authors (Stier et al., 2020), city size is the critical factor influencing the virus's spread in the United States. Policymakers should protect larger cities more aggressively (Stier et al., 2020). Further studies should be carried out to comprehensively understand city size and the density and prevalence of infectious diseases.

3. Materials and methods

In this study, we collected data from confirmed COVID-19 residents[1] and their socio-economic profiles[2] from 78 subdistricts of the Special Region of Yogyakarta province, Indonesia. The Special Region of Yogyakarta province consists of four districts and one city, which describes as follows: Bantul district (17 subdistricts), Gunungkidul district (18 subdistricts), Sleman district (17 subdistricts), KulonProgo district (12 subdistricts) and city of Yogyakarta (14 subdistricts).

Then, four dependent variables were analyzed, namely:

(1) The number of days between the first case in the subdistrict and the first case nationally (Days to First Case, DFC), which represented external transmission.

(2) The ratio of the infected population per 1000 populations in the subdistrict on September 30, 2020 (Cases per 1000 Population, C1000) represented the intensity of transmission.

(3) The exponential growth of transmission from the first day of infection to December 10, 2020 (Exponential Growth Rate, G).

(4) The exponential growth of transmission since the first day of infection until December 10, 2020, per 1000 population (Exponential Growth Rate per 1000 population, G1000).

December 2020 was the early stage of COVID-19 pandemic with relatively uniform policies in the form of large-scale social restriction regulations, which resulted in remote learning and working activities as well as strict restrictions on social and commercial service and religious activities. Additionally, strict restriction on interregional movement, such as during the Eid-Fitr celebrations, was implemented. In January 2021, the restriction policy became more relaxed. If there was one, the order to comply with it began to decline. Furthermore, 29 independent variables represented location characteristics such as distance to the main urban center, built-up area, and land use characteristics, including the dominance of the type of use and its intensity. The data on the variety of these independent variables is shown in Appendix A–D[3].

Data were statistically analyzed by Phyton and Statistical Product and Service Solutions (SPSS) software. Phyton was employed to analyze the correlation, direction, and power between two variables using the Chatterjee New Coefficient of Correlation (CCC). It has a very simple asymptotic theory under the hypothesis of independence, which is roughly valid even for a small sample size, $n = 20$ samples (Chaterjee, 2021). It also can identify whichever X variables correlate with Y variables. The standard coefficient value ranges from 1 to –1. Value 1 indicates a strong positive correlation in which the increased value of variable 1

[1] Obtained from the provincial government website: www.corona.jogjaprov.go.id.

[2] Obtained from the Central Statistics Agency of Indonesia report.

[3] Here and below, Appendix A-D can be found at the link: https://escjournal.spbu.ru/article/view/13364/10600. Appendix A–D is given in the author's edition.

increases the value of the Y variable. Value –1 indicates a strong negative correlation in which the increased value of variable 1 decreases the value of the Y variable. A zero coefficient indicates no correlation. Next, the correlated X variables were analyzed using multiple regression analysis using SPSS to investigate the simultaneous effects of X variables against Y variables.

Then, the multiple regression test with a method of entry was performed to analyze the association between a single dependent variable and several independent variables. All the independent variables were calculated by using equation (2). All variables were computed into the regression equation in ArcGIS, followed by spatial regression analysis. Spatial regression analysis is conducted by inputting the regression equation from the SPSS analysis results into a new field in ArcGIS. All data obtained (Appendix A–D) is inputted into ArcGIS. The Table will be formed as a field with attributes in the form of data which are the variables of this study, namely Y (independent variable) and X (dependent variable). The result is each regression equation's value by utilizing the feature field calculator in ArcGIS and inputting the regression equation from the SPSS calculation. Then, these results become the value of each spatial unit (in this case, the district) on the map. The maps showed the spatial distribution of the analyzed data.

4. Result and discussion

4.1. Influence of socio spatial aspect variables on the spread of COVID-19

29 socio-spatial characteristics variables were analyzed using the Chatterjee New Coefficient of Correlation (CCC) (Table 1[4]). We found 26 independent variables that met the requirements to estimate the impacts of these variables on the spread of COVID-19. Furthermore, there were three variables, namely GDP per capita, ratio of population of the labour force, and number of tourist visitor per year, which were not included in data analysis due to their low correlation coefficient value (less than 0.1). Regression analysis was then performed to show their roles on the dependent variables. The basic formula of multiple regression is as follows:

$$Y = \mathrm{a} + \mathrm{bX}_1 + \mathrm{cX}_2 + \mathrm{dX}_3 + \mathrm{eX}_4 + \mathrm{fX}_5\mathrm{mX}_{12} \ldots + \mathrm{zX}_{26}. \qquad (2)$$

Table 1 summarizes the coefficients a to z as a result of the analysis of the four formulas that explain the four dependent variables investigated.

Our study demonstrated several key findings to describe the COVID-19 infection in The Special Region of Yogyakarta province. First, the socio-spatial variables in our models explain 45 % to 89.1 % (Table 1, row 5) of the variability of the spread of COVID-19 (Table 1). The constant value in the regression model should not be interpreted as usual, e. g. given all dependent X variables are 0. The value of Y variable equals to the constant value. In this study, almost all X variables, such as GDP per capita, population number, and area were not 0. However, the regression model (the increased or decreased value of X variable can alter the value of Y variable) was applied in this study. The constant value was considered to balance the equation so that the Y calculation was reasonable.

Secondly, the multiple regression analysis revealed that the distance to the main urban center, population number, gross population density, rate of GDP growth, educational

[4] Here and below, Table 1 can be found at the link: https://escjournal.spbu.ru/article/view/13364/10599. The table is given in the author's edition.

facility units per population, net health facility density, and net economy facility density contributed to the reduction of COVID-19 infection in the early pandemic. It also indicated that a region far from the COVID-19 epicenter in the region and supported with sufficient economic and spatial capacities could run economic activities without relying too much on the other parties from outside the region to reduce the risk of COVID-19 exposure. Conversely, the increased value of several variables such as built-up area, educational level, working age population, gross health facility density, net education facility density, and economy facility unit per population accelerated the transmission of COVID-19. Those variables could be considered as the external forces that attracted people from the surrounding areas to the COVID-19 epicenter.

The third finding was the determining factor of C1000. The variables contributing to the increase of COVID-19 infection were marked with positive values such as population number, both gross and net population density, the number of population of the labor force, rate of GDP growth, education level, labor force ratio, net economic facility density, and accessibility gross density (road length / tot area). The level of economic development in the region, characterized by its demographic character and infrastructure density, raised the risk of infection among residents. It could be predicted that community activities were increasing in the more developed part of the region, thus becoming a route of viral transmission among residents. Furthermore, the availability of health facilities, including variable gross as well as net density of health facility minimized the COVID-19 infection effectively. In contrast, the number of health facility units per population, net education facility density, and net economic facility density increased the viral infection whereas gross and net density of education facility and the number of economic facility per population decreased the viral infection within the region.

The fourth finding was associated with the determining factor of exponential growth (G). In the first day of infection to December 10, 2020, the exponential growth was –0.054 and 21 socio-spatial variables were found to stimulate the exponential growth. Only 5 variables, such as labor force ratio (% of non primary to primary), accessibility (road Length per Population), gross education facility, net health facility density, and number of shopping center suppressed the exponential growth. Further studies should be conducted to explore the contributing factor of exponential growth. However, government regulation, particularly remote working and learning, might partially affect the exponential growth.

Another key finding was related to the factors contributing to the exponential growth per 1000 population (G1000). Multiple regression analysis showed that the estimated exponential transmission rate per 1000 population was –5.153. Similar to the exponential growth (G) analysis, 21 socio-spatial variables induced the exponential growth per 1000 population (G1000). There were only 5 variables, including education level, education facility unit per population, gross health facitity density, net economic facility density, and the number of shopping center suppressed G1000. It might be associated with implementing work and study from home regulation.

4.2. Spatial Pattern of Covid Spread

Fig. 3 represents spatial regression of four variables derived from the actual/reported data. To compare the patterns of the two types of maps, the number of classes on each map is made the same, namely 10 classes. However, the consequence is that the range of

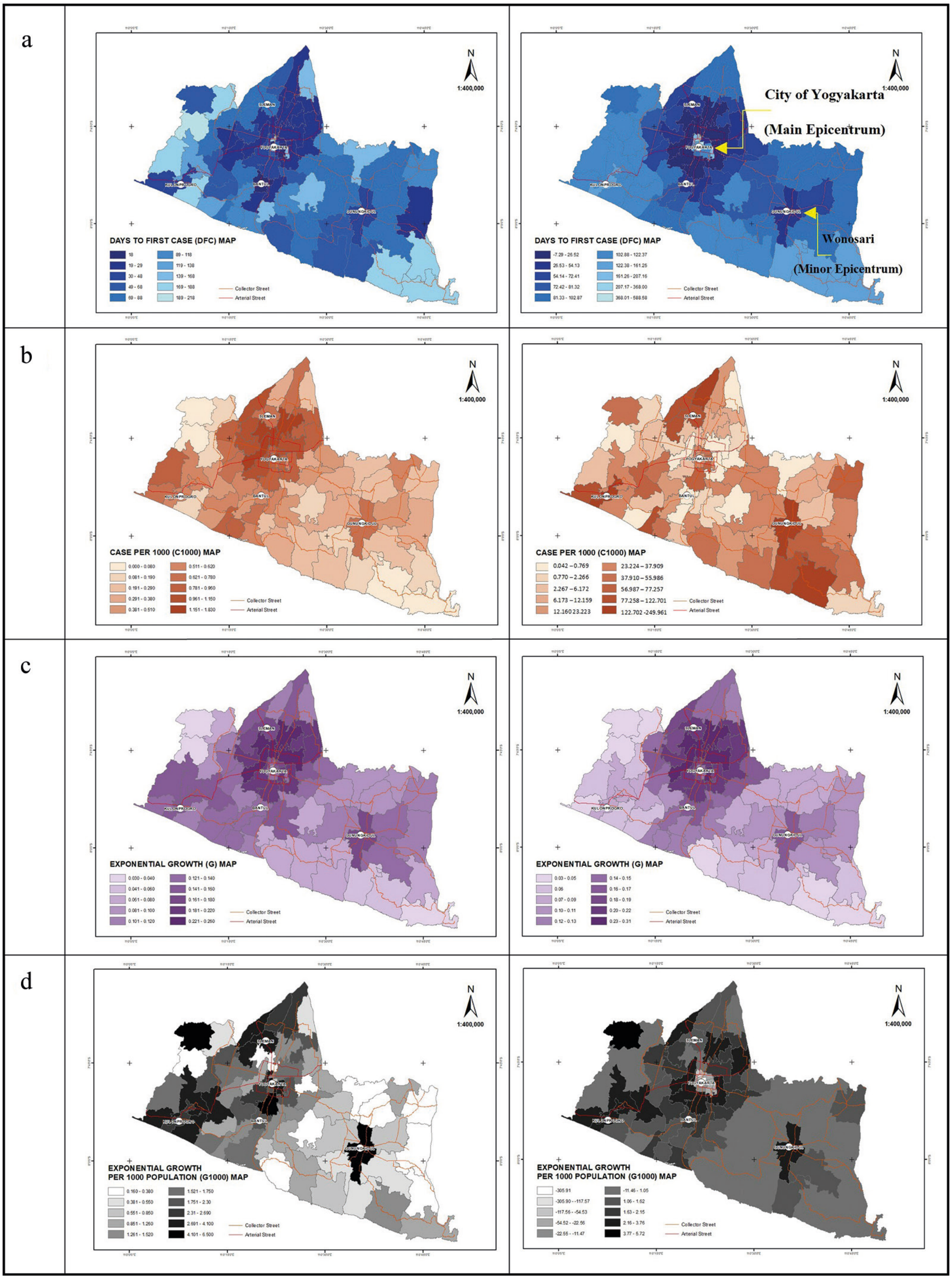

Fig. 3. Spatial regression of four variables derived from the actual/reported data:

a — Days to First Case (DFC); b — Cases per 1000 (C1000); c — Exponential Growth (G); d — Exponential Growth per 1000 population (G1000). Left maps are based on actual data from goverment; right maps are based on Spatial Regression model data from field calculator of ArcGIS each class in the indicator can be different between maps based on actual data and maps from modeling. It is more descriptive than forcing the range indicator class to be the same between the two types of maps to understand spatial patterns. The difference in spatial pattern is obvious in the days to first case variable (Fig. 3, a). On the map predicted by the model, the impression of a radial pattern with urban centers as the start of the distribution is stronger. It can be seen on the right map Fig. 3a, Yogyakarta city as province capital city which is the main node of the region becomes the main epicentrum, and Wonosari City as a city in a lower hierarchy and is located separately from the main city center being the minor epicenter. The findings related to this different pattern also occur for the exponential growth variable (Fig. 3, c). The strengthening of the spatial pattern impression by the prediction model also occurs in cases per 1000 and exponential growth per 1000 population. In these two variables, the spatial pattern formed is not radial but clusters. There are several separate parts of the place that have the same color of darkness. It means there is a tendency for spatial clustering between several neighboring areas, which mutually influences the density of exposure cases per 1000 population and their exponential growth.

The pattern of COVID-19 transmission, as illustrated in Fig. 3, was relatively consistent with the reported data, suggesting our robust model. The predicted model described the transmission of COVID-19 at initial phase with relatively uniform policies in the form of large-scale social restriction regulations such as remote learning and working activities, as well as strict restrictions on social and commercial activities and religious activities. Furthermore, the spatial pattern in Fig. 3 confirmed our previous correlation and multiple regression analysis where COVID-19 transmission followed the city development pattern. It is important to note that the city development pattern followed the centrifugal pattern. However, then it combined with a ribbon development pattern.

5. Conclusions

The study identifies the socio-spatial factors that can modulate COVID-19 infection. In the first year of pandemic, the general pattern of COVID-19 transmission followed the city development pattern. The study also finds that regulating community activity restrictions, such as remote working and learning, effectively decelerates the viral infection, particularly in the educational and economic. Hypothetically, it increases the association among variables, as described in equation 1. For future research, it is interesting to explore the role of the high level of mobility and interaction that is affected by the socio-economic of the community (e. g., the income level, the dominance of the nonagricultural sector, and the level of education) in the COVID-19 transmission.

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Социально-пространственные аспекты, способствующие распространению COVID-19 в провинции Джокьякарта (Индонезия)

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В начале пандемии положительные случаи COVID-19 преимущественно регистрировались в крупных городах Индонезии. Однако вирус быстро и широко распространился по другим городам и районам. Это показывает, что пандемия COVID-19 не ограничена городскими районами и широко распространилась на более отдаленные территории. Исследование направлено на изучение корреляции между социально-экономическими характеристиками и распространением подтвержденных случаев COVID-19. В этом исследовании мы собрали данные жителей с подтвержденным положительным результатом на COVID-19 и их социально-экономические профили в 78 районах особого региона провинции Джокьякарта, Индонезия. Собранные данные были подвергнуты статистическому анализу в три последовательных этапа, включающих тест корреляции, классический тест предположений (например, тесты нормальности, гомоскедастичности и немультиколлинеарности) и множественный регрессионный тест для определения корреляции между зараженными COVID-19, численностью населения и социально-экономическими данными в каждом подрайоне. Результаты показали, что регионы с более урбанизированным характером, особенно социально-экономически развитые, были более восприимчивы к инфекции COVID-19 в течение первого года пандемии. Однако социально-пространственные аспекты, такие как плотность населения (одна из главных черт «компактных городов») и доля застроенной территории, не способствовали передаче вируса. Социально-пространственные аспекты могут влиять на риск передачи вируса, но не так существенно, как социальные факторы и поведение человека в определенной местности. Поэтому усилия по предотвращению распространения вируса COVID-19 должны быть в большей степени сосредоточены на социальных факторах и поведении людей.

Ключевые слова: COVID-19, социально-пространственный аспект, социально-экономический аспект, передача инфекции, Джокьякарта — Индонезия.

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