Geo-clusters and socio-demographic profiles at village-level associated with COVID-19 incidence in the metropolitan city of Jakarta: An ecological study

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Abstract
The Special Capital Region of Jakarta is the epicentre of the transmission of COVID-19 in Indonesia. However, much remains unknown about the spatial and temporal patterns of COVID-19 incidence and related socio-demographic factors explaining the variations of COVID-19 incidence at local level. COVID-19 cases at the village level of Jakarta from March 2020 to June 2021 were analyzed from the local public COVID-19 dashboard. Global and local spatial clustering of COVID-19 incidence was examined using the Moran’s I and local Moran analysis. Socio-demographic profiles of identified hotspots were elaborated. The association between village characteristics and COVID-19 incidence was evaluated. The COVID-19 incidence was significantly clustered based on the geographical village level (Moran’s I = 0.174; p = .002). Seventeen COVID-19 high-risk clusters were found and dynamically shifted over the study period. The proportion of people aged 20–49 (incidence rate ratio [IRR] = 1.016; 95% confidence interval [CI]: 1.012–1.019), proportion of elderly (≥50 years) (IRR = 1.045; 95% CI = 1.041–1.050), number of households (IRR = 1.196; 95% CI = 1.193–1.200), access to metered water for washing, and the main occupation of the residents were village level socio-demographic factors associated with the risk of COVID-19. Targeted public health responses such as restriction, improved testing and contact tracing, and improved access to health services for those vulnerable populations are essential in areas with high-risk COVID-19.

KEYWORDS
COVID-19, Indonesia, inequality, spatial analysis, socio-demographics

1 | INTRODUCTION

The coronavirus disease 2019 (COVID-19) is caused by a new type of virus namely severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). It has been declared as a public health emergency of international concern by the World Health Organization (WHO) since it first emerged in Wuhan, China, in late December 2019 (WHO, 2020; Zhu et al., 2020). As of 19 August 2021, more than 100 million cases and 2.3 million deaths have been reported worldwide (WHO, 2021). Fever, cough, and shortness of breath are the clinical symptoms that occur at the beginning of the infection and may develop into dyspnoea and lead to severe complications and death (C. Huang, Wang, et al., 2020; Yan et al., 2020). Asymptomatic COVID-19 is common, making the public health and disease control difficult (Mizumoto et al., 2020). COVID-19 is mainly transmitted through respiratory droplets and human-to-human contact (Chan et al., 2020; Kutti-Sridharan et al., 2020).
Indonesia has also encountered the impacts of the COVID-19 pandemic. The first confirmed COVID-19 case was reported in March 2020. As of 19 August 2021, more than 3.9 million people were tested positive and 123,981 people died due to COVID-19 (Indonesia COVID-19 Task Force, 2021). Indonesia is one of the Southeast Asian countries with a high number of COVID-19 cases. The Special Capital Region of Jakarta has reported more than 800,000 cases, accounting for approximately 20% of the total COVID-19 cases nationally. To control the transmission, the government of Indonesia is implementing extensive public health measures, which are outlined in the Decree of the Indonesian Ministry of Health No. 9 of 2020 (Cabinet Secretariate of Republic of Indonesia, 2020). In addition, vaccination programmes have now been rolled out since January 2021, targeting healthcare workers, the elderly, and the general population.

Jakarta, the capital city of Indonesia, is the epicentre of COVID-19 transmission. The first COVID-19 case in Jakarta was confirmed on 3 March 2020. As of 19 August 2021 in Jakarta, a total of 822,399 people were tested positive and 13,132 people died due to COVID-19 (Jakarta COVID-19 Taskforce, 2021). In order to control the transmission, several public health responses are being implemented such as stay-at-home order, travel bans, promoting face masks use, public places closure, contact tracing, and extensive testing (Government of The Special Capital Region of Jakarta, 2020). Prompt and effective responses are, therefore, crucial to reduce and eliminate COVID-19 incidence. As of 19 August 2021, up to 9.2 million Jakartans had received at least one dose of COVID vaccines.

The spatiotemporal variations of COVID-19 incidence have been studied extensively as knowledge regarding the epidemiology of COVID-19 is growing. Understanding patterns of the disease, spatially and temporally, will help researchers and policymakers to identify and target areas and populations that are at most risk, supporting better resource allocation. Much remains unknown about variations of COVID-19 incidence and factors related to this heterogeneity across Jakarta. The use of spatial analysis to support disease outbreak control has been discussed in other studies (Fletcher-Lartey & Caprarelli, 2016). A recent paper reviewed the use of geographic information systems (GIS) and spatial analysis on COVID-19 cases (Franch-Pardo et al., 2020). For instance, a study in China analyzed the spatiotemporal patterns of COVID-19 using Moran statistics and found that COVID-19 incidence was spatially clustered in China (R. Huang, Liu, et al., 2020). A study in England demonstrated that spatial analyses can be used to assess inequalities of environmental and socio-economic attributes that contributed to spatial heterogeneity of COVID-related deaths (Sun et al., 2021). Further, studies revealed significant associations between COVID-19 spatial heterogeneities as well as environmental and socio-demographic factors (Chakraborty, 2020; Kwok et al., 2020; Lakhani, 2020; Luo et al., 2020; Nicodemo et al., 2020; Nakada & Urban, 2020). The GIS techniques can be applied to locate hotspots and to understand factors associated with the disease distribution. These techniques help improve our knowledge regarding the epidemiology of COVID-19 to help design public health responses at various levels (i.e. national, sub-national, and local).

Although there have been studies on the transmission pattern of COVID-19 in Indonesia (Aisyah et al., 2020; Eryando et al., 2020), the variation and dynamic of COVID-19 incidence at the local level, especially in Jakarta, and socio-demographic factors associated with COVID-19 distribution, are poorly investigated. An investigation on the transmission patterns at a finer scale (i.e. village level) and the characteristics of high-risk neighbourhoods could help local health authorities design more effective and targeted interventions to control COVID-19 transmission. This paper explored the spatial pattern of COVID-19 transmission in Jakarta from March 2020 to June 2021 to understand the geographical diffusion of COVID-19 at a fine scale, locate and profile high-risk areas, and examine the association between COVID-19 incidence and its socio-demographic factors at the village level.

# MATERIALS AND METHODS

## 2.1 Study site

An ecological study was performed in the Special Capital Region of Jakarta (6.208°S, 106.846°E). It has an area of 623,33 square kilometres and is inhabited by about 10 million people. Administratively, Jakarta has six districts, 44 sub-districts, and 267 villages. One district (Kepulauan Seribu or Thousand Islands) is off the coast of the Java Sea, comprising of 105 small islands with a population of 21,000 people. The population density ranges from 2423 to 18,761 people per square kilometres.

## 2.2 Data collection

### 2.2.1 COVID-19 data

Aggregated village level data on daily confirmed COVID-19 cases from 1 March 2020 to 30 June 2021 were retrieved from the government’s COVID-19 Taskforce website (https://corona.jakarta.go.id/en). COVID-19 case definitions were applied based on the guidelines of the Indonesian Ministry of Health (Ministry of Health of Indonesia, 2020). A total of 458,837 confirmed SARS-CoV-2 positive cases were analyzed.

### 2.2.2 Socio-demographic data

Socio-demographic data included the proportion of people aged 20–49 years, the proportion of people aged 50 and above, population density, number of households, the proportion of villages that had access to safe water infrastructure (metered water), and type of occupation for most residents in a village. All of these are the known risk factors of COVID-19 transmission (Jefferies et al., 2020; Nicodemo et al., 2020; Russell et al., 2020; White & Hébert-Dufresne, 2020). Data on
the population by age (i.e. the proportion of people aged 20–49 years and over 50 years) at a village level were obtained from the Jakarta Demographic and Civil Registration Office. Data for population density, number of households, access to metered water (categorized into metered, not metered, and borehole), and occupation of residents (categorized into employment in manufacture, trade and retail, transportation and communication, and service sectors) for each village were collected from the Provincial Bureau of Statistics and 2018 Village Survey or Potensi Desa (PODES) conducted by the National Bureau of Statistics. Additionally, data on road density (km per square kilometres) collected from each village were estimated using the GIS. Vector data on the road network were retrieved from the GIS database. Road density was then determined by dividing the length of the road by the area of each polygon (village). Road density is one of the urban factors correlated with the spread of COVID-19 (Kwok et al., 2020; Li et al., 2020).

2.3 | Data analysis

2.3.1 | Mapping COVID-19 incidence and socio-demographic characteristics at the village level

In this analysis, villages were used as the spatial unit of analysis. Monthly and cumulative COVID-19 incidence for each village was calculated. Maps of cumulative incidence, monthly incidence of COVID-19, and socio-demographic characteristics were produced using QGIS version 3.2.0-Bonn.

Global spatial clustering

Global Moran’s I analysis (Moran, 1950) was carried out to examine spatial clustering of the COVID-19 incidence in Jakarta from March 2020 to June 2021. A queen-based spatial contiguity weight matrix was constructed prior to the analysis. The municipality of the Thousand Islands was excluded in the analysis as it influenced spatial weight estimates. The Moran’s I coefficient ranges from −1 to 1. A positive coefficient indicates a positive spatial autocorrelation, while a negative coefficient means negative spatial autocorrelation. When the coefficient is zero, that means there is no spatial autocorrelation. The significance of Moran’s I of the COVID-19 incidence was assessed using the Monte Carlo randomization with 999 permutations. A significance value was set at $p < .05$, meaning that the incidence is geographically clustered or dispersed.

2.3.2 | Local spatial clustering

Local Moran’s analysis was performed to locate significant high-high (HH) clusters, low-low (LL) clusters, and spatial outliers (low-high and high-low clusters) (Anselin, 1995). HH clusters (later defined as high-risk areas) are areas with high rates surrounded by more areas with high rates and so on. Both global and local analyses were performed using the GeoDa version 1.8 software (Anselin et al., 2006).

3 | RESULTS

3.1 | Mapping incidence and socio-demographic factors

The cumulative COVID-19 incidence varied spatially at a village level across Jakarta (Figure 1). Villages with high incidence were...
identified in the central and south Jakarta. The spatial-temporal maps of monthly incidence showed that the dynamic shift in incidence of COVID-19 at the village level varied across Jakarta over the period studied (Figure 2). An increase in incidence per 10,000 people was gradually observed at village level since September 2020. The highest incidence was observed in Jagakarsa (857/10,000 people) in January 2021. In June 2021, high COVID-19 incidence was observed in north Jakarta including Kapuk (1330/10,000 people), East Cengkareng (1123/10,000 people), and Pejagalan (1098/10,000 people).

The maps of socio-demographic factors demonstrated a variation at the village level (Figure 3). The proportion of the population aged 20–49 years was likely to be randomly distributed across the city. Although the proportion of people aged over 50 was relatively higher in central villages compared to northern villages. The number of households living in slums was relatively high and clustered in the northern villages of Jakarta. Villages in Northern and Central Jakarta had a relatively higher population density and road network density.

3.2 Global and local measures in clustering of COVID-19 incidence

In general, COVID-19 incidence was significantly clustered across Jakarta over the period studied (Moran’s I = 0.174; p = .002). Monthly observations revealed significant Moran’s I coefficients, except in October (I = 0.013; p = .233) (Table 1). The Moran’s I coefficient fluctuated over time, ranging from 0.120 in November up to 0.320 in July.

The local Moran’s analysis identified 17 significant HH spatial clusters during the research period, with total population at risk was 330,599 people. However, the analysis also found 41 LL clusters across Jakarta. The significant HH clusters belonged to 10 sub-districts including Cipayung (7 villages), Kebayoran Baru (1), Makassar (1), Cempaka Putih (1), Setia Budi (2), Sawah Besar (1), Gambir (1), Tanah Abang (1), Kramat Jati (1), and Senen (1). Spatial clusters of HH were dynamically shifted over time (Figure 4). A small set of HH clusters were steadily concentrated in central Jakarta during the period studied. In addition, the HH clusters dynamically emerged in the south of Jakarta. These HH clusters newly emerged and expanded significantly in the south of Jakarta during December 2020 and January 2021. This HH cluster re-emerged in June 2021. A high number of HH clusters were observed in July 2020 (23 villages) and January 2021 (24 villages) with a total population at risk was 617,055 and 752,726 people, respectively. A low number of HH clusters was reported in October 2020 (six villages) with a total of 107,395 people at risk (Table 2).

3.3 Socio-demographic profiles of spatial clusters of COVID-19

Table 3 summarizes the socio-demographic differences of the identified HH and LL clusters of COVID-19 in Jakarta. Compared to the LL clusters, the HH clusters were likely to have lower people density (p < .001), have less road network density (p < .05), have fewer households (p < .001), a small proportion of the village had access to metered water (17.6%, p < .001), and most of its residents had a primary occupation in service sectors (47%, p = .001). While it is not statistically different (p > .05), the HH cluster was likely to have a high proportion of people aged above 50 years (20.6%) and a low proportion of people aged 20–49 years (48.7%), compared to the LL clusters.

3.4 The association between COVID-19 incidence and socio-demographic characteristics at the village level

The bivariate and multivariate Poisson regression analyses are presented in Table 4. In the bivariate analysis, an increased SD of the proportion of people aged 20–49 was associated with a 5.9% (95% CI: 5.6%–6.2%, p < .001) increase in the risk of COVID-19. Each SD increase in the number of households was associated with a 15.3% (95% CI: 15%–15.6%, p < .001) increase in the COVID-19 incidence. The risk of COVID-19 incidence was 8.7% (95% CI: 8%–9.3%, p < .001) higher in villages where most households used borehole water for bathing or washing. A village where most people worked at service industries was likely to have higher incidence by 23.5% (95% CI: 22.4%–24.6%, p < .001) compared to the village where people predominantly worked at manufacturing.

In the multivariate analysis, an increased SD of the population aged 20–49 and above 50 was associated with a 1.6% (95% CI: 1.2%–1.9%) and 4.5% (95% CI: 4.1%–5%) increase in the risk of COVID-19, respectively. Each SD increase in number of households was associated with a 19.6% increase in the incidence of COVID-19 (95% CI: 19.3%–20%, p < .001). The COVID-19 incidence was 3.7% (95% CI: 36.4%–39.1%, p < .001) higher in the communities that used borehole water compared to metered water. Further, the risk was 1.2 and 1.4 times higher in the community where most people worked in transportation, communication, and service industries, respectively, after controlling for other socio-demographic factors.

4 DISCUSSION

All provinces in Indonesia have been impacted by the pandemic, of which Jakarta is the most hit region by COVID-19 (Eryando et al., 2020). In this ecological study, we explored spatial variation in the incidence of COVID-19 at the village level across the city of Jakarta and summarizes socio-demographical features of the high-risk villages by using spatial statistics approach. This study is the first one investigating spatial variations of COVID-19 incidence in relation to socio-demographic factors across Jakarta. The study demonstrates dynamic patterns in the spatial clustering and distribution of the COVID-19 hotspots over the 16 months (March 2020 to June 2021). Further, our study reveals that socio-demographical variation at neighbourhood level explained the heterogeneity in risk of COVID-19 across the city. These findings could help inform better strategies for effective targeted intervention to curb the transmission of COVID-19.
FIGURE 2  Monthly incidence of COVID-19 at the village level in Jakarta (March 2020 to June 2021)
TABLE 1  Monthly spatial clustering of COVID-19 incidence in Jakarta, March 2020 to June 2021

| Month  | I   | SD  | z-Values | p-Values |
|--------|-----|-----|----------|----------|
| 2020   |     |     |          |          |
| March  | 0.139 | 0.022 | 6.5      | .001     |
| April  | 0.262 | 0.036 | 7.472    | .001     |
| May    | 0.165 | 0.036 | 4.638    | .001     |
| June   | 0.174 | 0.025 | 6.978    | .002     |
| July   | 0.320 | 0.035 | 9.103    | .001     |
| August | 0.155 | 0.032 | 4.916    | .001     |
| September | 0.158 | 0.033 | 4.863    | .001     |
| October | 0.013 | 0.029 | 0.610    | .233     |
| November | 0.120 | 0.035 | 0.349    | .002     |
| December | 0.243 | 0.035 | 6.953    | .001     |
| 2021   |     |     |          |          |
| January | 0.283 | 0.036 | 7.885    | .001     |
| February | 0.238 | 0.035 | 6.900    | .001     |
| March  | 0.226 | 0.036 | 6.243    | .001     |
| April  | 0.138 | 0.036 | 3.942    | .003     |
| May    | 0.132 | 0.034 | 3.934    | .005     |
| June   | 0.153 | 0.033 | 4.598    | .002     |
| Overall | 0.174 | 0.035 | 5.040    | .002     |

The heterogeneity in incidence over space and time was likely due to the impact of behavioural changes (e.g. face mask use and stay-at-home order) and the implementation of control measures (e.g. travel ban and testing). It is important to note that the trends in COVID-19 incidence was fluctuated over the period. We observed an increased incidence in December to February, which was likely driven by Christmas and New Year holidays (Figure S1). Further, an increased incidence might indicate the emergence of new SARS-CoV-2 variants in the population, yet more evidence is needed. In addition to promoting adequate health protocols, lockdowns or large-scale social restrictions seem to have contributed to reducing the transmission. Our visual examination of the trends in people’s mobility (indicated by changes in travel distance) and in the number of daily cases indicated the effect of mobility restriction on COVID-19 cases (Supporting information). People’s mobility was reduced significantly as lockdown was implemented. This has helped flatten the epidemic curve at some points (October 2020 and March 2021). The impact of such intervention on the spatial distribution incidence is reflected by the reduced power and significance of spatial clustering (as indicated by a reduced I coefficient). However, further investigation is necessary to examine the impact of public health interventions and change in behaviour and mobility due to the spread of COVID-19 at the population level.

This study identified 17 high-risk spatial clusters of COVID-19. A small set of high-risk villages was found in central Jakarta over the period of study. Interestingly, the study reveals the emergence of high-risk villages on the south border of Jakarta from December 2020 to March 2021. This could be partly driven by underlying socio-demographical factors (i.e. population structure, mobility, behavioural, and activities). The comparative analysis showed that these high-risk villages were different from low-risk villages. High-risk areas are characterized by a mixture of commercial and office activities which allow higher mobility and interactions, thus leading to a greater risk of SARS-CoV-2 transmission. Similar clustering phenomena of COVID-19 cases
have also been reported in other countries (Kim & Castro, 2020; Yang et al., 2020).

This study suggested that area-level incidence was associated with population composition higher incidence was likely occurred in that area with a high proportion of senior residents. The elderly, particularly those with comorbidities, were reported to be at higher risk of contracting severe illnesses (Jefferies et al., 2020; Liu et al., 2020; Russell et al., 2020). Our finding also indicates that area-level incidence was associated with the proportion of people aged 20–49 years and COVID-19 incidence. Young and productive populations are relatively highly mobile (Kronbichler et al., 2020; Lai et al., 2020; Tan et al., 2020) that can facilitate transmission. The findings highlight that appropriate non-pharmaceutical intervention (NPI) should be targeted towards these populations (e.g. promoting face masks and social distancing). As COVID vaccines are now available, putting the elderly and active population on the top of the list is recommended. Besides, routine health monitoring towards these elderly population should be improved. Local health authorities can utilize digital tools such as telehealth and telemedicine services to facilitate access to care and continue providing care for the community during the pandemic.

These spatial variations of COVID-19 incidence appear to be driven by different socio-demographic profiles at the village level. Villages, where most residents work in the transportation, communication, and public service sectors, were likely to have a higher incidence of COVID-19; this finding is consistent with other studies (Koh, 2020; Kwok et al., 2020). Some occupations, such as healthcare workers (HCWs) and public staff, have been more at risk of COVID-19 infection (Gholami et al., 2021; Koh, 2020). These workers are likely to have frequent contact with people and thus potentially increase the risk of being exposed to the circulating virus. Local epidemiological reports have documented that most of the COVID-19 transmission occurred in workplaces and households. Thus, robust health and safety protocols should be applied.

In this study, we included road network density to reflect connectivity. This is a known factor associated with the transmission of respiratory infection (Vu et al., 2013). Our finding is inconsistent with a study in Hong Kong that reported a positive correlation between road network density and COVID-19 incidence (Kwok et al., 2020). One possible reason is that while in some way dense road networks may likely promote higher people’s mobility, several unmeasured factors might have also indirectly contributed to lowering the risk of transmission (e.g. mobility restrictions, face mask use, stay-at-home order and traffic manipulation).

A higher number of families within the village were associated with the increased COVID-19 incidence. The effect of overcrowding could be the reason for this situation, which has also been reported by other studies (Ahmad et al., 2020; Daras et al., 2021). Further, in areas (e.g. the southern part of Jakarta) where access to tapped water is limited, the incidence were likely higher. Studies showed that poor housing and inequality in access to basic services are known social factors associated with COVID-19 (Ahmad et al., 2020; Das et al., 2020). This suggests that improving access to basic services is essential to facilitate a proper hygiene behaviour in the community.

Unexpectedly, an inverse association between COVID-19 incidence and population density was found. This is contradictory to previous
| Months  | Spatial cluster | COVID-19 cases | Number of villages | Estimated population-at-risk |
|---------|----------------|----------------|--------------------|------------------------------|
| March   | High-high      | 37             | 10                 | 109,244                      |
|         | Low-low        | 16             | 27                 | 1,258,650                    |
|         | Low-high       | 7              | 7                  | 193,355                      |
|         | High-low       | 15             | 6                  | 121,357                      |
| April   | High-high      | 388            | 18                 | 500,588                      |
|         | Low-low        | 141            | 27                 | 1,031,725                    |
|         | Low-high       | 49             | 9                  | 225,048                      |
|         | High-low       | 45             | 4                  | 128,130                      |
| May     | High-high      | 220            | 12                 | 331,142                      |
|         | Low-low        | 91             | 20                 | 909,340                      |
|         | Low-high       | 22             | 8                  | 234,708                      |
|         | High-low       | 18             | 3                  | 68,598                       |
| June    | High-high      | 470            | 15                 | 332,141                      |
|         | Low-low        | 197            | 34                 | 1,636,460                    |
|         | Low-high       | 62             | 10                 | 242,277                      |
|         | High-low       | 20             | 2                  | 44,109                       |
| July    | High-high      | 912            | 23                 | 617,055                      |
|         | Low-low        | 172            | 15                 | 492,610                      |
|         | Low-high       | 68             | 7                  | 161,792                      |
|         | High-low       | 211            | 7                  | 296,492                      |
| August  | High-high      | 1072           | 19                 | 467,808                      |
|         | Low-low        | 728            | 23                 | 1,197,522                    |
|         | Low-high       | 232            | 11                 | 298,632                      |
|         | High-low       | 508            | 10                 | 324,561                      |
| September | High-high    | 1755           | 17                 | 349,721                      |
|         | Low-low        | 1916           | 25                 | 1,016,095                    |
|         | Low-high       | 644            | 9                  | 306,827                      |
|         | High-low       | 373            | 3                  | 118,115                      |
| October | High-high      | 400            | 6                  | 107,395                      |
|         | Low-low        | 1477           | 21                 | 814,962                      |
|         | Low-high       | 549            | 8                  | 253,210                      |
|         | High-low       | 641            | 6                  | 171,584                      |
| November| High-high      | 503            | 9                  | 142,087                      |
|         | Low-low        | 2763           | 38                 | 1,581,976                    |
|         | Low-high       | 324            | 7                  | 174,004                      |
|         | High-low       | 108            | 2                  | 37,514                       |
| December| High-high      | 2775           | 19                 | 408,031                      |
|         | Low-low        | 4235           | 39                 | 1,748,645                    |
|         | Low-high       | 894            | 10                 | 274,986                      |
|         | High-low       | 436            | 3                  | 80,896                       |

(Continues)
| Months  | Spatial cluster | COVID-19 cases | Number of villages | Estimated population-at-risk |
|---------|-----------------|----------------|--------------------|------------------------------|
|         |                 |                |                    |                              |
| 2021    |                 |                |                    |                              |
| January | High-high       | 8285           | 24                 | 752,723                      |
|         | Low-low         | 9281           | 44                 | 1,899,924                    |
|         | Low-high        | 1614           | 5                  | 222,719                      |
|         | High-low        | 1265           | 5                  | 144,483                      |
| February| High-high       | 4004           | 14                 | 442,744                      |
|         | Low-low         | 7213           | 39                 | 1,655,714                    |
|         | Low-high        | 1244           | 10                 | 221,546                      |
|         | High-low        | 474            | 3                  | 60,918                       |
| March   | High-high       | 3086           | 9                  | 525,929                      |
|         | Low-low         | 3739           | 31                 | 1,549,970                    |
|         | Low-high        | 1203           | 8                  | 361,464                      |
|         | High-low        | 340            | 1                  | 62,981                       |
| April   | High-high       | 620            | 9                  | 174,477                      |
|         | Low-low         | 1869           | 31                 | 1,307,569                    |
|         | Low-high        | 289            | 8                  | 153,581                      |
|         | High-low        | 67             | 1                  | 21,771                       |
| May     | High-high       | 592            | 10                 | 167,750                      |
|         | Low-low         | 1764           | 37                 | 1,570,404                    |
|         | Low-high        | 226            | 5                  | 130,524                      |
|         | High-low        | 159            | 3                  | 65,569                       |
| June    | High-high       | 6074           | 17                 | 368,813                      |
|         | Low-low         | 11,138         | 31                 | 1,490,754                    |
|         | Low-high        | 1657           | 9                  | 179,574                      |
|         | High-low        | 140            | 1                  | 9642                         |

**TABLE 3**  Socio-demographic profiles of the identified high- and low-risk spatial clusters of COVID-19 in Jakarta

| Characteristics                                      | Spatial cluster | HH (n = 17)         | LL (n = 41)         | p-Values |
|------------------------------------------------------|-----------------|---------------------|---------------------|----------|
|                                                      |                 | Population density per km²# | 9.138 (5.104–11.251) | 30.799 (12.625–46.095) | <.001   |
|                                                      |                 | % people aged 20–49 years## | 48.71 (47.76–50.15)  | 49 (47.37–50.70) | .704    |
|                                                      |                 | % people aged 50+ years##  | 20.65 (17.58–22.65)  | 19.63 (15.13–22.29) | .413    |
|                                                      |                 | Road network density (in km/km²) # | 11.66 (6.53–15.62)  | 15.12 (10.08–19.23) | .048    |
|                                                      |                 | Number of households##   | 7.597 (3.038–9.779)  | 15211 (6.294–22.552) | <.001   |
|                                                      |                 | % of village had access to metered water for bathing/washing | 17.6 | 70.7 | <.001 |

% of village where most of residents working in:  
- Manufacture: 5.9 | 36.6 
- Trade and retail: 0 | 2.4 
- Transport and communication: 47.1 | 53.7 
- Service: 47.1 | 7.3  

Abbreviations: 95% CI, 95% confidence interval; HH, high-high; LL, low-low.
#Results expressed as mean (95% CI).
TABLE 4  Associations between COVID-19 incidence and socio-demographic factors at the village level

|                          | Bivariate |                                      | Multivariate |                                      |
|--------------------------|-----------|---------------------------------------|--------------|---------------------------------------|
|                          | IRR       | 95% CI Lower                        | IRR          | 95% CI Lower                        |
| Population density (person/km²) | 0.905***  | 0.901 0.908                         | 0.937***     | 0.933 0.940                         |
| People aged 20–49 years (%) | 1.059***  | 1.056 1.062                         | 1.016***     | 1.012 1.019                         |
| People aged 50+ years (%) | 0.947***  | 0.944 0.950                         | 1.045***     | 1.041 1.050                         |
| Road network density (in km/km²) | 0.952***  | 0.950 0.955                         | 0.986***     | 0.982 0.989                         |
| Number of households      | 1.153***  | 1.150 1.156                         | 1.196***     | 1.193 1.200                         |

Main source of water for bathing/washing

|                          |          |                                      |              |                                      |
|--------------------------|----------|---------------------------------------|--------------|---------------------------------------|
| Metered water            | 1        |                                      |              |                                      |
| Non-metered water        | 1.015    | 0.992 1.038                         | 0.824***     | 0.805 0.843                         |
| Borehole                 | 1.087*** | 1.080 1.093                         | 1.037***     | 1.030 1.044                         |

Village where most of residents working in

|                          |          |                                      |              |                                      |
|--------------------------|----------|---------------------------------------|--------------|---------------------------------------|
| Manufacture              | 1        |                                      |              |                                      |
| Trade and retail         | 0.696*** | 0.650 0.746                         | 0.921        | 0.859 0.986                         |
| Transport and communication | 1.044*** | 1.035 1.053                         | 1.239***     | 1.228 1.251                         |
| Service                  | 1.235*** | 1.224 1.246                         | 1.378***     | 1.364 1.391                         |

Abbreviations: 95% CI = 95% confidence interval; IRR = incidence rate ratio.

* p < .1
** p < .05
*** p < .01

studies (You et al., 2020; Whittle and Díaz-Artiles, 2020) although one recent study in China suggested insignificant association between both variables (Xiong et al., 2020). This inconsistent finding may be partly explained by the local behaviours and the difference in spatial extent. However, this finding needs further investigation.

This study has some limitations. First, the analysis was based on the cases reported by health facilities, which are prone to many uncertainties. For example, surveillance and testing capacity had not been optimally established during the early phase of the pandemic. Delayed and incomplete epidemiological reports due to lack of technical and human resources had also challenged data accuracy (Aisyah et al., 2020). Furthermore, a substantial proportion of asymptomatic cases might have not been detected at the beginning of the pandemic, and thus the real burden of COVID-19 might have been underreported. Second, we did not consider meteorological variables in the analysis despite its importance on COVID-19 (Tosepu et al., 2020). Given Jakarta is a relatively small area, we assumed that meteorological variability at the village level might not be significantly heterogeneous. Thus, it might be not a good predictor for area-level COVID incidence. Also, limited by data availability, we could not include individual and behavioural risks (e.g. chronic conditions, face mask use, and smoking). Lastly, all available socio-demographic data at the village level were obtained from past censuses and reports, which may not reflect the actual condition. Further local scale population-based study is encouraged to better understand the epidemiology of COVID-19 in Jakarta. Despite these limitations, this study highlights the benefit of GIS and available administrative data in understanding the distribution and factors associated with COVID-19 incidence in Jakarta.

Mapping the disease spread and understanding the underlying drivers would help locate the source of transmission to immediately suppress COVID-19 transmission. Public health measures, such as localizing hotspots, identifying, and instructing high-risk populations for quarantine, promoting improved NPIs, as well as improving health systems, could be appropriately applied to the identified high-risk areas. Moreover, it is also important to regularly monitor the LL clusters in the city as they have the potential to become new hotspots for COVID-19. They require attention for detection and control of COVID-19 transmission, for example, by conducting more frequent early detection, contact tracing, clinical management, and healthcare delivery.

5 CONCLUSIONS

To sum up, the distribution of COVID-19 incidence was spatially heterogeneous at the village level throughout Jakarta. From March 2020 to June 2021, 17 significant hotspots existed mainly in the central part of the city. The geographical variations were significantly related to the social inequalities that exist in the city. Area-specific and targeted intervention measures to those high-risk villages and vulnerable communities, in addition to NPIs, adequate testing strategies, comprehensive contact tracing, equal access to treatment and social protection,
could help mitigate the spread of the virus and reduce the risk amongst vulnerable communities.

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CONFLICT OF INTEREST
The authors declare no conflict of interest.

ETHICS STATEMENT
The research protocol of this study was reviewed and approved by the Health Research and Development, Indonesian Ministry of Health. Providing the data. The study was supported by the National Institute of Health Research and Development, Indonesian Ministry of Health.

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