UCL DEPARTMENT OF GEOGRAPHY

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EXAM CANDIDATE ID:	**LTKB8**
MODULE CODE:	**GEOG0114**
MODULE NAME:	**Principles of Spatial Analysis**
COURSE PAPER TITLE:	**Spatial Analysis for Early COVID-19 Mitigation Strategies: A Case Study of Jakarta, Indonesia at the Ward Level**
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I acknowledge the use of Artificial Intelligence (AI) of ChatGPT (https://chatgpt.com/) to assist in improving my writing and troubleshooting code. Specifically, I used ChatGPT to make my writing more concise and clear. I reviewed and ensured the core ideas that I want to convey in my work remained intact. Additionally, I used ChatGPT to help resolve errors in my code. For instance, I encountered difficulties on how to set my ggplot map to align with research journal standards, as tmap did not produce the output that I was looking for. To resolve this, I used the prompt of "*"how can I add the name of the jakarta_main3 on the plot? "ggplot() + # Plot the wards with transparent borders geom_sf(data = overall_metrics, aes(fill = significance), color = scales::alpha("black", 0.4), size = 0.1)*". I further adjusted the color, size, and opacity manually to achieve the final map design that I was looking for. Moreover, I credited all ChatGPT-assisted code sections directly within the R script submitted for this coursework. My use of ChatGPT was primarily aimed at enhancing the readability of my writing and addressing specific coding errors.

Introduction

As of December 8, 2024, the WHO Dashboard reported 777 million COVID-19 cases and over 7 million deaths worldwide (WHO, 2024). Furthermore, COVID-19 pandemic pushed an estimated 71–100 million people into extreme poverty, disproportionately affecting lower and developing countries due to inadequate virus control measures and weak healthcare systems (Levin et al., 2022; Committee for the Coordination of Statistical Activities., 2020). The fallout from the COVID-19 pandemic reinforces the urgent need for policymakers to learn from this crisis in resource allocation and develop proactive strategies to mitigate future health pandemic, especially in developing countries like Indonesia (Gonzalez & Suzuki, 2024).

Indonesia, the fourth most populous country with 270 million people, faced significant challenges in handling the COVID-19 pandemic. As of December 8, 2024, the country reported 6,829,888 cumulative COVID-19 cases and 162,059 deaths (WHO, 2024). This can be accounted for by the fact that much of its population has severe barriers in accessing quality healthcare (Surendra et al., 2023). Jakarta, the largest metropolitan area in Southeast Asia, recorded the highest number of cases in Indonesia. Furthermore, studies also reveal inequalities in COVID-19 risk within Jakarta, with certain groups being more vulnerable to disease than the others which further complicated the outbreak's management in the capital (Harapan et al., 2023; Azizah et al., 2021; Miftahussurur et al., 2022; Rukmana and Ramadhani, 2021).

Jakarta highlights socio economic dualism, where wealthy and poor neighborhoods coexist (Dillon and Rukmana, 2021; Rukmana and Ramadhani, 2021). According to Samudra and Setyonaluri (2020), this inequality worsened COVID-19 transmission, as lower-income groups faced poor living conditions and limited healthcare access which made them highly vulnerable. Samudra and Setyonaluri (2020) also noted that Socioeconomic barriers like poverty and disabilities further restricted access to accurate information and COVID-19 testing, disproportionately affecting disadvantaged groups. To mitigate the impact of outbreaks on vulnerable populations, early intervention is crucial, and spatial analysis can offer an effective approach (Harapan et al., 2023).

This study aims to help policymakers develop early mitigation strategies for future health crises by analyzing the spatial patterns of COVID-19 cases in Mainland Jakarta. *Kepulauan Seribu Regency* was excluded from the analysis due to its separation from Jakarta's main population. The analysis targets the early pandemic period (March–October 2020) at Jakarta's ward (*kelurahan*) level, Indonesia's smallest administrative unit. Key questions include whether there is a spatial clustering of COVID-19 cases at the ward level and whether socioeconomic inequalities can explain the spatial case distributions. The study will use stepwise regression to select significant variables and global models (Linear Regressions, Spatial Lag, Spatial Error) will be compared in terms of explaining the relationship between COVID-19 cases and independent variables. Lastly, Geographically Weighted Regression (GWR) will be utilized to assess the effect of each independent variable on COVID-19 cases at each specific wards.

Understanding the spatiotemporal dynamics of COVID-19 is crucial for effective mitigation, as it clarifies the pandemic's spread and helps decision-making process (Franch-Pardo et al., 2020). Several studies have used spatial analysis to monitor and predict

COVID-19 cases and deaths in Indonesia, employing methods like LISA (Mahmudah et al., 2021), linear regression (Setyowati & Amalina, 2024; Istanabi et al., 2023), GWR (Widiawaty et al., 2022), multivariable ordinal logistic regression (Surendra et al., 2023), and emerging hotspots with space–time cubes (STC) (Purwanto et al., 2021). However, most studies focus on the national level, which is too broad to generate actionable insights for disease mitigation and spatial studies at the subdistrict level or lower remain limited (Surendra et al., 2022).

Several studies have analyzed COVID-19 spatial data in Jakarta's wards. Arini et al. (2023) used Ordinary Least Squares to predict COVID-19 cases based on the number of stations, terminals, and markets per wards. Dhewantara et al. (2021) applied Poisson regressions to assess COVID-19 death risk in Jakarta's wards using socio-demographic factors such as population age, density, and occupations. Pribadi et al. (2021) used GWR to model the average positive cases per ward in Jakarta with urban structure variables as predictors.

This study differs from previous analyses of COVID-19 spatial data in Jakarta's wards by incorporating regression methods that account for spatial dependency, a key aspect of spatial analysis (Mohebbi, Wolfe, & Jolley, 2011; Griffith & Haining, 2006). Unlike the non-spatial methods used by Arini et al. (2023) and Dhewantara et al. (2021), this study employs Spatial Lag, Spatial Error, and GWR models to address residual spatial dependence. While it also uses GWR, as in Pribadi et al. (2021), this study utilizes 2020 socioeconomic and demographic data as independent variables, rather than the urban structure variables used by Pribadi et al.

Data and Methods

Data for this study were primarily sourced from official Jakarta government websites. Most data were in PDF report format, thus requiring manual extraction of data tables. Furthermore, data regarding health facilities and places of interest were grouped into broad categories as shown in (Table 1). COVID-19 positive case data (March–October 2020) were obtained from Dinas Kesehatan Provinsi DKI Jakarta (2023). The vulnerability index data were collected from Badan Pusat Statistik Provinsi DKI Jakarta (2022). Population data on males, individuals over 60, and people with disabilities were collected from the Department of Population and Civil Registration (2023). Data on health facilities, markets, restaurants, and hotels were gathered from Badan Pusat Statistik Provinsi DKI Jakarta (2021a–e). Spatial data and maps were obtained from GADM (n.d.) and The Humanitarian Data Exchange (2024a, 2024b).

Table 1: Description of Study Variables, Datasets, and Sources

Category	Variable Name	Source
Dependent Variable	COVID-19 Positive Case per Ward Population	(Dinas Kesehatan Provinsi DKI Jakarta, 2023)
Independent Variables	Poverty vulnerability index Environmental and health vulnerability index Physical infrastructure vulnerability index	(Badan Pusat Statistik Provinsi DKI Jakarta, 2022)

	Security and Order Vulnerability Index	
	Male Population Percentage	(Dinas Kependudukan dan Pencatatan Sipil Provinsi DKI Jakarta , 2021)
	Population aged 60 years and above	
	Physical Disability Population Percentage	(Department of Population and Civil Registration, 2023)
	Cognitive Disability Population Percentage	
	Cognitive and Physical Disability Population Percentage	
	Hospital Coverage Percentage	(Badan Pusat Statistik Provinsi DKI Jakarta, 2021a, 2021b, 2021c, 2021d, 2021e)
	Health Centers Coverage Percentage	
	Doctor's Practice and Pharmacy Coverage Percentage	
	Restaurant and Store Coverage Percentage	
	Hotel and Accommodation Coverage Percentage	
	Market Coverage Percentage	
Spatial Data	Indonesia Fourth Level Administrative Subdivision Data	(GADM, n.d.)
	Indonesia Second Level Administrative Subdivision Data	
	Indonesia Airports Points Data	(The Humanitarian Data Exchange, 2024a, 2024b)
	Indonesia Seaports Points Data	

For the analysis, Linear Regression, Spatial Lag, Spatial Error, and GWR models were employed. First, the performance of the global regression models was compared, with the model exhibiting the lowest Akaike Information Criterion (AIC) selected as the best fit. Once the optimal global model was identified, the corresponding coefficients were reported to assess the impact of each variable. Subsequently, GWR analysis was conducted to evaluate local regression effects at the ward level, identifying specific areas in need of targeted intervention by the Jakarta government.

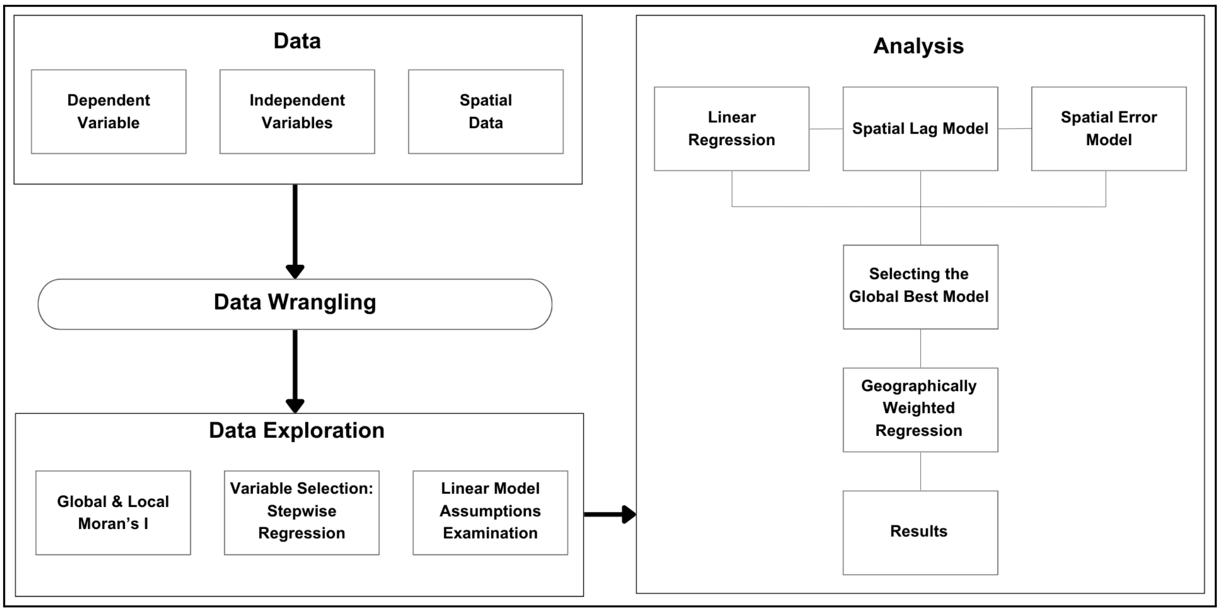

Figure 1: Research Methodology Workflow

Due to the large number of independent variables, Stepwise regression was employed to simplify the model by selecting the most significant predictors. The Stepwise regression analysis resulted in an adjusted R-squared value of 0.3324 and a p-value of <

2.2e-16, indicating that the selected variables collectively explain 33.24% of the variation in the dependent variable. The final set of variables used in subsequent analyses are listed in Table 2. The Physical Infrastructure Vulnerability Index was based on four variables: number of fire incidents, number of flood incidents, slum levels, and population density. The Health Centers variable was found to be statistically insignificant and, therefore, excluded from the regression models. This exclusion may result in a slight decrease in the Adjusted R-squared value. Furthermore, given that many variables are discrete, a log transformation will be applied to convert them into continuous variables, which is more appropriate for linear regression analysis. For columns containing zero values, a small constant (0.0001) will be added prior to transformation to prevent potential computational issues.

Table 2: Stepwise Regression Coefficients

Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	-29.02382	8.95887	-3.24	0.001357**
Physical Infrastructure Vulnerability Index	-0.11935	0.03571	-3.342	0.000956***
Male Population Percentage	7.06447	2.2549	3.133	0.001934**
Population aged 60 years and above percentage	0.78154	0.13571	5.759	2.45e-08***
Cognitive Disability Population Percentage	0.12963	0.04011	3.232	0.001393**
Health Centers Coverage Percentage	0.05186	0.02811	1.845	0.06622
Doctor's Practice and Pharmacy Coverage Percentage	-0.08441	0.02937	-2.874	0.004395**
Hotel and Accommodation Coverage Percentage	0.05034	0.01244	4.045	6.94e-05***

Residual standard error	0.3737 on 253 degrees of freedom
Multiple R-squared	0.3503
Adjusted R-squared	0.3324
F-statistic	19.49 on 7 and 253 DF
p-value	< 2.2e-16

Figure 2 indicates that none of the variables are normally distributed. In terms of correlation, most variables exhibit very low correlations, with an average value of only 0.072. Regarding multicollinearity, all variables show Variance Inflation Factor (VIF) scores below 10, indicating the absence of multicollinearity among the independent variables. Additionally, when fitting a linear regression model, it is crucial to assess whether the residuals satisfy the following assumptions: normality of distribution and minimal deviation from the line of best fit in the Q-Q plot (Musah, 2024a).

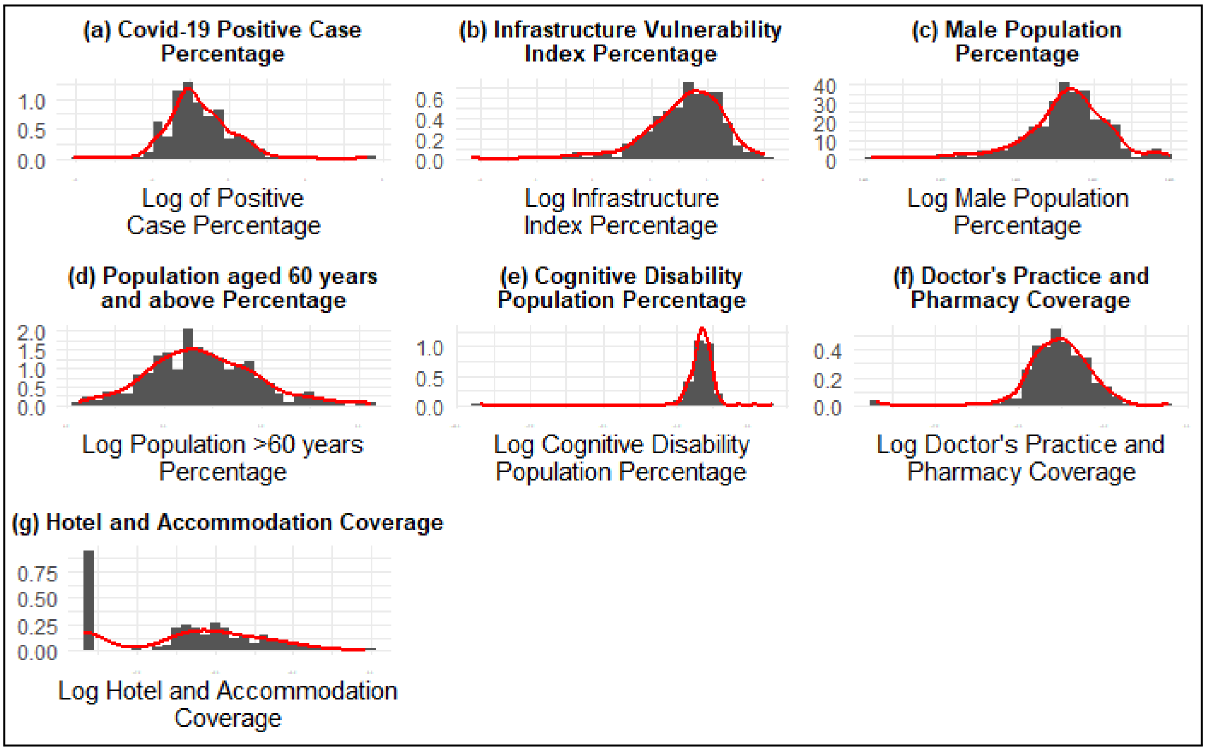

Figure 2: Variables Distribution

The histogram in Figure 3a displays a bell-shaped distribution centered slightly below zero and the Q-Q plot in Figure 3b shows that most points closely align with the line, although slight deviations are observed in the tails. These patterns suggest that, while the residuals approach close to normality, they do not fully satisfy the assumption. This is further supported by the Shapiro-Wilk test, which resulted in a p-value of 3.579e-05, indicating the residuals deviate from normality. Additionally, the residuals resulted in a statistically significant low spatial autocorrelation, as indicated by a Global Moran's I value of 0.1121 with a p-value of 0.0047. Therefore, spatial lag and error regression models are more appropriate for this analysis.

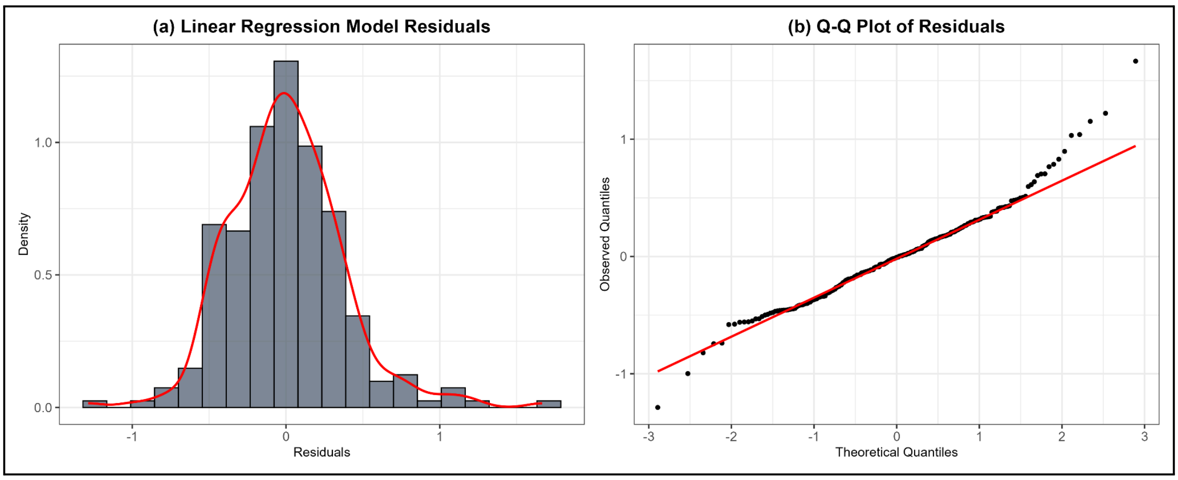

Figure 3: (a) Histogram and (b) Q-Q Plot of Linear Model Residuals

Results

Figure 4a shows that the highest percentage of COVID-19 cases per ward population is primarily clustered in Central Jakarta and parts of South Jakarta. The Global Moran's I coefficient of 0.2231 and p-value of 0.0017 indicates a statistically significant but mild positive spatial autocorrelation, suggesting weak clustering of cases across Jakarta from March to October 2020. Additionally, Figure 4b highlights high-high LISA clusters in Central and South Jakarta.

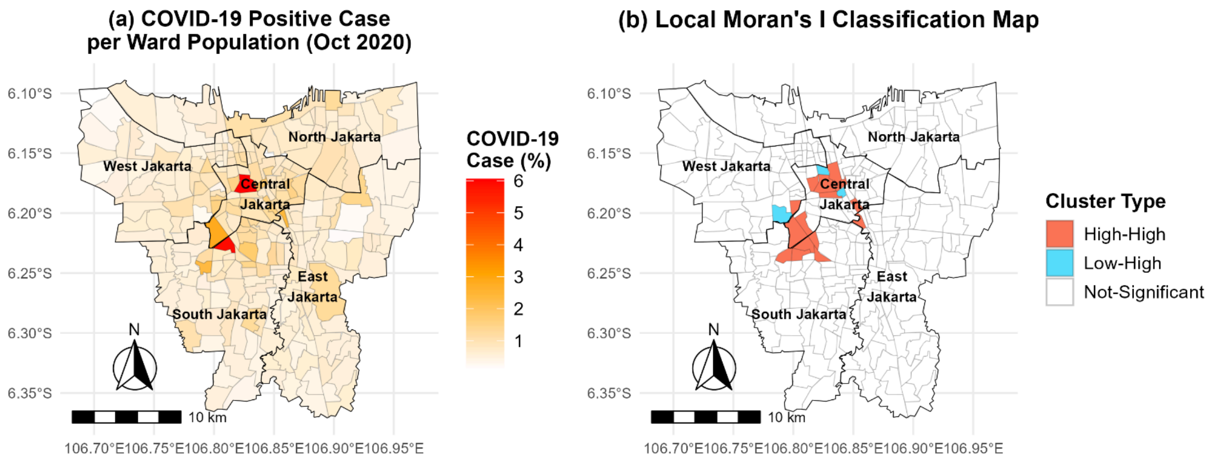

Figure 4: Spatial Analysis of COVID-19 Cases: (a) Positive Cases Distribution Map, (b) Local Moran's I Map

To further analyze the global spatial distribution of clusters, linear regression, spatial lag, and spatial error models were compared. As shown in Table 3, the spatial lag model had the lowest AIC, indicating the best fit. Additionally, Moran's I test on the residuals of the lag model resulted in a p-value of 0.8891, suggesting no evidence of spatial autocorrelation and also performed the highest in comparison to the other models. These results indicate that the spatial lag model outperforms the linear and error models in addressing spatial autocorrelation and providing a superior fit (Musah, 2024a)

Table 3: Comparison of Spatial Global Models

	Linear Regression Model	Spatial Lag Model	Spatial Error Model
AIC	238.28	221.85	232.62
Model p-value	< 2.2e-16***	7.1663e-06***	0.0012181**
Moran's I Residual p-value	0.004704**	0.8991	0.5175

The results from the spatial lag model show a ρ (rho) value of 0.3127 (p-value = 1.76e-05), indicating statistically significant evidence of a positive spillover effect of Covid-19 cases from neighboring wards. The direct, indirect, and total effects of the independent variables from Table 4 are all statistically significant, except for the indirect effect of the Doctor's Practice and Pharmacy Coverage Percentage variable (p-value: 0.101). Notably, the primary influence of the independent variables arises from their direct effects. Among these, the male population percentage exhibits the largest total impact of 7.24, indicating that a 1% increase in the male population percentage is associated with a 7.24% increase in positive Covid-19 cases in a ward (on the log-scale) (Musah, 2024a). Specifically, the direct effect of the male population percentage plays the most significant role in this total impact where a 1% increase in the male population within a ward results in a 5.1% increase in the log of positive Covid-19 cases in that same ward

Table 4: Summary of Impact Measure Statistics for Spatial Lag Model

Variables	Direct		Indirect		Total	
	Impact Measures	p-values	Impact Measures	p-values	Impact Measures	p-values
Physical Infrastructure Vulnerability Index	-0.13	2.27E-05	-0.057	0.009	-0.19	0.0001
Male Population Percentage	5.10	0.012	2.13	0.03	7.24	0.01
Population aged 60 years and above percentage	0.54	9.44E-05	0.22	0.001	0.77	4.15E-05
Cognitive Disability Population Percentage	0.11	0.0047	0.046	0.02	0.15	0.006
Doctor's Practice and Pharmacy Coverage Percentage	-0.056	0.044	-0.023	0.07	-0.08	0.04
Hotel and Accommodation Coverage Percentage	0.04	0.0006	0.017	0.006	0.057	0.0005

In terms of local regression in each GWR from the plot, it is evident that regions with the highest local R-squared values are located in Central Jakarta, North Jakarta, and West Jakarta, with local R-squared values ranging from 0.5 to 0.6 indicates the model performed well in these areas (see Figure 5). Conversely, the areas with the lowest local R-squared values are found in East Jakarta, ranging from 0.26 to 0.30 (Musah, 2024b).

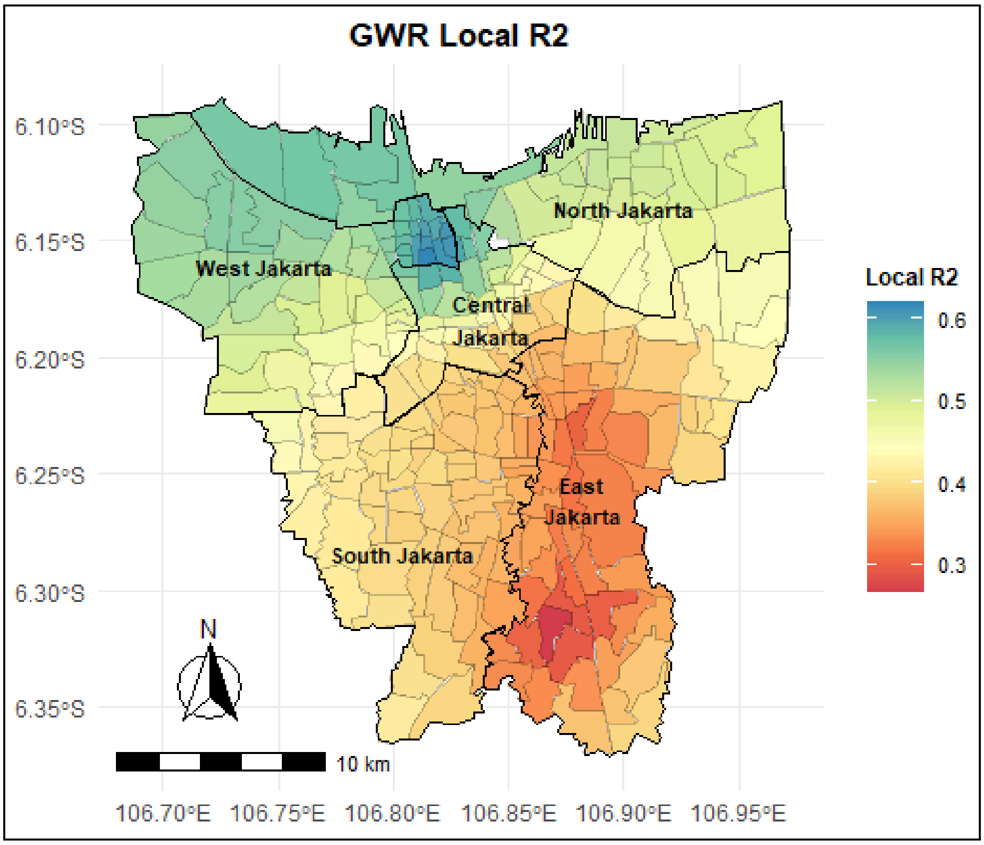

Figure 5: Local R-squared Values from GWR by Wards

Figure 6 shows where each of the independent variables are statistically significant based on GWR. Notably, the infrastructure vulnerability index and hotel coverage variables display a comparable trend. A reduction in the infrastructure vulnerability index is associated with a decrease in positive COVID-19 cases, while an increase in hotel coverage correlates with a rise in positive cases. These patterns are observed across most of Jakarta, except for a few wards in East Jakarta. This suggests that during the period of March–October 2020, factors like slum areas and population density did not significantly drive increases in positive COVID-19 cases. Instead, the rise in cases appeared to be linked to areas with a high concentration of hotels, implying that at that time, the spread of COVID-19 was largely driven by the movement of people from long distances who stayed in hotels. This finding aligns with Harapan et al. (2023), who noted the role of travel in spreading COVID-19 in Jakarta.

The variables for the male population and the population aged over 60 years showed a similar pattern. An increase in both of these variables is associated with a higher likelihood of positive COVID-19 cases, particularly in areas near Jakarta's borders with neighboring cities. This may suggest that the male population, who are typically the primary workers in Indonesia, played a significant role in transmitting the virus to their own neighborhoods. Meanwhile, the older population, being more vulnerable to the disease, faced a higher risk, especially if they were not receiving adequate support from the government. These findings align with Surendra et al. (2022), who identified older age and male sex as independent risk factors for COVID-19. Furthermore, this also might explain why the male population variable has the largest total impact in direct measures in spatial lag models.

Another pair of variables that show a similar pattern is the cognitive disability population and doctor's practice and pharmacy coverage. These two variables share a significance pattern predominantly in North, West, and Central Jakarta. An increase in the cognitive disability population and a decrease in doctor's clinics and pharmacies correlate with a higher likelihood of positive COVID-19 cases in the affected wards. This may be because individuals with cognitive disabilities may lack the understanding necessary to protect themselves from exposure to COVID-19. Furthermore, these areas might highlight systemic neglect, where both the population and the government fail to provide inclusive support or special treatment for individuals with cognitive disabilities. This aligns with Samudra and Setyonaluri (2020), who argued that disadvantaged groups, including people with disabilities, often face barriers to proper healthcare, accurate information and access to COVID-19 testing. Consequently, the combined impact of limited healthcare access and a vulnerable population with impairments can potentially cause a significant increase in the risk of new COVID-19 clusters emerging in these areas.

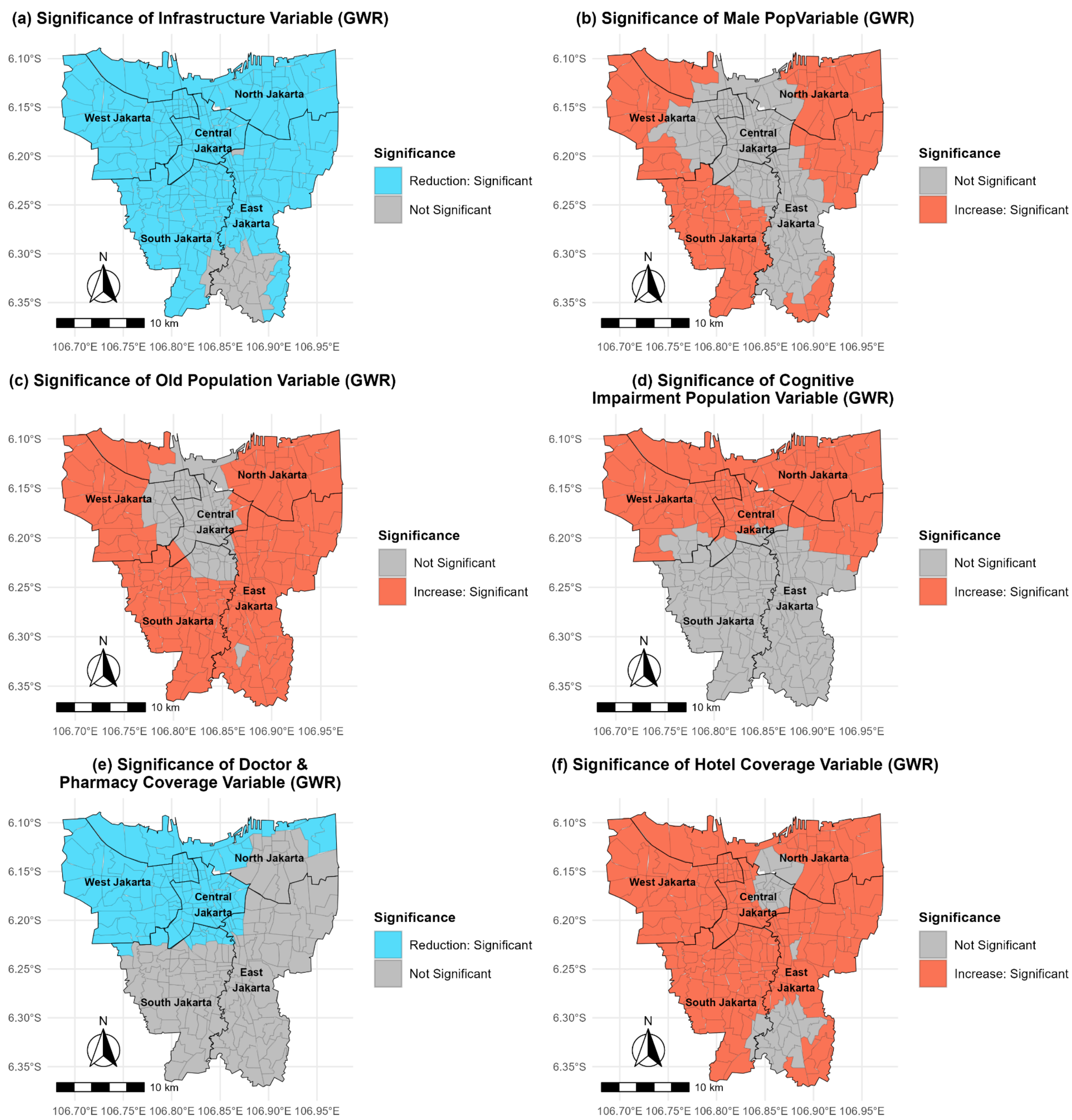

Figure 6: GWR Significance Maps of Each Variable by Wards

Figure 7 highlights wards in North and West Jakarta where all independent variables are statistically significant. These areas differ from the clusters in Figures 4a and 4b, as they represent wards with the highest potential COVID-19 risk. This contrast is also a possible indication that the residents in Central Jakarta–where the clusters in COVID-19 cases in Jakarta were located–likely had better access to testing and mitigation efforts. Conversely, the high-risk areas with vulnerable populations and slums may have experienced limited access, resulting in lower reported cases and absence of COVID-19 clusters, despite being in the high-risk areas during the early pandemic period. The high risk wards are also located near the largest airport and seaport in the Jakarta Metropolitan Area, suggesting that travel activities may have significantly influenced virus spread during this period.

These high-risk areas should be prioritized by the Jakarta government to mitigate virus transmission in the early stages of the pandemic. Specific actions include expanding access to healthcare by increasing the number of doctors and pharmacies, enhancing health monitoring, and regulating hotel operations. Targeted health tracing should focus on wards with high concentrations of male and elderly populations. Additionally, inclusive programs are needed to protect individuals with cognitive impairments from COVID-19 exposure.

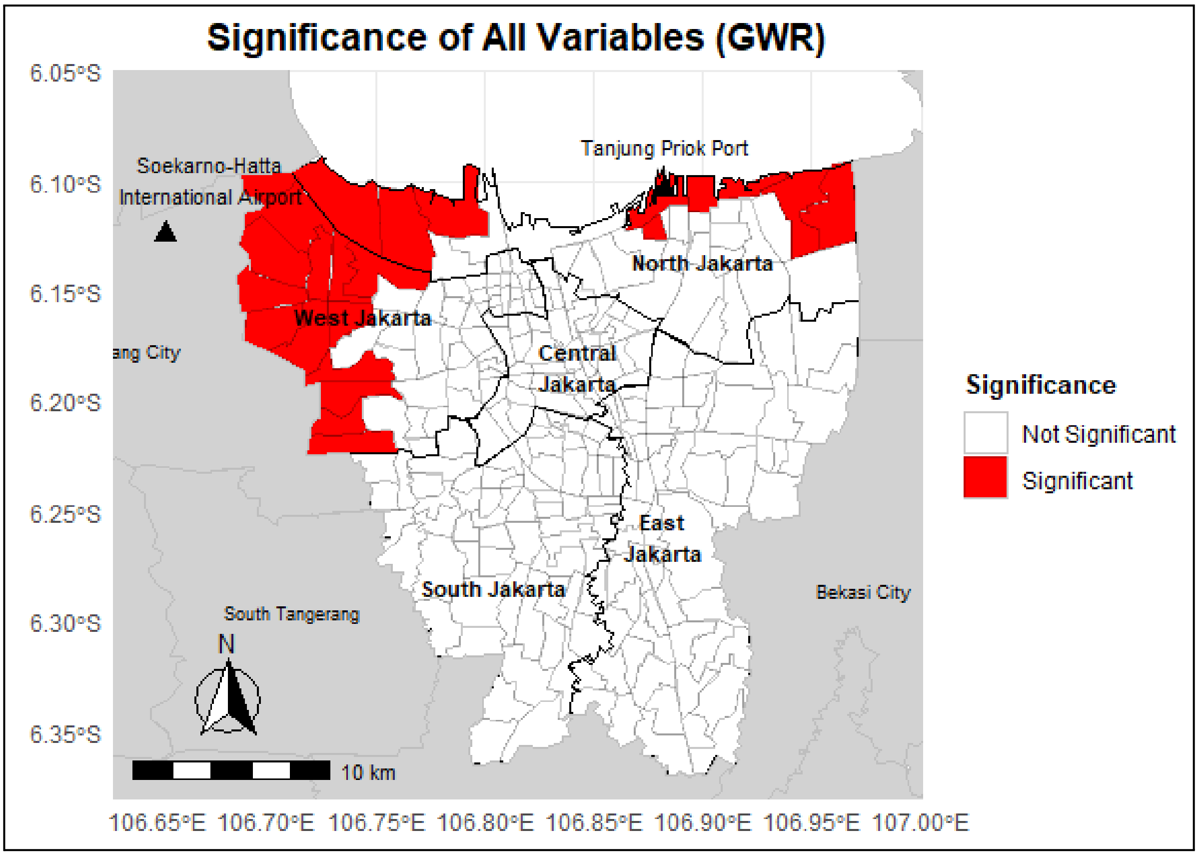

Figure 7: Map of Wards with All Significant Variables

The primary limitation of this study is the potential inaccuracy of positive COVID-19 case data due to delays and imperfect contact tracing during the study period, which may have led to underreporting of COVID-19 cases (Harapan et al., 2023; Surendra et al., 2022). This may explain why COVID-19 clusters are concentrated in Central Jakarta rather than in high-risk wards, as shown in Figure 7. Another limitation is the ecological fallacy, as populations in high-risk areas may not uniformly experience the same level of risk, given variations in personal hygiene behaviors and underlying health conditions (Surendra et al., 2023). Additionally, factors such as accessibility to transportation stations (Arini et al., 2023), road network density (Pribadi et al., 2021), and mobility behaviors influenced by district-level health policies (Dhewantara et al., 2021; Pribadi et al., 2021) may act as confounders in explaining the spatial clusters of COVID-19 cases in Jakarta. Future studies should account for these potential confounders to build on the findings presented here.

Conclusion

The COVID-19 pandemic has caused significant disruptions, particularly among disadvantaged groups, highlighting the need for policymakers to address inequalities and develop proactive strategies to prevent future health crises, including in Indonesia. This study demonstrates the effectiveness of spatial analysis in monitoring COVID-19 case clusters at the ward level in Jakarta from March to October 2020, with clusters primarily located in Central and parts of South Jakarta. The findings suggest that socioeconomic inequalities contribute to the spatial distribution of cases. The spatial lag model proved most effective in explaining the relationship between socioeconomic indicators and COVID-19 cases. Furthermore, GWR analysis identified wards in North and West Jakarta as high-risk areas requiring additional government attention. These insights provide a valuable framework for early identification of high-risk areas during a potential disease outbreaks, enabling more effective resource allocation and mitigation strategies to protect vulnerable populations.

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