# A Spatial Model of the Social Vulnerability Index for Vaccine COVID-19 in Java, Indonesia

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## Abstract

The COVID-19 vaccine coverage in Indonesia remains low, with uneven distribution across Java, while COVID-19 cases continue to pose a public health concern. This study seeks to develop a spatial model using the Social Vulnerability Index (SVI) approach to identify the spatial pattern of COVID-19 vaccination and the factors influencing it in Java. The study adopts an ecological design with a spatial approach, encompassing 118 districts/cities. The dataset used in this research focuses on the coverage of COVID-19 vaccination for the second dose, spanning from March 15, 2021, to January 11, 2022. Spatial statistical techniques such as spatial autocorrelation and Geographically Weighted Regression were employed to analyze the data. The findings reveal that the Human Development Index, unemployment rate, and housing conditions significantly impact the spatial distribution of COVID-19 vaccine coverage, indicating the presence of spatial interaction among regions. Socioeconomic factors emerged as key variables influencing the study outcomes. Given that enhancing the community's economy requires time, interventions tailored to the prevailing conditions are necessary. Therefore, interventions to increase COVID-19 vaccine coverage should prioritize health promotion efforts, particularly in areas with low socioeconomic conditions.

## Keywords

COVID-19; spatial; vaccine

# Introduction

The coronavirus (COVID-19) has developed into a worldwide pandemic. Almost all countries worldwide have cases of COVID-19, which continue to increase. This virus spreads quickly and widely because it can be transmitted through human-to-human contact. Vigilance against COVID-19 is a concern for all affected countries due to its rapid and massive spread. COVID-19 is a highly contagious and pathogenic viral infection caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which emerged in Wuhan, China, and spread worldwide (Babu et al., 2021; Eryando et al., 2020; Faisal et al., 2022).

Based on the situation of the spread of COVID-19, which has almost reached all provinces in Indonesia, with the spread of COVID-19 cases concentrated on the island of Java (Widiawaty et al., 2022), the majority of patients (67.2%) in Indonesia were from Java Island (World Health Organization, 2023). The pandemic has had a significant psychosocial impact. Health anxiety, panic, adjustment disorders, depression, chronic stress, and insomnia are the leading causes. Misinformation and uncertainty cause panic in everyone, especially older adults. It cites the social isolation of older adults as a 'serious public health problem' because of their bio-psychosocial vulnerability (Banerjee, 2020).

Vaccine hesitancy, according to the World Health Organization (WHO), refers to delays in receiving or refusing a vaccine even though vaccine services are available (MacDonald, 2015). The average acceptance rate of COVID-19 vaccines is relatively low worldwide, especially in Indonesia (Arumsari et al., 2021; Triwardani, 2021; Utami et al., 2022; Yufika et al., 2020). Data from the Ministry of Health (2022) shows that the target for the older population to be vaccinated was nearly 21.6 million people. Data obtained as of April 2, 2022, showed that the achievement of COVID-19 vaccination for older adults had not been completed, with the first vaccination totaling just over 17 million people, the second dose of slightly more than 13 million people; and the third dose totaling nearly 2.4 million people. In various COVID-19 polemics in mid-January, precisely on January 13, 2022, the COVID-19 vaccination program in Indonesia began to be carried out. The level of trust in the COVID-19 vaccine was one of the reasons for hesitation to take the COVID-19 vaccine, the lack of public information about vaccine safety, and distrust of the health system, especially among health circles and systems, especially among the community (Soares et al., 2021).

Comprehensive and evenly distributed vaccination coverage globally was urgently needed to stop the COVID-19 pandemic, making it more vulnerable to transmission of the SARS-CoV-2 virus. However, research on vaccines in developing countries is still limited. This could be due to developing countries with less capacity to introduce new vaccines (Nichter, 1995) and the difficulty of convincing the public about the importance of COVID-19 vaccination to stop the spread of SARS-CoV-2. Acceptance of vaccinations is the norm in most populations globally. A small number refuse some vaccines but agree with others, and some delay or receive vaccinations but are unsure about doing so (MacDonald, 2015).

Previous studies have shown a significant impact of socioeconomic factors on vaccination (communicable disease), regardless of pre-existing risk factors (Endrich et al., 2009). Another study explored the spatial relationship between the incidence of COVID-19 and environmental, socioeconomic, and demographic variables and found that income inequality could explain the considerable variance in COVID-19 (Endrich et al., 2009; Lee & Huang, 2022; Mollalo & Tatar, 2021).

Indonesia is a Southeast Asia with relatively low vaccine coverage and high vaccine uncertainty (Harapan et al., 2020; Syiroj et al., 2019; Yufika et al., 2020). Several spatial models have previously been used to analyze and model COVID-19 vaccine uncertainty regarding vaccine coverage and socioeconomics (Hanifa et al., 2022; Mollalo & Tatar, 2021; Soares et al., 2021).

The Centers for Disease Control and Prevention (CDC) and Agency for Toxic Substances and Disease Registry (ATSDR) (2022) developed a Social Vulnerability Index (SVI) to assist health workers in supporting the health of the most vulnerable during public health emergencies or the COVID-19 pandemic. The SVI assesses community resilience to outbreaks of public health problems at risk for public health crises (Flanagan et al., 2011; Rivera & Mollalo, 2022). The SVI consists of socioeconomic status, with one of the country's socioeconomic indicators being the poverty rate of its population. The Indonesian Central Bureau of Statistics states that the poverty rate can be measured using the level of income, level of expenditure, and a combination of both. This shows that the SVI approach is very appropriate for this study.

This study aims to provide an overview of the coverage of the second dose of provincial COVID-19 vaccination in districts/cities on each island of Java. The administrative area analysis unit in Indonesia for district and city [*kabupaten*] forms a province administrative area. In this study, the kabupaten was used as a spatial analysis unit to obtain the spatial interaction of the COVID-19 vaccine.

# Materials and methods

## Study area

The research area was all districts/cities in Java Island, which included six provinces: Banten, DKI Jakarta, West Java, Central Java, Yogyakarta, and East Java. The province of West Java has the highest population, at approximately 48.8 million people (31.9%). In contrast, the province with the highest annual population growth rate is the province of Banten at 1.76%, and the highest population density is in the province of DKI Jakarta at 15,976 per km$^2$. Of the total area of the six provinces, East Java province has the largest area of 47,803,049 km$^2$ (36.93%), while the lowest is DKI Jakarta with 664,001 km$^2$ (0.62%). The value of the Human Development Index (HDI) in Indonesia in 2021 was 72.29, with the provinces with the lowest scores being East Java (72.14) and Central Java (72.16).

## Sampling designs and methods

This study aimed to obtain spatial modeling and determine the pattern of COVID-19 vaccination coverage and the factors that affect COVID-19 vaccine coverage using indicators from the SVI. This research uses an ecological study design with a spatial approach. Ecological models serve various purposes, from illustrating ideas to parameterizing complex real-world situations. They are used to make general predictions for statistical and spatial analysis, the development of which is a statistical approach designed to test spatial autocorrelation to obtain spatial patterns (Koenig, 1999; Legendre & Fortin, 1989).

This study used spatial analysis employing secondary data, data from the routine registration of the district and city Health Office. This study also used district and city-level data to map the distribution of risk and identify the spatial SVI of the COVID-19 vaccine in six provinces consisting of 118 districts/cities on the island of Java. The population in this study was the entire population in each district and city on the island of Java, and the research sample was all data on cases of COVID-19 and the vaccine coverage of both district and city residents on the island of Java.

## Data management and analysis

This study used data from the daily COVID-19 and vaccine status reports by the Indonesian Ministry of Health, obtained from the official website of the Indonesian Ministry of Health (https://vaksin.kemkes.go.id/#/vaccines). On the Ministry of Health website, data can be selected on COVID-19 vaccination coverage for each dose and data on cases of COVID-19 in every district and city on Java Island; the data is updated daily based on the situation in the field. Data on COVID-19 and the second vaccine status were taken from March 15, 2021, to January 11, 2022.

The SVI is a concept developed by the CDC. The SVI consists of 15 indicators and is grouped into four groups of vulnerabilities: socioeconomic status, household composition, disability, minority status and language used, housing, and transportation, but it does not use the variables of gender and age. The SVI data was obtained from the Badan Pusat Statistik (BPS) [Central Statistics Agency] per province in 2021, which is secondary data that can be accessed at https://www.bps.go.id/publication.html. The Provincial Statistics Agency is a provincial statistical agency tasked with providing several socioeconomic and population indicators for the province. Since this study used secondary data on all provincial-level indicators derived from published national and provincial reports, ethical approval was not required for this study.

The dependent variable in this study is the COVID-19 vaccine in each district and city in the form of percentage coverage of the second vaccine in each province. District-level indicators associated with COVID-19 vaccine hesitation (second dose) were selected based on previous research on contributing factors (Faisal et al., 2022; Lee & Huang, 2022) using an approach from the SVI-CDC and COVID-19 case variables. The theory presented by SVI-CDC is socioeconomic status, household composition and disability, minority status and language, housing type, and transportation (Flanagan et al., 2011).

For this study, only socioeconomic status was selected, namely the result index number of the HDI. The HDI is a composite variable of life expectancy, school year expectancy, average length of schooling, and per capita expenditure figures (Al Rifai et al., 2021). Population poverty variables include data on the percentage of low-income families (Fauzi & Paiman, 2020; Soares et al., 2021) and unemployment (Gangopadhyaya & Garrett, 2020). The household variable uses data on the percentage of elderly, the percentage of ownership of health insurance BPJS Health Contribution Assistance Recipient program (Cordes & Castro, 2020; Gangopadhyaya & Garrett, 2020), and the housing type variable uses data on the percentage of house area that is less than 19 $m^2$ (Al Rifai et al., 2021; Barry et al., 2021). Moreover, the independent variables utilized in this study, including the number of COVID-19 cases per province, are consistent with those employed in previous studies documented in the existing literature (Cordes & Castro, 2020; Kang et al., 2020).

Data analysis was performed with descriptive statistics to present each variable's mean, standard deviation (SD), minimum, and maximum values. The correlation between each independent and COVID-19 case was tested using the Pearson correlation or Spearman's Rank (Eryando et al., 2020).

The spatial analysis used Local Moran's I to identify the spatial autocorrelation and local autocorrelation of the COVID-19 risk score. Global Moran's I inform the data's spatial dependence or independence (Anselin & Getis, 1992; Buyong, 2007).

$$\boldsymbol{Z(I)} = \frac{I - E(I)}{S(I)} \quad (1)$$

Where (I) is Moran's Index, Z (I) is Moran's I test statistic value. Global Moran's I value (between -1 and 1), which is higher than the expected value of Moran's I – E(I) observed – indicates positive spatial autocorrelation (that is, more significant data similarity between neighboring locations or clustering of high and low values in the data set). The results of the Moran Index value show the distribution pattern of the variables if the value I > E(I) has a clustered spatial pattern and if the value I < E(I) has a spreading pattern. However, suppose the Global Moran's I value is lower than E(I). In that case, it indicates a negative spatial autocorrelation (i.e., difference or dispersion of high and low values in the data set). Spatial autocorrelation was also evaluated with Global Moran's I-significant p-value ($p < .05$) using 999 permutations criteria.

Furthermore, Local Moran's I, or Local Indicator Spatial Autocorrelation (LISA), can test Moran's I for each district. The findings from the LISA indicate whether the values of the observed variables in a given area have a statistically significant spatial autocorrelation with values at other locations (that is, they are related to, have an influence on, or are affected by the values of other locations). This study applied LISA to identify areas with high-low risk categories for COVID-19 vaccine hesitation and areas with low-high categories. The High-High region category in Quadrant I explains that the region has high cases and is surrounded or adjacent to other areas with high cases. Quadrant II has a Low-High type where areas with low cases are surrounded or adjacent to areas with a high number of cases. The Low-Low type in Quadrant III explains that areas with a low number of cases surround areas with a low number of cases. High-Low type in Quadrant IV means that areas with high cases are surrounded by areas that have a low number of cases (Buyong, 2007).

This study used Geoda 1.8.10 to perform spatial analysis. Moran's Index Map and LISA Map only consider areas where the Moran index is significant ($p < .05$).

Geographically Weighted Regression (GWR) is a linear regression model for continuous response variables considering location aspects. The GWR model is a global linear regression (OLS) model development. The GWR model is a local linear regression model that generates estimates of localized regression model parameters for each point or location where the data is collected. In the GWR model, the dependent variable Y is predicted by an independent variable where each regression coefficient depends on the location where the data is observed (Fotheringham et al., 2002). The GWR model can be formulated as follows,

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} x_{ik}\, \beta_k(u_i, v_i) + \varepsilon_i;\ i=1,2,\ldots,n \quad (2)$$

While;

$y_i$ : the "$I$" response variable of observation value

| | |
|---|---|
| $x_{ik}$ | : the "$k$" independent variable of the observation value on the "$I$" observation |
| $\beta_0(u_i, v_i)$ | : GWR regression model intercept value |
| $\beta_k$ | : regression coefficient |
| $u_i$, $v_i$ | : The coordinates (latitude, longitude) of the "$I$" location |
| $\varepsilon_i$ | : $[\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n]^T$ ~ in $(0,\sigma^2)$ |

One of the most commonly used weighting functions is the fixed bi-square function (*Gaussian Distance Function*). This function is used in the GWR model if the distance function is continuous and monotonically descending.

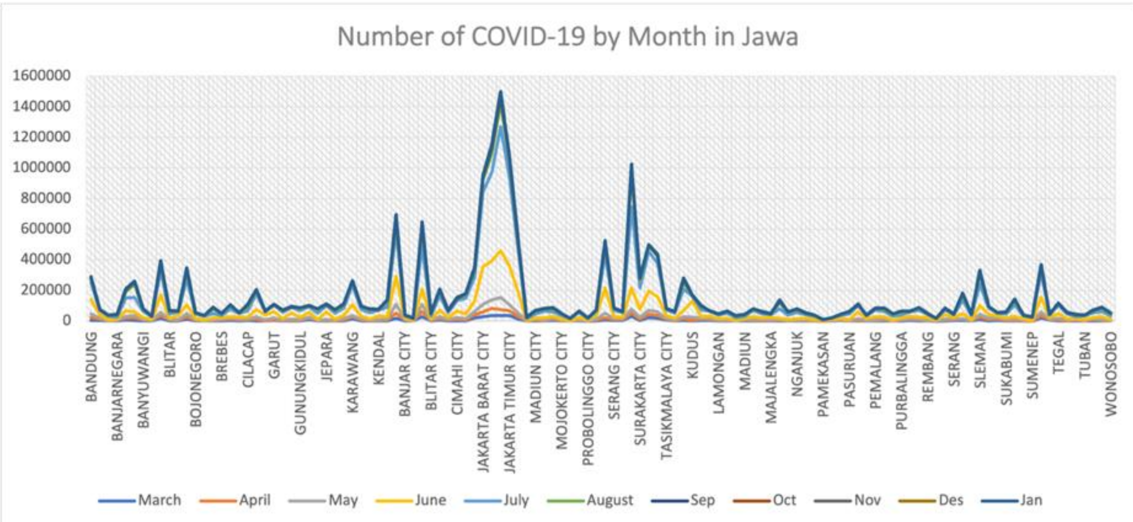
This study used district or city-level data available in the public domain; therefore, ethical approval was not required.

# Results

## Characteristics of COVID-19 cases and coverage of the second dose of COVID-19 vaccine

The distribution of COVID-19 cases per month on Java Island (except in Kepulauan Seribu District) from March 15, 2021, to January 11, 2022, can be seen in Figure 1. The peak of the wave of COVID-19 cases occurred in July–August 2021 and rose again in January 2022. In July 2021, the Delta variant of COVID-19 (G/452R.V3) was found (Cahyadi et al., 2022; Dyer, 2021).

**Figure 1:** Number of COVID-19 Cases by Month in Java




The percentage of second-dose vaccination achievement in 118 districts/cities in Java Island was classified from 45.27–215.5%, with details in as many as 44 districts/cities falling into the "very low" category (45.27–79.33%). Most areas fell into the "low" category, with as many as 63 districts/cities. There were only two cities classified as "very high" (181.53–215.5%), namely Central Jakarta (DKI Jakarta province) and the City of Yogyakarta (province of the Special Region of Yogyakarta). Figure 2 shows that the coverage of the second dose of vaccine is clustered in the west of the island of Java.

**Figure 2:** The Coverage of the Second Dose of the Vaccine

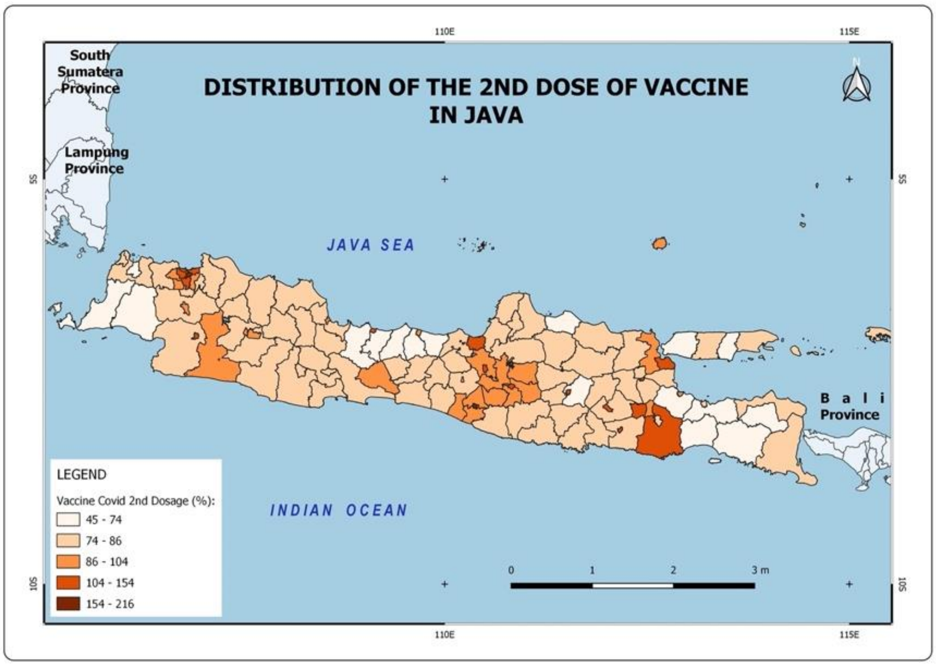



Table 1 shows the independent variables' mean, standard deviation, and minimum and maximum values. Several independent variables were also found to have a statistically significant correlation with the coverage of the second dose of vaccine (*p* value < .05), with a correlation ranging from low to moderate. Several variables included in the SVI, namely the HDI ($r = 0.713$), poverty ($r = -0.480$), housing ($r = 0.515$), and the proportion of COVID-19 cases ($r = 0.357$), were statistically significantly correlated with the COVID-19 vaccine. However, there was no correlation between unemployment, health insurance, and older adults related to COVID-19 vaccine coverage.

**Table 1:** Statistical Correlation Results

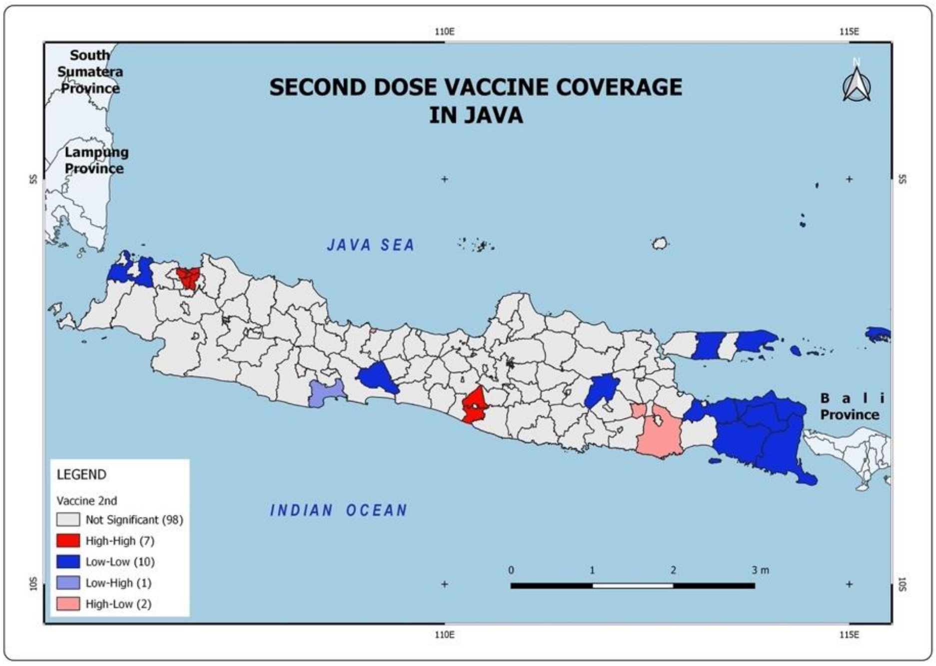
| Variables | Mean (SD) | Min; Max | *r* | *p* value |
|---|---|---|---|---|
| **Dependent Variable** | | | | |
| Vaccine second dosed (%) | 87.77 (22.67) | 45.27; 215.60 | | |
| **Independent Variables** | | | | |
| **Socioeconomic characteristics** | | | | |
| Human Development Index | 72.96 (5.35) | 62.80; 87.18 | 0.714 | .0001* |
| Poverty (%) | 10.72 (4.52) | 2.58; 27.86 | -0.480 | .0001* |
| Unemployment (%) | 5.10 (7.63) | 0.22; 45.62 | 0.012 | .894 |
| **Household** | | | | |
| Health insurance (%) | 38.39 (11.34) | 13.59; 74.88 | -0.098 | .291 |
| Elderly (%) | 7.90 (6.31) | 0.27; 26.53 | 0.030 | .749 |
| **Housing** | | | | |
| House area < 19 $m^2$ (%) | 3.16 (5.83) | 0.10; 34.16 | 0.515 | .0001* |
| **COVID-19** | | | | |
| COVID-19 cases (%) | 5.08 (7.39) | 0.29; 32.78 | 0.357 | .0001* |

*Note: m2 = square meters; SD = standard deviation; Min = minimum value; Max = maximum value; r=correlation coefficient; p value = from Spearman's Rank correlation;(*) significant .05*

## Spatial autocorrelation of COVID-19 vaccine second dose

This study used spatial regression analysis (Geographically Weighted Regression) rather than multiple linear regression statistical analysis. The results of the spatial autocorrelation analysis showed the percentage number of the second dose of COVID-19 vaccine coverage using the rook contiguity weighting. The results of the second dose of COVID-19 vaccine coverage had a Moran's (I) value of 0.202 with $p$ value = .009 ($p$ value = $\alpha < .05$). This value is greater than E(I) = -0.0086, indicating a clustered positive autocorrelation or data pattern with similar characteristics at adjacent locations, as shown in Figure 3. The results of the LISA cluster map of the second dose vaccine coverage showed that only 19 districts/cities were significant in local spatial autocorrelation ($p < .05$), and seven districts/cities were in the High-High cluster; this indicated locations that had high observed values surrounded by locations that had high observed values, namely in the provinces of DKI Jakarta (East Jakarta, West Jakarta, North Jakarta, South Jakarta, and Central Jakarta) and Yogyakarta (Bantul District and Sleman District) provinces. While two districts/cities, namely East Java province (Malang District) and Central Java province (Tegal City), were included in the High-Low category, this shows that locations with low observed values surround locations with high observation values.

**Figure 3:** LISA Vaccine Coverage Second Dose




## Spatial model SVI on the second dose of COVID vaccine coverage

Modeling in answering the effect of SVI on hesitations about implementing the second dose of the COVID-19 vaccine was carried out using multiple linear regression and Geographically Weighted Regression (GWR) approaches. The multiple linear regression analysis results showed that the HDI, health insurance, and house area < 19 $m^2$ variables significantly influenced the hesitation in implementing the second dose of the COVID-19 vaccine. The spatial effect test is seen from the results of the Breusch Pagan value, which shows a $p$ value

< .05 (.0001) so that spatial heterogeneity is identified, then GWR modeling is needed where there is a random area effect, namely the difference between one location and another.

Table 2 shows the parameter estimates of the GWR model developed using the Adaptive Bi-square weighting function. Generally, the GWR model provides a second COVID-19 vaccine hesitation model that is better than the linear regression model, indicated by a higher adjusted $R^2$ value (0.732) and a lower AIC value (217.003). The minimum and maximum values of the regression coefficients of the same model selected are shown in Table 2.

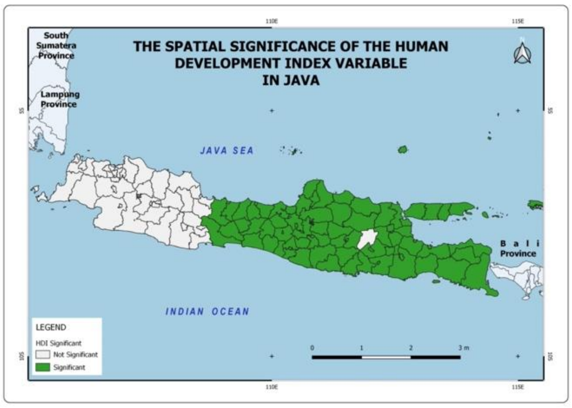
**Table 2:** Spatial Modelling

| Variable | Global Regression | | Geographically Weighted Regression (Spatial Kernel: Bisquare Adaptive) | |
|---|---|---|---|---|
| | **Estimate** | ***p* value** | **Min** | **Max** |
| Intercept | 0.000 | 1 | -0.051 | -0.007 |
| HDI | 0.339 | .001* | 0.172 | 0.390 |
| Poverty (%) | 0.012 | .894 | -0.023 | 0.045 |
| Unemployment (%) | -0.089 | .350 | -0.545 | -0.056 |
| Health Insurance (%) | 0.130 | .041* | 0.080 | 0.119 |
| Elderly | 0.033 | .582 | 0.047 | 0.084 |
| House area < 19 $m^2$ (%) | 0.619 | .001* | 0.329 | 0.131 |
| COVID-19 cases (%) | 0.020 | .835 | 0.137 | 0.156 |
| **Model Diagnosis for Linear Regression** | | | | |
| *Diagnostics For Heteroskedasticity* | | | | |
| Breusch-Pagan Test | *p* value = | .0001 | | |
| *Diagnostics For Spatial Dependence* | | | | |
| Lagrange Multiplier (Lag) | *p* value = | .1231 | | |
| Lagrange Multiplier (Error) | *p* value = | .0390 | | |
| **Model Fit** | | | | |
| AIC | 223.659 | | 211.589 | |
| $R^2$ | 0.660 | | 0.732 | |
| Adjusted $R^2$ | 0.638 | | 0.692 | |

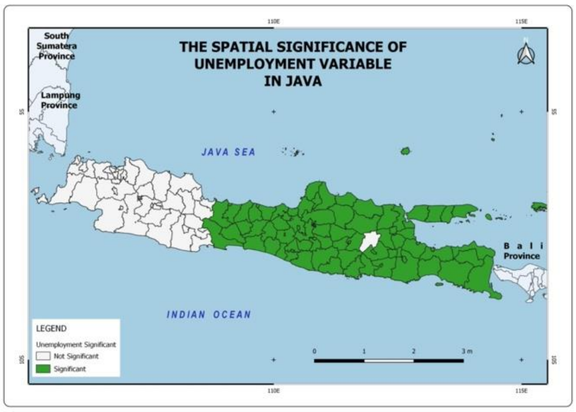
*Note: AIC = Akaike Information Criterion; m = meters; Min = minimum value; Max = maximum value;(*) significant .05*

Based on the results of the GWR modeling of the second COVID-19 vaccine in each district and city, there were only three significant variables, namely HDI, unemployment, and house area < 19 $m^2$. The details of these three variables can be seen in Figure 4. The HDI and unemployment are variables dominant in Central Java Province (35 districts/cities), Yogyakarta Special Region (5 districts/cities), and most of East Java provinces (37 districts/cities). Meanwhile, the house area variable < 19 $m^2$ was only found in West Java (2 districts) and East Java (11 districts). The GWR approach's modeling results produced different spatial models in each district and city. Figure 4 (a–c) shows spatially significant variables. The R2 value in Figure 4d shows that the central part of the island of Java had a high $R^2$ value, meaning that the GWR model in this district/cites was a fit model.

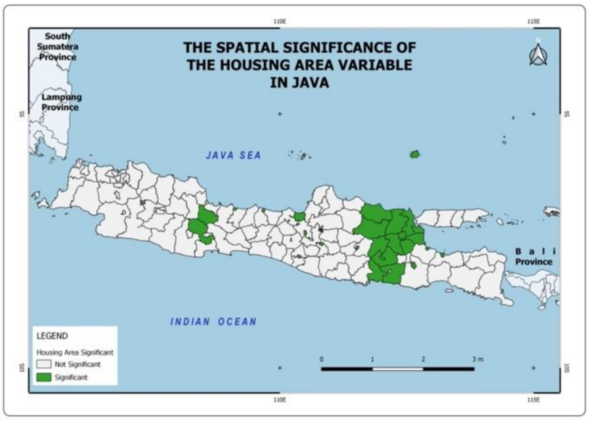
**Figure 4:** Significant Variables in Districts/Cities



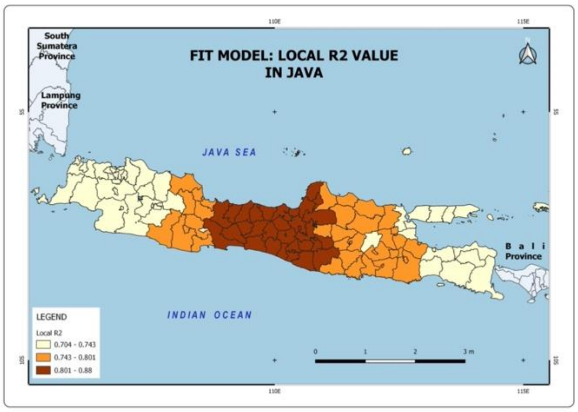

a. HDI




b. Unemployment




c. Housing




d. $R^2$ Value

# Discussion

Since early 2020, cases of COVID-19 have spread to more than 188 countries worldwide, affecting more than 106 million people and causing more than 2.3 million deaths (World Health Organization, 2023). The SARS-CoV-2 virus significantly impacted the global economy due to its highly infectious nature and the resulting implementation of social distancing measures and Large-Scale Social Restrictions (Pembatasan Sosial Berskala Besar [PSBB]), which aimed to mitigate the death rate (Flaxman et al., 2020; Leung et al., 2020). In early 2021, with the development of several vaccines with clinically proven efficacy and safety (Birhane et al., 2021; Thanh Le et al., 2020), significant challenges regarding the COVID-19 response were overcome to ensure timely mass vaccination and acceptance by all residents (Schaffer DeRoo et al., 2020; Wang et al., 2020). Vaccines are a way to actively increase a person's immunity to an antigen (from germs, viruses, or bacteria) so that when later exposed to the same antigen (germ), the person already has antibodies so that disease does not occur, where the aim is to prevent certain diseases from occurring on someone (Arumsari et al., 2021; Harapan et al., 2020). At that time, the COVID-19 vaccine was already available in Indonesia. The government had started a vaccination program to break the chain of the spread of coronavirus infection and suppress the number of COVID-19 cases, which was increasing.

The results of this study showed that the percentage of achievement of the second dose of COVID-19 vaccination in 118 cities/districts in Java was the highest at 74–86%. The first lowest vaccine coverage in Java was in Banten Province (Serang City and Lebak District) and East Java Province in Pamekasan District. The results of the LISA analysis showed that East Java province has a Low-Low cluster, where districts with low coverage surround districts with low coverage. For example, residents in urban-rural areas may face socioeconomic challenges, including substantial barriers to accessing healthcare services (Apparicio et al., 2008; Schnake-Mahl & Sommers, 2017). Coverage of COVID-19 vaccination in rural areas is lower than in urban areas, and people in rural areas are more likely to travel outside their area of residence for vaccination (Barry et al., 2021; Murthy et al., 2021). Efforts to increase vaccination coverage could focus on areas that are more vulnerable in terms of socioeconomic and household composition while adapting interventions based on urban areas, and vaccine hesitancy in rural areas is a significant obstacle that public health practitioners, health care providers, and local partners to achieve vaccination equality (Murthy et al., 2021).

The GWR modeling results show that hesitations about implementing the second COVID-19 vaccine are influenced by SVI, namely the HDI, unemployment, and house area < 19 $m^2$. The provinces of Central Java, the Special Region of Yogyakarta, and East Java have the highest number of districts/cities. Based on data from the BPS in 2022 shows that the provinces of East Java (72.14) and Central Java (72.16) are below the value of the Indonesian HDI (72.29), while the province of the Special Region of Yogyakarta (80.22) has an index value of above the Indonesian value. The interesting thing about the Special Region of Yogyakarta Province is that, despite the high HDI rate, it is a significant variable in the SVI in the second COVID-19 vaccine. If the HDI score is high, it usually indicates that the socioeconomic condition of the population is in a good category. Still, in this study, the SVI for the second COVID-19 vaccine shows a statistically significant number, which means that a high HDI number does not always indicate the population's well-being. In addition to HDI, health and sociodemographic indicators can provide meaning related to vaccination.

The SVI variable regarding housing that has a spatially significant value to the coverage of the second COVID-19 vaccine is the condition of the house area, which is less than 19 $m^2$. Lack of housing structure and access to minimal resources, such as water and basic sanitation, both on the outskirts of big cities and in cities in the country's interior, can increase the risk of disease from COVID-19 (de Souza et al., 2020). A study analyzed the determinants of poverty by measuring the probability of a household being poor by finding that household characteristics such as housing conditions significantly affect the status of poor households in Indonesia (Rini & Sugiharti, 2017).

Vaccine hesitancy refers to a reluctance to receive vaccines, even though vaccination services are available and easy to access. The problem arises when misinformation about vaccines spreads in the community (Wiyeh et al., 2018). Such contextualized vaccine skepticism research is critical to ensuring the effectiveness, efficiency, and equity of vaccination services (Wiysonge et al., 2022).

Seven districts/cities achieved second dose vaccination in the “High-High” Quadrant, where five districts/cities came from DKI Jakarta Province. Quadrant I (High-High) is an area with a high vaccination rate surrounded by areas with a high vaccination rate. The spatial model further shows that vaccine indecision among residents of one region is directly related to vaccine indecision in nearby areas. In line with findings of spatial clustering in vaccine acceptance (Lee & Huang, 2022; Valckx et al., 2022). As with DKI Jakarta, the nation’s capital and government center make it easier for local governments to carry out the second vaccination dose. It has resulted in the districts/cities around DKI Jakarta also increasing the coverage of the second vaccine. The ease of accessibility makes distributing vaccines in several districts around the capital effortless. Besides that, these districts/cities do not have a shortage in general. This will improve the health status of the community for the better because of access to health services that are getting better (Faisal et al., 2022; Mollalo & Tatar, 2021).

This research only discusses areas in the "High-Low" and "Low-High" categories because these two areas are outlier areas, meaning that these areas are the focus of implementing programs for these two categories. In contrast, areas with "Low-Low" and "High-High" categories are areas that have categories that are in accordance with their neighbors, where areas with high scores will affect the surrounding area (also affected) as well as areas with the "Low-Low" category. The results of the LISA analysis show that some districts/cities fall into the "High-Low" and "Low-High" categories. The two categories are included in the district and city, with the outlier category (Park et al., 2016). Districts/cities that fall into the "High-Low" category are Malang district in East Java province and Tegal City in Central Java province. It showed that the Malang district has no influence on the surrounding area and the City of Tegal and that the coverage of the second COVID-19 vaccine in the two provinces does not show any neighborhood effect. The high coverage of the second COVID-19 vaccine in the Malang district is because the health center team carries out vaccination activities "door to door," especially for older adults, so the vaccine coverage target can be met (Rufaindah et al., 2021)

The results of GWR modeling, HDI variables, unemployment, and house area < 19 $m^2$ are significant variables in several districts/cities. The HDI and unemployment variables are found in all districts/cities in Central Java and Yogyakarta Provinces, mostly (80.43%) in East Java Province. The two variables are categorical socioeconomic variables of the SVI. The GWR model is expected to explain geographic characteristics in the health sector by exploring socioeconomic phenomena that vary by region (Park et al., 2016). Socioeconomics is a variable that influences the coverage of the second COVID-19 vaccine. Three provinces are located far east of the state capital DKI Jakarta. Those far from the capital will likely face socioeconomic problems and substantial barriers to accessing health services (Barry et al., 2021). Regional economic variables (HDI and unemployment) are essential indicators for vaccine distribution because they directly relate to health infrastructure. High HDI scores and better public welfare can reduce the growing problem of vaccine hesitation and help countries vaccinate people in less time (Roghani, 2021).

The results of this study, SVI indicator numbers, and differences in COVID-19 vaccination coverage continue and increase from time to time, even though access to vaccination is expanding. The existence of disparities related to socioeconomic status, household composition, and disability, especially in provinces with many districts/cities, will continue to increase. Access to COVID-19 vaccines will require focused efforts on increasing coverage in high SVI countries and adapting to local population needs, for example, by adding vaccine centers or relocating existing vaccine centers in densely populated districts/cities to increase coverage (Faisal et al., 2022). Furthermore, efforts could include walk-in vaccination clinics and public health messages about the importance of vaccination and the need for community intervention to help promote health (Barry et al., 2021; Harapan et al., 2020; Mofleh et al., 2022)

# Strengths and limitations

This study used GWR spatial analysis to model COVID-19 vaccine coverage in Java. The GWR analysis can estimate the local parameters of the factors related to the coverage of the COVID-

19 vaccine in each district. It can show the districts/cities that are spatially or locally significant. This analysis also considers spatial autocorrelation and data heterogeneity, with observations of 118 districts/cities able to show data variation and detect the significance of factors associated with COVID-19 vaccine coverage compared to previous ecological studies with few observations.

The limitation of this study is that many factors cause the transmission of COVID-19, so this study does not discuss the incidence of COVID-19. The time of data collection for COVID-19 cases and the status of the second COVID Vaccine were analyzed beginning from mid-March 2021 because data was only available from that date. In secondary data processing, no information related to individual vaccination data was obtained, whether based on the Identity Card or the area where the vaccination was carried out. In addition, vaccination coverage data were also obtained based on comparisons with targets and non-populations. Finally, these ecological studies may occur in ecological studies because the results may not reflect the individual level experience. All spatial analyzes are prone to regional unit research problems; this is due to the personal level data being collected to a higher spatial unit level (i.e., district or city level data) (Putra et al., 2022)

# Conclusion

Spatial analysis of the second COVID-19 vaccine coverage on the island of Java showed a clustered pattern. Spatial modeling results showed that spatially significant SVI variables were HDI, unemployment, and house area < 19 m$^2$, and they only existed in three provinces: Central Java, Special Region of Yogyakarta, and East Java. Socioeconomic factors of an area were still the main issue related to public health. Improving the socioeconomics of the region takes time, so to increase the coverage of the COVID-19 vaccine, the most important thing is health promotion to the public regarding the importance of the COVID-19 Vaccine.

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# References

Al Rifai, M., Jain, V., Khan, S. U., Nasir, K., Zhu, D., Vasudeva, R., Lavie, C. J., Dodani, S., Petersen, L. A., & Virani, S. S. (2021). Social vulnerability and COVID-19: An analysis of CDC data. *Progress in Cardiovascular Diseases*, *73*, 91–93. https://doi.org/10.1016/j.pcad.2021.09.006

Anselin, L., & Getis, A. (1992). Spatial statistical analysis and geographic information systems. *Annals of Regional Science*, *26*(1), 19–33. https://doi.org/10.1007/BF01581478

Apparicio, P., Abdelmajid, M., Riva, M., & Shearmur, R. (2008). Comparing alternative approaches to measuring the geographical accessibility of urban health services: Distance types and aggregation-error issues. *International Journal of Health Geographics*, *7*(1), Article 7. https://doi.org/10.1186/1476-072X-7-7

Arumsari, W., Desty, R. T., & Kusumo, W. E. G. (2021). Gambaran penerimaan vaksin COVID-19 di Kota Semarang [Overview of receiving COVID-19 vaccine in Semarang City]. *Indonesian Journal of Health Community*, *2*(1), 35–45. https://doi.org/10.31331/ijheco.v2i1.1682

Babu, G. R., Khetrapal, S., John, D. A., Deepa, R., & Narayan, K. M. V. (2021). Pandemic preparedness and response to COVID-19 in South Asian countries. *International Journal of Infectious Diseases*, *104*, 169–174. https://doi.org/10.1016/j.ijid.2020.12.048

Banerjee, D. (2020). The impact of Covid-19 pandemic on elderly mental health. *International Journal of Geriatric Psychiatry*, *35*(12), 1466–1467. https://doi.org/10.1002/gps.5320

Barry, V., Dasgupta, S., Weller, D. L., Kriss, J. L., Cadwell, B. L., Rose, C., Pingali, C., Musial, T., Sharpe, J. D., Flores, S. A., Greenlund, K. J., Patel, A., Stewart, A., Qualters, J. R., Harris, L., Barbour, K. E., & Black, C. L. (2021). Patterns in COVID-19 vaccination coverage, by social vulnerability and urbanicity—United States, December 14, 2020–May 1, 2021. *MMWR. Morbidity and Mortality Weekly Report*, *70*(22), 818–824. https://doi.org/10.15585/mmwr.mm7022e1

Birhane, M., Bressler, S., Chang, G., Clark, T., Dorough, L., Fischer, M., Watkins, L. F., Goldstein, J. M., Kugeler, K., Langley, G., Lecy, K., Martin, S., Medalla, F., Mitruka, K., Nolen, L., Sadigh, K., Spratling, R., Thompson, G., & Trujillo, A. (2021). COVID-19 vaccine breakthrough infections reported to CDC — United States, January 1–April 30, 2021. *MMWR. Morbidity and Mortality Weekly Report*, *70*(21), 792–793. https://doi.org/10.15585/mmwr.mm7021e3

Buyong, T. (2007). *Spatial data analysis for geographic information science*. Penerbit Universiti Teknologi Malaysia.

Cahyadi, M. N., Handayani, H. H., Warmadewanthi, I., Rokhmana, C. A., Sulistiawan, S. S., Waloedjo, C. S., Raharjo, A. B., Endroyono, Atok, M., Navisa, S. C., Wulansari, M., & Jin, S. (2022). Spatiotemporal analysis for COVID-19 Delta variant using GIS-Based Air Parameter and Spatial Modeling. *International Journal of Environmental Research and Public Health*, *19*(3), Article 1614. https://doi.org/10.3390/ijerph19031614

Centers for Disease Control and Prevention (CDC), & Agency for Toxic Substances and Disease Registry (ATSDR). (2022, November 16). *CDC/ATSDR Social Vulnerability Index*. Centers for Disease Control and Prevention. https://www.atsdr.cdc.gov/placeandhealth/svi/

Cordes, J., & Castro, M. C. (2020). Spatial analysis of COVID-19 clusters and contextual factors in New York City. *Spatial and Spatio-Temporal Epidemiology*, *34*, Article 100355. https://doi.org/10.1016/j.sste.2020.100355

de Souza, C. D. F., Machado, M. F., & do Carmo, R. F. (2020). Human development, social vulnerability and COVID-19 in Brazil: A study of the social determinants of health. *Infectious Diseases of Poverty*, *9*(1), Article 124. https://doi.org/10.1186/s40249-020-00743-x

Dyer, O. (2021). Covid-19: Indonesia becomes Asia's new pandemic epicentre as delta variant spreads. *BMJ*, *374*, Article n1815. https://doi.org/10.1136/bmj.n1815

Endrich, M. M., Blank, P. R., & Szucs, T. D. (2009). Influenza vaccination uptake and socioeconomic determinants in 11 European countries. *Vaccine*, *27*(30), 4018–4024. https://doi.org/10.1016/j.vaccine.2009.04.029

Eryando, T., Sipahutar, T., & Rahardiantoro, S. (2020). The risk distribution of COVID-19 in Indonesia: A spatial analysis. *Asia Pacific Journal of Public Health*, *32*(8), 450–452. https://doi.org/10.1177/1010539520962940

Faisal, K., Alshammari, S., Alotaibi, R., Alhothali, A., Bamasag, O., Alghanmi, N., & Bin Yamin, M. (2022). Spatial analysis of COVID-19 vaccine centers distribution: A case study of the city of Jeddah, Saudi Arabia. *International Journal of Environmental Research and Public Health*, *19*(6), Article 3526. https://doi.org/10.3390/ijerph19063526

Fauzi, M. A., & Paiman, N. (2020). COVID-19 pandemic in Southeast Asia: Intervention and mitigation efforts. *Asian Education and Development Studies*, *10*(2), 176–184. https://doi.org/10.1108/AEDS-04-2020-0064

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2011). A social vulnerability index for disaster management. *Journal of Homeland Security and Emergency Management*, *8*(1), Article 3. https://doi.org/10.2202/1547-7355.1792

Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J. T., Mellan, T. A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J. W., Monod, M., Imperial College COVID-19 Response Team, Perez-Guzman, P. N., Schmit, N., Cilloni, L., Ainslie, K. E. C., Baguelin, M., Boonyasiri, A., Boyd, O.,

… Bhatt, S. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature*, *584*(7820), 257–261. https://doi.org/10.1038/s41586-020-2405-7

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). *Geographically weighted regression: The analysis of spatially varying relationships*. Wiley.

Gangopadhyaya, A., & Garrett, B. (2020, March 1). *Unemployment, health insurance, and the COVID-19 recession*. Robert Wood Johnson Foundation. https://www.rwjf.org/en/insights/our-research/2020/03/unemployment-health-insurance-and-the-covid-19-recession.html

Hanifa, S., Puspitasari, D., Ramadhan, C., & Herastuti, K. O. (2022). COVID-19 vaccine prioritization based on district classification in Yogyakarta Province, Indonesia. *Geospatial Health*, *17*(s1), Article 1010. https://doi.org/10.4081/gh.2022.1010

Harapan, H., Wagner, A. L., Yufika, A., Winardi, W., Anwar, S., Gan, A. K., Setiawan, A. M., Rajamoorthy, Y., Sofyan, H., & Mudatsir, M. (2020). Acceptance of a COVID-19 vaccine in Southeast Asia: A cross-sectional study in Indonesia. *Frontiers in Public Health*, *8*, Article 381. https://doi.org/10.3389/fpubh.2020.00381

Kang, D., Choi, H., Kim, J.-H., & Choi, J. (2020). Spatial epidemic dynamics of the COVID-19 outbreak in China. *International Journal of Infectious Diseases*, *94*, 96–102. https://doi.org/10.1016/j.ijid.2020.03.076

Koenig, W. D. (1999). Spatial autocorrelation of ecological phenomena. *Trends in Ecology and Evolution*, *14*(1), 22–26. https://doi.org/10.1016/S0169-5347(98)01533-X

Lee, J., & Huang, Y. (2022). COVID-19 vaccine hesitancy: The role of socioeconomic factors and spatial effects. *Vaccines*, *10*(3), Article 352. https://doi.org/10.3390/vaccines10030352

Legendre, P., & Fortin, M. J. (1989). Spatial pattern and ecological analysis. *Vegetatio*, *80*(2), 107–138. https://doi.org/10.1007/BF00048036

Leung, K., Wu, J. T., Liu, D., & Leung, G. M. (2020). First-wave COVID-19 transmissibility and severity in China outside Hubei after control measures, and second-wave scenario planning: A modelling impact assessment. *The Lancet*, *395*(10233), 1382–1393. https://doi.org/10.1016/S0140-6736(20)30746-7

MacDonald, N. E. (2015). Vaccine hesitancy: Definition, scope and determinants. *Vaccine*, *33*(34), 4161–4164. https://doi.org/10.1016/j.vaccine.2015.04.036

Ministry of Health. (2022). *COVID-19 Vaccination*. https://covid19.go.id/vaksin-covid19

Mofleh, D., Almohamad, M., Osaghae, I., Bempah, S., Zhang, Q., Tortolero, G., Ebeidat, A., Ramphul, R., & Sharma, S. V. (2022). Spatial patterns of COVID-19 vaccination coverage by social vulnerability index and designated COVID-19 vaccine sites in Texas. *Vaccines*, *10*(4), Article 574. https://doi.org/10.3390/vaccines10040574

Mollalo, A., & Tatar, M. (2021). Spatial modeling of COVID-19 vaccine hesitancy in the United States. *International Journal of Environmental Research and Public Health*, *18*(18), Article 9488. https://doi.org/10.3390/ijerph18189488

Murthy, B. P., Sterrett, N., Weller, D., Zell, E., Reynolds, L., Toblin, R. L., Murthy, N., Kriss, J., Rose, C., Cadwell, B., Wang, A., Ritchey, M. D., Gibbs-Scharf, L., Qualters, J. R., Shaw, L., Brookmeyer, K. A., Clayton, H., Eke, P., Adams, L., … Harris, L. Q. (2021). Disparities in COVID-19 vaccination coverage between urban and rural counties—United States, December 14, 2020–April 10, 2021. *MMWR. Morbidity and Mortality Weekly Report*, *70*(20), 759–764. https://doi.org/10.15585/mmwr.mm7020e3

Nichter, M. (1995). Vaccinations in the third world: A consideration of community demand. *Social Science & Medicine*, *41*(5), 617–632. https://doi.org/10.1016/0277-9536(95)00034-5

Park, S.-Y., Kwak, J.-M., Seo, E.-W., & Lee, K.-S. (2016). Spatial analysis of the regional variation of hypertensive disease mortality and its socio-economic correlates in South Korea. *Geospatial Health*, *11*(2), Article 420. https://doi.org/10.4081/gh.2016.420

Putra, I. G. N. E., Rahmaniati, M., Sipahutar, T., & Eryando, T. (2022). Modeling the prevalence of tuberculosis in Java, Indonesia: An ecological study using geographically weighted regression. *Journal of Population and Social Studies*, *30*, 741–763. https://doi.org/10.25133/JPSSv302022.041

Rini, A. S., & Sugiharti, L. (2017). Faktor-faktor penentu kemiskinan di Indonesia: Analisis rumah tangga [Determining factors of poverty in Indonesia: Household analysis]. *Jurnal Ilmu Ekonomi Terapan*, *1*(2), 60–95. https://doi.org/10.20473/jiet.v1i2.3252

Rivera, K. M., & Mollalo, A. (2022). Spatial analysis and modelling of depression relative to social vulnerability index across the United States. *Geospatial Health*, *17*(2), Article 1132. https://doi.org/10.4081/gh.2022.1132

Roghani, A. (2021). The relationship between macro-socioeconomics determinants and COVID-19 vaccine distribution. *AIMS Public Health*, *8*(4), 655–664. https://doi.org/10.3934/publichealth.2021052

Rufaindah, E., Patemah, P., & Yuliyanik, Y. (2021). Pengabdian Masyarakat Stikes Widyagama Husada Malang Dalam Percepatan Vaksinasi COVID-19 Dengan Kunjungan Rumah Di Wilayah Kerja Puskesmas Karangploso Kabupaten Malang [Widyagama Husada Malang Stikes Community Service in the acceleration of COVID-19 vaccination with home visits in the work area of Karangploso Puskesmas, Malang District]. *SELAPARANG Jurnal Pengabdian Masyarakat Berkemajuan*, *5*(1), 862–866. https://doi.org/10.31764/jpmb.v5i1.6236

Schaffer DeRoo, S., Pudalov, N. J., & Fu, L. Y. (2020). Planning for a COVID-19 vaccination program. *JAMA*, *323*(24), 2458–2459. https://doi.org/10.1001/jama.2020.8711

Schnake-Mahl, A. S., & Sommers, B. D. (2017). Health care in the suburbs: An analysis of suburban poverty and health care access. *Health Affairs*, *36*(10), 1777–1785. https://doi.org/10.1377/hlthaff.2017.0545

Soares, P., Rocha, J. V., Moniz, M., Gama, A., Laires, P. A., Pedro, A. R., Dias, S., Leite, A., & Nunes, C. (2021). Factors associated with COVID-19 vaccine hesitancy. *Vaccines*, *9*(3), Article 300. https://doi.org/10.3390/vaccines9030300

Syiroj, A. T. R., Pardosi, J. F., & Heywood, A. E. (2019). Exploring parents' reasons for incomplete childhood immunisation in Indonesia. *Vaccine*, *37*(43), 6486–6493. https://doi.org/10.1016/j.vaccine.2019.08.081

Thanh Le, T., Andreadakis, Z., Kumar, A., Gómez Román, R., Tollefsen, S., Saville, M., & Mayhew, S. (2020). The COVID-19 vaccine development landscape. *Nature Reviews Drug Discovery*, *19*(5), 305–306. https://doi.org/10.1038/d41573-020-00073-5

Triwardani, R. (2021). Indonesian officials and media fight vaccine hesitancy, misinformation. *Asian Politics & Policy*, *13*(4), 635–639. https://doi.org/10.1111/aspp.12608

Utami, A., Margawati, A., Pramono, D., Nugraheni, A., & Pramudo, S. (2022). Determinant factors of COVID-19 vaccine hesitancy among adult and elderly population in Central Java, Indonesia. *Patient Preference and Adherence*, *16*, 1559–1570. https://doi.org/10.2147/PPA.S365663

Valckx, S., Crèvecoeur, J., Verelst, F., Vranckx, M., Hendrickx, G., Hens, N., Van Damme, P., Pepermans, K., Beutels, P., & Neyens, T. (2022). Individual factors influencing COVID-19 vaccine acceptance in between and during pandemic waves (July–December 2020). *Vaccine*, *40*(1), 151–161. https://doi.org/10.1016/j.vaccine.2021.10.073

Wang, J., Jing, R., Lai, X., Zhang, H., Lyu, Y., Knoll, M. D., & Fang, H. (2020). Acceptance of COVID-19 vaccination during the COVID-19 pandemic in China. *Vaccines*, *8*(3), Article 482. https://doi.org/10.3390/vaccines8030482

Widiawaty, M. A., Lam, K. C., Dede, M., & Asnawi, N. (2022). Spatial differentiation and determinants of COVID-19 in Indonesia. *BMC Public Health*, *22*(1), Article 1030. https://doi.org/10.1186/s12889-022-13316-4

Wiyeh, A. B., Cooper, S., Nnaji, C. A., & Wiysonge, C. S. (2018). Vaccine hesitancy 'outbreaks': Using epidemiological modeling of the spread of ideas to understand the effects of vaccine related events on vaccine hesitancy. *Expert Review of Vaccines*, *17*(12), 1063–1070. https://doi.org/10.1080/14760584.2018.1549994

Wiysonge, C. S., Ndwandwe, D., Ryan, J., Jaca, A., Batouré, O., Anya, B.-P. M., & Cooper, S. (2022). Vaccine hesitancy in the era of COVID-19: Could lessons from the past help in divining the future? *Human Vaccines & Immunotherapeutics*, *18*(1), 1–3. https://doi.org/10.1080/21645515.2021.1893062

World Health Organization. (2023). *Coronavirus disease (COVID-19) weekly epidemiological updates and monthly operational updates*. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports

Yufika, A., Wagner, A. L., Nawawi, Y., Wahyuniati, N., Anwar, S., Yusri, F., Haryanti, N., Wijayanti, N. P., Rizal, R., Fitriani, D., Maulida, N. F., Syahriza, M., Ikram, I., Fandoko, T. P., Syahadah, M., Asrizal, F. W., Aletta, A., Haryanto, S., Jamil, K. F., … Harapan, H. (2020). Parents' hesitancy towards vaccination in Indonesia: A cross-sectional study in Indonesia. *Vaccine*, *38*(11), 2592–2599. https://doi.org/10.1016/j.vaccine.2020.01.072