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# MATERNAL AND INFANT MORTALITY IN WEST JAVA, INDONESIA: SPATIAL CLUSTERS AND DETERMINANTS

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**Abstract:** Utilizing geographic information systems (GIS) for spatial analysis is crucial for examining, assessing, and visualizing the health status of different regions. There has been a high maternal and infant mortality rate in West Java, Indonesia, leading to a need for spatial information to support the government in planning healthcare. This study aims to examine and compare the geographic clusters between maternal mortality ratio (MMR) and infant mortality rate (IMR) utilizing tools in a GIS environment; it also aims to assess how those clusters relate to socioeconomic conditions. Data on mortalities and demography in 2020 were collected from the Department of Health Regional and Statistics Bureau. The Getis-Ord Gi* hotspot was applied for the IMR and MMR spatial clustering (low and high numbers—clusters). Further, the ordinary least square (OLS) was implemented to generate the correlation between MMR-IMR clusters and socioeconomic factors. Our results show that significantly low clusters of both MMR and IMR (with 95–99% confidence levels) were located close to urban and highly developed areas. The spatial pattern of hot and cold MMR clusters was similar to the IMR clusters (> 0.68). OLS models showed a high relationship between selected variables and IMR ($R^2$ = 0.80), but low relationship with MMR ($R^2$ = 0.20). A significant correlation was found between IMR and population density, income, and percentage of the population without education, while MMR was related to the number of health facilities. These findings illustrated the performed analysis capability to identify priority areas for maternal and childcare services.

**Keywords:** GIS; maternal mortality; infant mortality; West Java

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## 1. Introduction

Maternal and infant health is one of the critical concerns in a national healthcare system since it is linked to the well-being of a country. Globally, improving maternal and infant health is also a crucial priority, as stated in the Sustainable Development Goals (SDGs) in target number 3 (United Nations General Assembly, 2015; WHO, 2024). The maternal mortality ratio (MMR) and infant mortality rate (IMR) are measured indicators that provide insight into the effectiveness of regional and national healthcare. Although there was a reduction in global MMR from 2000 to 2015, the trend stagnated between 2016 and 2022 (UNICEF, 2023a). Likewise, it is reported that 11 children per 1,000 have a risk of dying before reaching the age of one year on a global level (UNICEF, 2023b). Therefore, maternal and infant mortality rate status assessment is required to identify potential issues, challenges, and intervention priorities, particularly at the national or subnational level.

Indonesia has the fourth highest MMR (173 per 100.000 live births) in Southeast Asia, following Timor-Leste, Cambodia, and Myanmar (WHO, 2023). It is in the top 10 countries with the highest newborn mortality rates (National Population and Family Planning Board (BKKBN) et al., 2018). Specifically, the Province of West Java, Indonesia, is a highly populated and intensively developing province, with 45.2% of regions in the urban area (UNFPA, 2015). However, according to the long-form Population Census 2020 (Statistics Indonesia, 2023), West Java ranked first for MMR (187 deaths per 100,000 births) and second for IMR (13.56 deaths per 1,000 births) among provinces in Java island. On the other hand, a lower discrepancy in healthcare quality was shown in the province close to West Java, the Province of Jakarta, which also has high industrial activities. In Jakarta, hospitals are primarily reachable within 5–10 km, indicating good access to the health facilities (Silalahi et al., 2020). The high incidence of MMR and IMR in West Java, therefore, is a sign of serious problems in the healthcare system, which can reflect population health, poverty, socioeconomic status, and low access to quality and sustainable health infrastructure (Owusu et al., 2021; Susilowati et al., 2024). Particular attention must be paid to promoting a better healthcare system for pregnant women and new mothers. In this context, spatial information on IMR and MMR can contribute to a more comprehensive understanding of the geographic patterns and inequality in maternal and infant health status.

Spatial data analysis using GIS technology offers valuable tools for visualizing data, modeling, and measuring health conditions to support community health assessment better (Bramdito et al., 2021; Mutalazimah et al., 2009). Geospatial techniques, such as geovisualization, can also help identify high-risk areas and inform targeted interventions (Yasobant et al., 2015). The implementation of GIS for health and epidemiology analyses has mainly been presented to evaluate health accessibility (Ouko et al., 2019), detect clusters and disparities in health indicators (Iyanda et al., 2018). This creates the potential for geospatial analysis using GIS to help identify high-risk (hotspot) areas and ultimately improve access to essential maternal and neonatal healthcare services. Among other methods, the Getis-Ord Gi* statistic is a frequently used technique for clustering (Lun et al., 2022). It is a powerful tool for identifying spatial clusters because it considers the value of a feature and the values of features in neighboring areas. The presence of spatial clusters can also be determined by whether they have high or low significance.

Furthermore, spatial clustering can be valuable for understanding the mortality phenomenon's underlying pattern and driving factors. In fact, maternal and child mortality rates in several regions of Indonesia are still high. Access to health services and facilities, particularly in remote areas, as well as the presence of unhealthy traditional and cultural practices, can significantly impact maternal and child health (Rumpiati, 2022). The government in developing countries must keep investing in a quality health sector, particularly in regions with limited access to healthcare (Olonade et al., 2019; Saripah et al., 2024). Therefore, knowing which socioeconomic condition relates to maternal and infant health status is essential for guiding intervention programs to the most needed areas in an earlier stage.

The explicit use of GIS tools for maternal and infant mortality case clustering is required to help identify areas with high-risk mortality rates and guide the intervention programs. Also, more understanding is needed of the relationship of these clusters to socio-economic conditions in the spatial context. Therefore, the objectives of this study are to (1) determine the IMR and MMR spatial clusters, (2) compare the IMR and MMR spatial hotspots and coldspots, and (3) investigate the relationship between IMR, MMR, and the socioeconomic data of the region. The clusters of high and low numbers were determined using the Getis-Ord Gi* statistic technique, and the ordinary least squares (OLS) were implemented to assess the MMR and IMR cluster's correlation with the socioeconomic conditions. Applying the spatial approach with GIS can contribute to dealing with healthcare issues where location matters, especially for improving the mother and newborn care system.

## 2. Materials and method

### *2.1. Study area and used data*

The chosen study area is located in the Province of West Java, Indonesia. It geographically lies between 5°50′S and 7°50′S, and 104°48′E and 108°48′E (Figure 1). Administratively, it has 18 regencies and nine cities (27 regions in total). West Java Province has a diverse landscape that includes mountains, plateaus, valleys, and beaches, as well as physico-geographical features with mountainous areas in the central and southern parts, and lowlands in the northern region (Hartono, 2022). This topographic variety gives West Java different socioeconomic characteristics across the region. The population in 2010 was 43,227,107 people, while the population in 2020 reached 49,935,858 people, indicating a population growth rate of 1.33% each year (Statistics of West Java, 2024).

In terms of mortality cases, Figure 2 shows a slightly higher value in 2017 compared to 2016 and 2018, but it is also less than the values for 2015, 2016, and 2020. Although infant deaths have shown a declining trend within the past five years, infant mortality is still a challenge. According to UNICEF Provincial snapshot (UNICEF, 2019), there are 17 per 1,000 babies who died during their first month in the area.

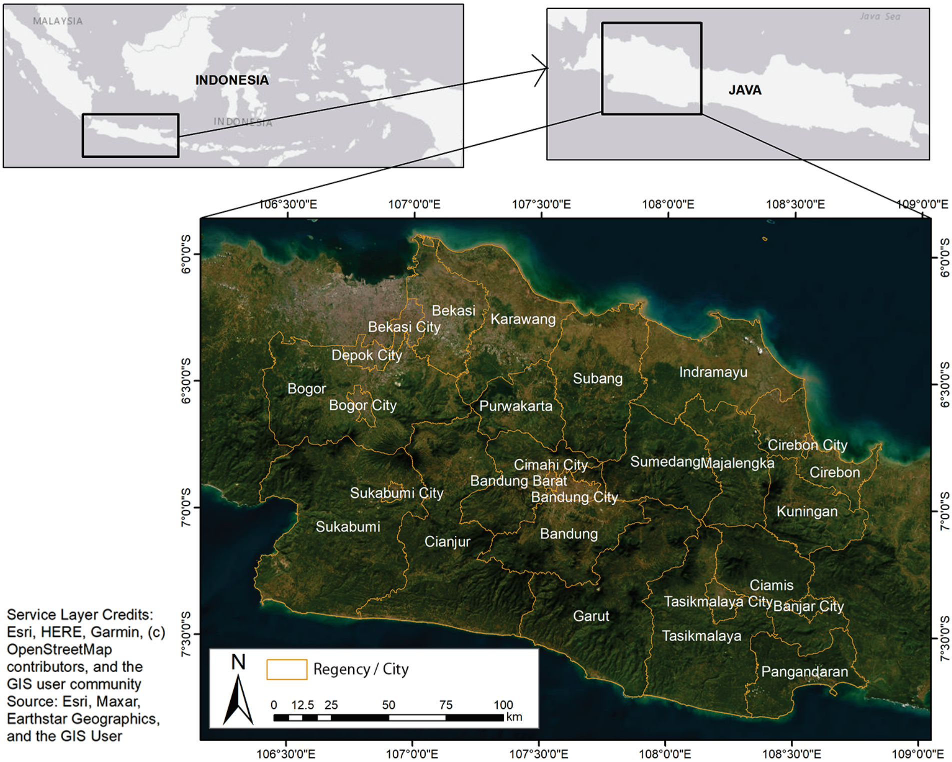


**Figure 1.** Study area in West Java, Indonesia.

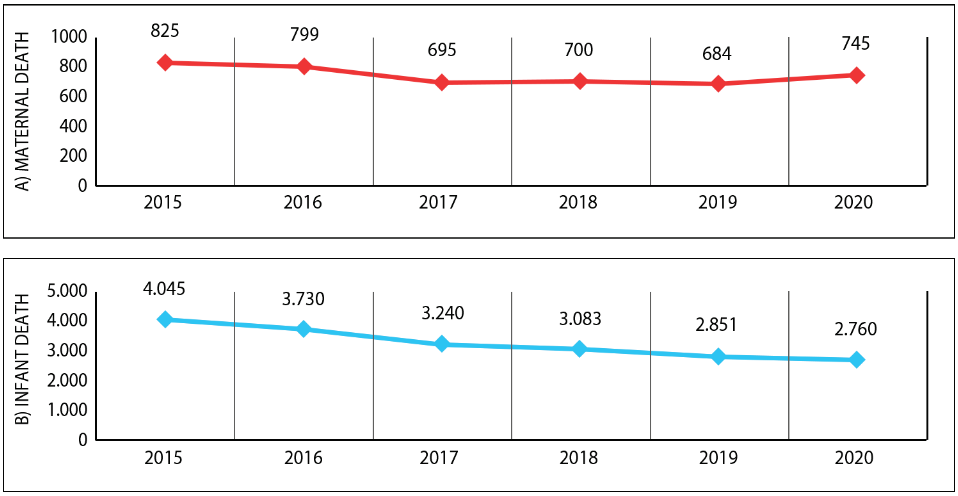


**Figure 2.** The trend of maternal and infant deaths between 2015 and 2020 in West Java.

To achieve the study's objectives, three primary datasets were prepared. First, the data regarding administrative boundaries were collected for analysis at the regency and city levels. Second, the data on both maternal and infant mortality cases were collected. Third, a socio-economic dataset was prepared to analyze the factors associated with mortality rates. All the data are from secondary sources, including the administrative boundaries, mortality, and socio-economic data for 2020. Table 1 provides all the data, descriptions, and their sources.

**Table 1.** Description and sources of data used in the study

| Data | Source | Description |
|---|---|---|
| Administrative boundaries | Global Administrative Areas (GADM) (https://gadm.org/) (University of California, Berkley, 2022) | Country-to-village level boundaries |
| Number of population | Statistics of West Java (https://jabar.bps.go.id/) | - |
| Number of births, maternal deaths, and infant deaths | West Java health profile 2020 (https://diskes.jabarprov.go.id/) Long Form Population Census 2020 (https://jabar.bps.go.id/) | - |
| Population density | Statistics of West Java | - |
| Income | Statistics of West Java | Gross regional domestic product by regency/city |
| Number of health facilities | West Java health profile 2020 (https://diskes.jabarprov.go.id/) | Health facilities cover three facilities: general hospital, specialized hospital, puskesmas (community health center), and posyandu (integrated health posts) |
| Early marriage | Welfare Statistics of West Java 2020 (https://jabar.bps.go.id/) | Percentage of population aged 15–19 years and marital status |
| Percentage of people without formal education | Welfare Statistics of West Java 2020 | Percentage of the female population aged above 15 years without an education certificate |

### *2.2. Methodology*

MMR is a crucial indicator of maternal health. It is an important consideration when analyzing spatial clusters as it measures the risk of a mother’s death associated with pregnancy and childbirth. The MMR was calculated using the following formula (WHO, n.d.-a).

$$MMR = \frac{\text{Number of maternal deaths in childbirth}}{\text{Number of total live births}} \times 100{,}000 \quad (1)$$

IMR is an important metric for assessing maternal and infant health. It reflects the risk of death among infants, indicating the quality of health facilities in the area. The IMR was determined using the following formula (WHO, n.d.-b).

$$MMR = \frac{\text{Number of deaths of children less than one year old}}{\text{Number of live births in the same year}} \times 1{,}000 \quad (2)$$

The categorization of IMR and MMR was done automatically through ArcGIS Pro software (ESRI, 2011) using the natural breaks (Jenks) method (Brewer & Pickle, 2002; Jenks, 1967).

Regarding the relevant socio-economic conditions to health, prior studies have indicated that much of the burden of infant mortality in several African countries was concentrated among the poor population, where education opportunities are also limited (Adeyeye et al., 2023). In another study, it was noted that high infant mortality rates were found in communities living in regions with limited access to public provision (Ortigoza et al., 2021). Similarly, inadequate health support, long distances to health centers, and lack of doctor availability were closely associated with high rates of maternal deaths (Cameron et al., 2019). This study, therefore, examines the relevance of population density, income, number of health facilities, percentage of population with early marriage and without formal education to the MMR and IMR. Figure 3 shows an overview of the steps taken to cluster IMR and MMR data and to determine their correlation with the socioeconomic condition in West Java.

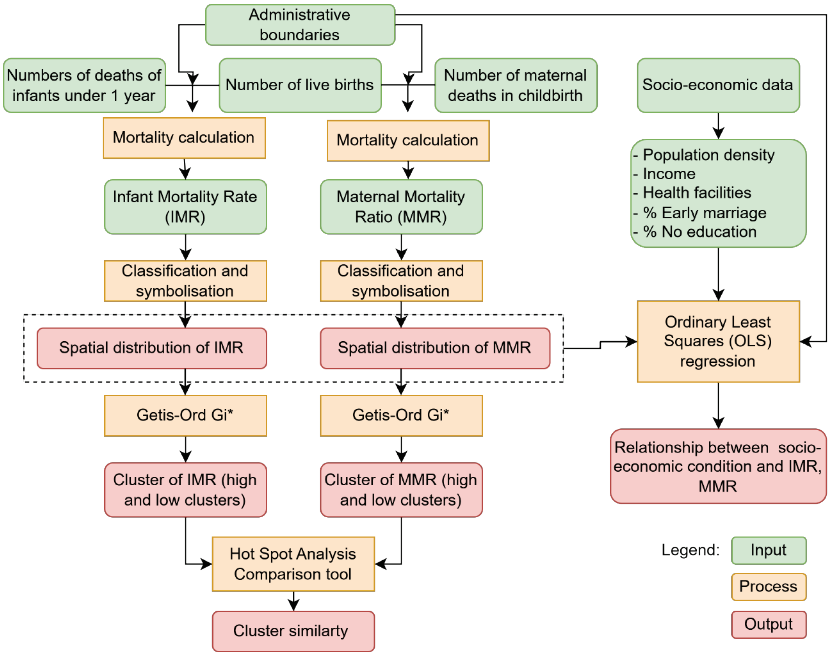


**Figure 3.** Flowchart showing the data and steps of analysis for the mortality spatial clusters and factors assessment.

To identify the mortality clusters, modeling based on Getis-Ord Gi* was implemented for both MMR and IMR cases. Using this clustering method, the clusters of high and low values with statistical significance can be singled out (Zhang et al., 2023). A Gi* statistic (z-score) is returned for each feature in the dataset by comparing the value of each feature with the surrounding features. The intensity of the high-value clustering (hot spot or hot region) rises with the rising z-scores in the case of statistically significant positive z-scores. In contrast, the intensity of the low-value clustering (cold spot or cold region) increases with the decreasing z-scores when there are statistically significant negative z-scores. The Getis-Ord Gi* index is computed from Equation (3) in the ArcGIS Pro platform (Getis & Ord, 1996; Razavi-Termeh et al., 2021):

$$Getis-Ord\ Gi^* = \left( \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} x_i x_j}{\sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j} \right) \tag{3}$$

where $x_i$ and $x_j$ are numbers of mortality cases in polygon i and j, respectively, $N$ is total number of maternal and infant mortalities, and $w_{ij}$ is spatial weight between polygons.

To investigate the similarity between the MMR and IMR clusters further, they are compared using the 'Hot Spot Analysis Comparison' tool in ArcGIS Pro to assess whether they have a significant similarity. This tool calculates how two hotspot or coldspot layers spatially coincide and how similar they are. The similarity and correlation between both mortality cases are determined by comparing the significance level categories (cold to hot) between matching features (and their neighbors) in MMR and IMR clusters. The outcome value is 0 to 1, where a score close to 1 means very high similarity.

OLS statistic test was performed to model the spatial relationship between MMR-IMR cases and the socioeconomic data. OLS is a multiple regression aiming to find the line of best fit that reduces the sum of the squared differences between observed and predicted values (ESRI, 2024). The OLS utilization has been successfully demonstrated to model the COVID-19 outbreak (Isazade et al., 2023), dengue fever (Yue et al., 2018), and tuberculosis incidence, indicating the high feasibility of OLS for evaluating the relationship between different types of disease with chosen indicators. In this study, the OLS model was generated in ArcGIS Pro based on the following equation (ESRI, 2024):

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n + \varepsilon \tag{4}$$

where $y$ represents mortality cases as the dependent variable, $\beta_0$ is intercept, $\beta_1 \beta_2 \beta_n$ are coefficients of socio-economic variables as the independent variables, and $\varepsilon$ is error term.

## 3. Results and discussion

### *3.1. Spatial clusters of MMR and IMR*

Figure 4 shows the distribution of MMR and IMR in 2020 in West Java. The groups with high and moderate MMR were located in the northern and central parts of the province. The regions of the north have dominantly high cases of maternal mortality. This highlights the higher priority for the coastal areas to receive intervention programs. In contrast, Bandung Regency and Bandung City (the province's capital) had very low mortality rates, indicating that better health facilities contributed. According to WHO's target (UNICEF, 2024), it is to reduce the maternal death rate to a maximum of 70 per 100,000 live births. Hence, there are still 21 regions that need to be programmed to achieve the target.

Conversely, most regions in West Java were in high levels of infant mortality cases, mainly shown in the western part of the province. The areas with a very low number of mortalities were the Cities of Bekasi, Depok, and Bogor, which are close to the big city of Jakarta. Bandung City, the capital of West Java, was also in the very low class of infant mortality, implying significant disparities in the health status of mothers, newborns, and childcare across the province. The maximum death rate is to be lowered to 12 per 1,000 babies, according to WHO targets (UNICEF, 2024). Therefore, 23 regions still require interventions in order to meet the goal.

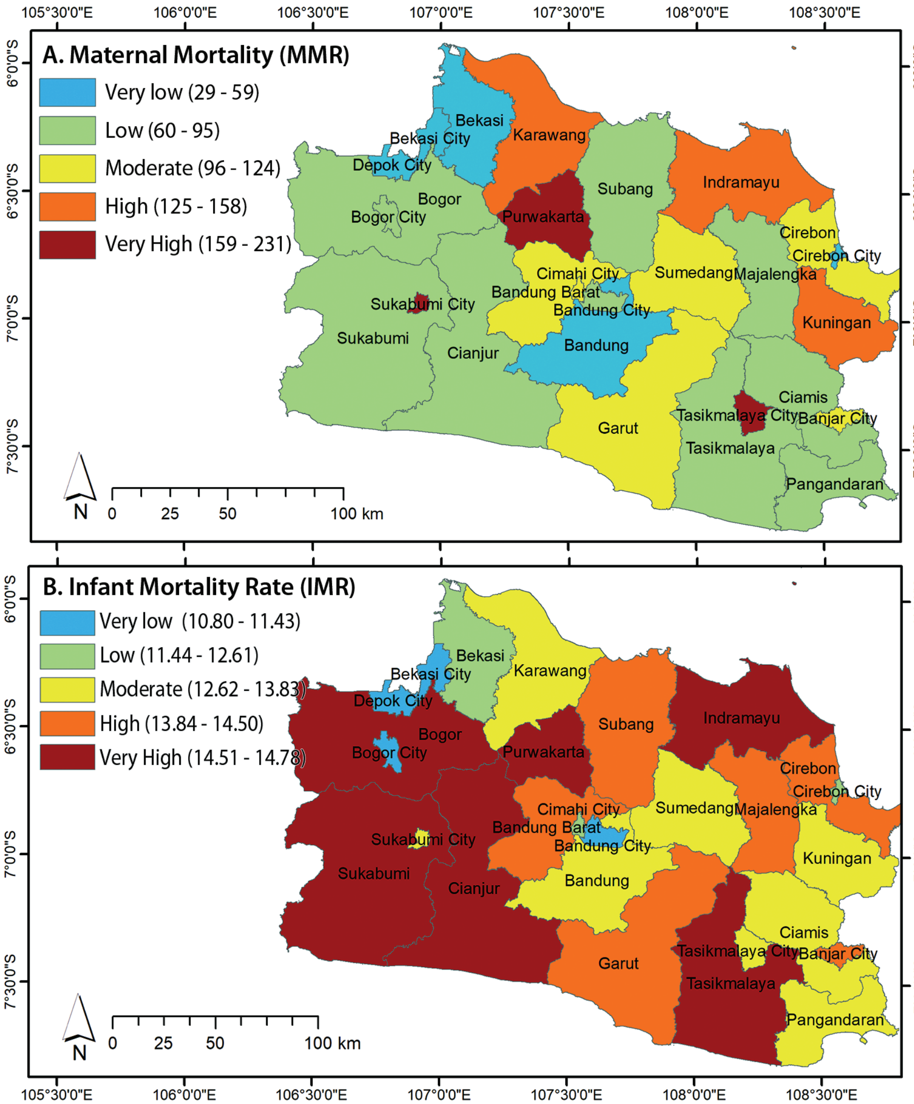


**Figure 4.** Spatial distribution of MMR (A) and IMR (B) in 2020 across the study area.

Tables 2 and 3 summarize the regions/cities with very low and high mortality rates. As observed, more than 22% of the areas were in the high and very high class of MMR, while more than 51% were in the high and very high class of IMR.

**Table 2.** Summary of Maternal Mortality Ratio (MMR) classes in the study area

| Class | Range | Number of regions | % | Regions |
|---|---|---|---|---|
| Very low | 29–59 | 5 | 18.52 | Bekasi City, Bekasi, Cirebon City, Bandung, Depok City |
| Low | 60–95 | 10 | 37.04 | Bogor, Bandung City, Bogor City, Majalengka, Cianjur, Tasikmalaya, Subang, Pangandaran, Sukabumi, Ciamis |
| Moderate | 96–124 | 6 | 22.22 | Banjar City, Cirebon, Cimahi City, Garut, Sumedang, Bandung Barat |
| High | 125–158 | 3 | 11.11 | Indramayu, Karawang, Kuningan |
| Very high | 159–231 | 3 | 11.11 | Purwakarta, Tasikmalaya, Sukabumi City |
| Total | | 27 | | |

**Table 3.** Summary of Infant Mortality Rate (IMR) classes in the study area

| Class | Range | Number of regions | % | Regions |
|---|---|---|---|---|
| Very low | 10.80–11.43 | 4 | 14.81 | Bekasi City, Bandung City, Depok City, Bogor City |
| Low | 11.44–12.61 | 3 | 11.11 | Cimahi City, Bekasi, Cirebon City |
| Moderate | 12.62–13.83 | 8 | 29.63 | Tasikmalaya City, Sumedang, Kuningan, Ciamis, Sukabumi City, Bandung, Karawang, Pangandaran |
| High | 13.84–14.50 | 6 | 22.22 | Bandung Barat, Banjar City, Subang Cirebon, Garut, Majalengka |
| Very high | 14.51–14.78 | 6 | 22.22 | Purwakarta, Bogor, Sukabumi, Cianjur, Tasikmalaya, Indramayu |
| Total | | 27 | | |

### *3.2. Comparison between MMR and IMR's spatial clusters*

Figure 5 shows the clusters of high and low MMR and IMR cases. It is the location of hot spot (significant high values clusters) and cold spot (significant low values clusters), represented by red and blue color, respectively. As shown in Figure 5, significantly low-low clusters of MMR and IMR were found in the western and northwestern areas of the province. IMR cold spots were observed in the northwestern regions, whereas most other parts of West Java showed no significant hot or cold clusters. For MMR, the hot spot was identified in the southwest region (Sukabumi). Although Sukabumi is classified as low-class MMR (Table 2), the area was assigned as the hot spot because it has MMR = 93 and is surrounded by Sukabumi city (MMR = 231), which is the highest value in the study area, and Cianjur (MMR = 82) as the neighbors. The Getis-Ord Gi* clustering evaluates the statistic of a feature within the context of its neighbours within a specific distance, hence not only considering an individual feature.

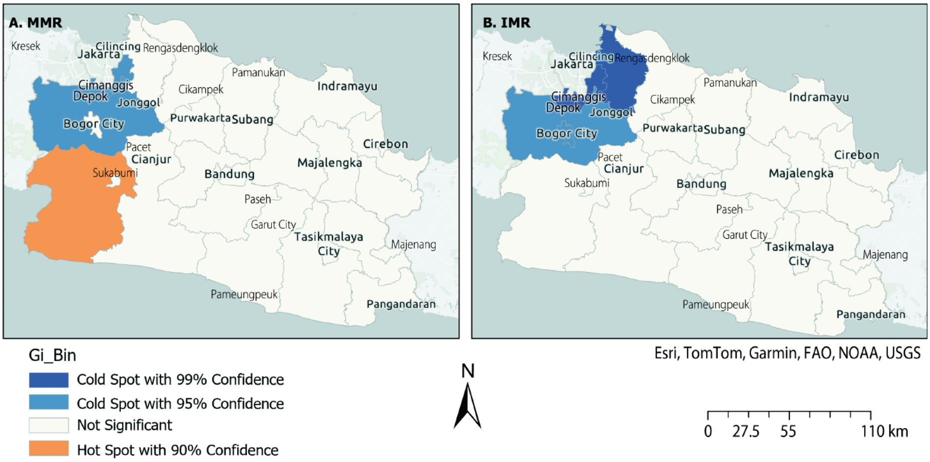


**Figure 5.** Spatial clusters of maternal (A) and infant mortality (B) based on Getis-Ord Gi* statistics.

Figure 6 presents the cluster comparison between MMR and IMR cases using the hotspot comparison tool. It shows that most regions had a similar pattern between MMR and IMR groups. Low similarity, however, was found in the southwestern part, the Sukabumi regency. This is because Sukabumi had contrasting classes with low MMR but very high IMR (Figure 4).


**Figure 6.** Cluster similarity analysis between maternal and infant mortality cases based on comparing hotspot and coldspot locations.

### *3.3. MMR and IMR distribution relationship with socioeconomic conditions*

Figure 7 presents the distribution of socioeconomic conditions, including the population density, income, number of health facilities, percentage of married people under 20 (early marriage), and rate of people without formal education. As observed, areas with high populations were located in the three regions: central, northeast, and west of the province. A similar spatial pattern has been shown in the groups with high income and a high percentage of people without formal education. Those groups were seen in the northern part of West Java. The western regencies had a more significant number of health facilities than the other parts. Meanwhile, a high portion of early marriage areas was found in the middle part of the province.

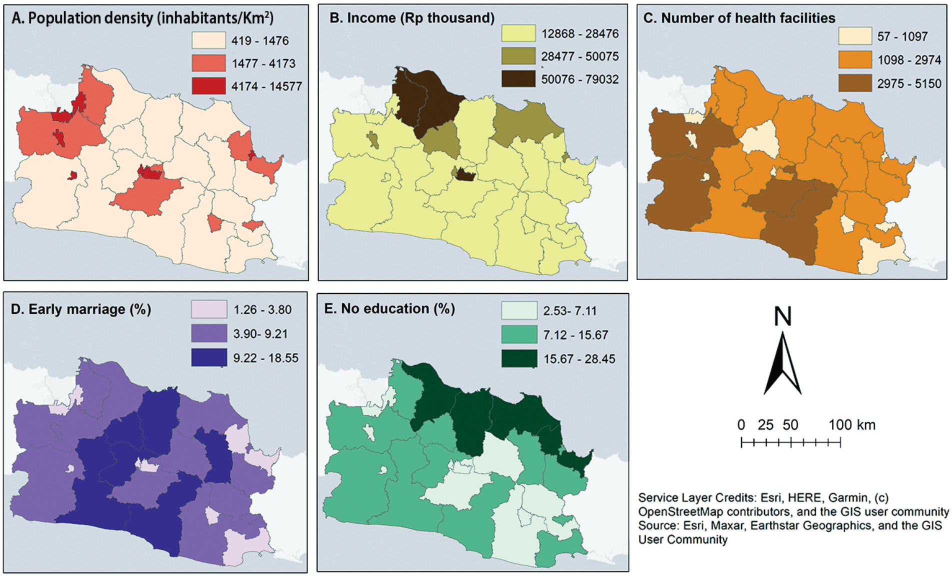


**Figure 7.** Socioeconomic spatial distribution in the study area, showing the: (A) population density; (B) income; (C) number of health facilities; (D) percentage of early marriage; and (E) percentage of population without formal education.

The results of the OLS-based relationship model between MMR-IMR cases and socioeconomic factors are shown in Figure 8 and Table 4. Figure 8 represents how the OLS model can accurately predict IMR values ($R^2$ = 0.80), but is less accurate for MMR ($R^2$ = 0.20) based on socioeconomic factors as the explanatory variables. Red areas show that the actual values are more significant than the estimated values, while blue ones mean that the exact values are smaller than the calculated values. The resulting figure indicates that MMR and IMR can be explained by the chosen variables with low standard deviation (indicated by yellow region) in most parts of the province.

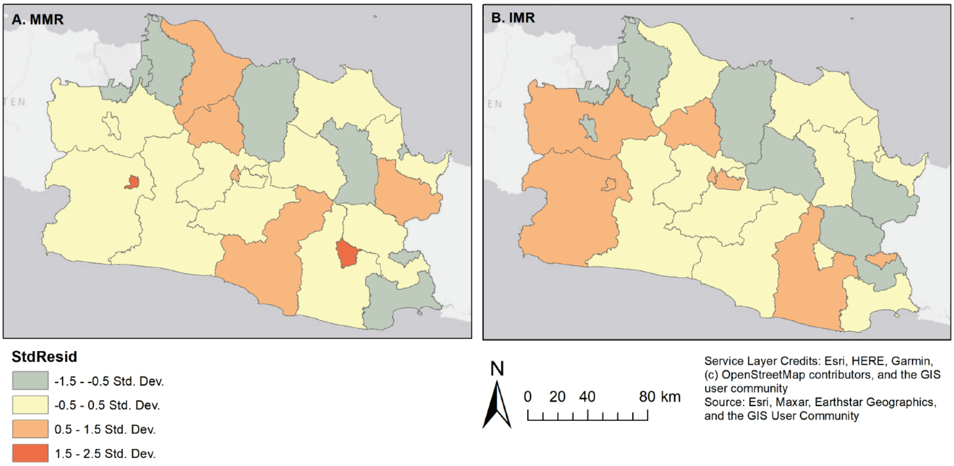


**Figure 8.** Standard residuals of the OLS models from (A) MMR and (B) IMR.

From Table 4, it can be seen that the percentage of underage marriages in a regency or city in West Java does not significantly correlate with maternal mortality during childbirth. On the one hand, the lower number of health facilities is statistically significant in correlation with the higher number of MMR in West Java. The data findings show that the two aforementioned independent variables were not significantly correlated with the IMR at birth. Opposite to the correlation with the MMR, a large number of health facilities and the high percentage of early marriages in regencies/cities in West Java are directly proportional to the high infant mortality rate. However, statistically, it is not significant. The Variance Inflation Factor (VIF) was also calculated, measuring the redundancy among variables. As shown in Table 4, no VIF results were above 7.5, meaning none of the selected variables are redundant in explaining IMR and MMR.

**Table 4.** Summary of OLS models between MMR, IMR, and socioeconomic variables.

| Variable | MMR | | | IMR | | |
|---|---|---|---|---|---|---|
| | Coefficient | Probability | *VIF* | Coefficient | Probability | *VIF* |
| Intercept | 146.472068 | 0.000848*** | - | 13.382401 | 0.000000*** | - |
| Population density | -0.003633 | 0.283128 | 2.24 | -0.000135 | 0.003045*** | 2.24 |
| Income | -0.000061 | 0.921379 | 1.33 | -0.000013 | 0.097642* | 1.33 |
| Health facilities | -0.015253 | 0.088410* | 1.26 | 0.000030 | 0.774920 | 1.26 |
| Early marriage | -0.849622 | 0.765462 | 1.54 | 0.051349 | 0.149066 | 1.54 |
| No education | 0.887175 | 0.650523 | 1.59 | 0.053324 | 0.034190** | 1.59 |
| R-squared | | 0.20 | | | 0.80 | |

*Note.* * *p*-value ($p < .1$), ** *p*-value ($p < .05$), ***significant *p*-value ($p < .01$).

As shown in Table 4, the less densely populated a regency/city in West Java is, the more likely the possibility of maternal and infant deaths during birth, while the IMR is way more statistically significant than the MMR. In contrast, the greater the number of population who receive education, the smaller the possibility of maternal and infant deaths during birth in the province, while the IMR is more statistically significant than the MMR. Karawang-Subang Regency (Purwasuka DA) and Indramayu-Cirebon Regency (Ciayumajakuning DA) have the highest number of less educated population. The aforesaid is located on the north coast of Java, which is widely known for its low education rate (Budiarto, 2017). One of the regencies even has a particular tradition named *'luru duit'*, which means 'seeking money', especially for women at a young age. It is assumed that women at a young age have a high economic value for the family by early (or even underage) marriage or by working overseas rather than pursuing education (Grijns & Horii, 2018).

The lower the average income per capita in a regency/city in West Java is, the higher the possibility of maternal and infant death at birth. Thus, statistically speaking, the IMR is more significant than the MMR. This study supports evidence from previous observations that only a part of the variation in maternal mortality rates may be explained by wealth indicators. However, measures of wealth are less clearly connected with national maternal mortality rates than other drivers, such as women's age, educational attainment, and the percentage of birth deliveries by skilled health staff (Rizqi et al., 2023; Tarsikah et al., 2020). The cities/regencies with the highest average income per capita are Bandung City, West Java's Capital, and Karawang-Bekasi Regencies, which are industrial regencies. Karawang Regency, located on the north coast of West Java, has the second highest average income per capita after Bandung City and has a high number of MMR. The proximity to Jakarta and the influence of this megapolitan city becomes the critical factor, which includes a more diverse population from various cultures, global information, higher average educational attainment, and more job opportunities for women (Marshan et al., 2013). One interesting case is Sukabumi Regency, which has a high IMR while the MMR is low. Sukabumi has adequate maternal healthcare (e.g., skilled birth attendants and facilities for childbirth) but limited pediatric care or neonatal services. Based on Sukabumi Regency Census data in 2024, in several sub-districts alone, the number of midwives ranges between 50-60 midwives per sub-district, while the number of paediatricians is only around 3 doctors per sub-district.

Finally, the comparison between maternal and infant mortality rates explored in this study has shown the potential use of GIS to assist public health management in reducing mortality cases in mothers and infants. GIS can visualize the mortality rates and detect and compare mortality patterns in a spatial context. Further, the correlation between mortality cases and socioeconomic factors was also facilitated in GIS. The OLS model, however, relies on the linear assumption between independent and dependent variables. This condition might not be fit for all diseases related to the environment, hence requiring further investigation on optimum relationship modeling. For future works, exploring physical characteristics is recommended to develop a complete picture of mortality in mothers and infants. Investigations into topography conditions and road distributions, for instance, make it possible to gain a better understanding of the accessibility of healthcare facilities. A multi-temporal analysis of mortality is also suggested to observe mortality patterns and determine how health quality has changed in the study area.

## 4. Conclusion

This study demonstrated the use of GIS in providing information on the maternal and infant mortality spatial clusters in West Java, Indonesia. It was found that the significant low-value clusters of both MMR and IMR were located close to the highly developed area (95–99%

confidence levels). A high similarity was observed between the pattern of MMR and IMR clusters (> 0.68). OLS models showed a high relationship between selected variables and IMR ($R^2$ = 0.80). In contrast, the relationship between socio-economic variables and MMR was very low ($R^2$ = 0.20), indicating other variables need to be explored to explain MMR better. We also identified a significant correlation between IMR and population density ($p$ < .01), income ($p$ < .1), and percentage of the population without education ($p$ < .05). However, only the number of health facilities was associated with MMR ($p$ < .1). The presented clustering method could clearly identify spatial maternal and infant mortality clusters, informing targeted interventions and resource allocation. Despite the correlation between socio-economic indicators and mortalities observed, the current analysis has only evaluated at the city level. An in-depth assessment is potential when merged with census data at the district level. Future works may consider other relevant geophysical conditions to investigate related factors further, such as topography and road network.

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