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Integration of Remote Sensing Data and Official Statistics: Spatial Analysis of Environmental, Social, And Basic Access Dimensions on Infant Mortality in Eastern Indonesia, 2022

Fais Jefli[1*], Avril Irene Hutauruk[1], Kezia Dianrani Hutagalung[1], Muh Yusuf. S[1], Nadine Rolanda Cantika[1], Nurul Izzah[1], Fitri Kartiasih[1]

[1] Politeknik Statistika STIS, Jakarta, Indonesia

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A B S T R A C T

In 2022, Eastern Indonesia continued to experience a relatively high infant mortality rate (IMR) compared to the national average, with several regions in Papua categorized as having high IMR levels. This situation highlights the urgency of identifying the underlying determinants. Various dimensions, including environmental, social, and access-to-basic-services factors, are important to investigate. However, since environmental variables are not available in official statistical data, remote sensing data were utilized as an alternative source. This study integrates official statistical data and remote sensing data to identify the determinants of IMR. The remote sensing data were obtained through Google Earth Engine script processing. Preliminary modeling indicated the presence of spatial heterogeneity; therefore, a Geographically Weighted Regression (GWR) approach was employed to examine the local variation in the effects of each independent variable. Based on the significance mapping of model parameters, substantial spatial variation in IMR was observed across Eastern Indonesia. The GWR results indicate that environmental variables were generally not the dominant factors contributing to higher IMR, as most local coefficients reflected infrastructure disparities. The only environmental variable that consistently showed a significant effect was Land Surface Temperature (LST). In contrast, social conditions and access to basic services played a more substantial role in explaining variations in IMR across Eastern Indonesia. Barriers to healthcare access, low levels of welfare, and limited infrastructure were identified as the main factors contributing to the high infant mortality rates in Eastern Indonesia in 2022.

Pada tahun 2022, Indonesia bagian Timur terus mengalami angka kematian bayi (IMR) yang relatif tinggi dibandingkan dengan rata-rata nasional, dengan beberapa wilayah di Papua dikategorikan memiliki tingkat IMR yang tinggi. Situasi ini menyoroti urgensi untuk mengidentifikasi faktor-faktor penentu yang mendasarinya. Berbagai dimensi, termasuk faktor lingkungan, sosial, dan akses terhadap layanan dasar, penting untuk diteliti. Namun, karena variabel lingkungan tidak tersedia dalam data statistik resmi, data penginderaan jauh digunakan sebagai sumber alternatif. Studi ini mengintegrasikan data statistik resmi dan data penginderaan jauh untuk mengidentifikasi faktor-faktor penentu IMR. Data penginderaan jauh diperoleh melalui pemrosesan skrip Google Earth Engine. Pemodelan awal menunjukkan adanya heterogenitas spasial; oleh karena itu, pendekatan Regresi Tertimbang Geografis (GWR) digunakan untuk memeriksa variasi lokal dalam pengaruh setiap variabel independen. Berdasarkan pemetaan signifikansi parameter model, variasi spasial yang substansial dalam IMR diamati di seluruh Indonesia bagian Timur. Hasil GWR menunjukkan bahwa variabel lingkungan umumnya bukan faktor dominan yang berkontribusi terhadap IMR yang lebih tinggi, karena sebagian besar koefisien lokal mencerminkan kesenjangan infrastruktur. Satu-satunya variabel lingkungan yang secara konsisten menunjukkan pengaruh signifikan adalah Suhu Permukaan Tanah (LST). Sebaliknya, kondisi sosial dan akses terhadap layanan dasar memainkan peran yang lebih substansial dalam menjelaskan variasi IMR di seluruh Indonesia Timur. Hambatan akses layanan kesehatan, tingkat kesejahteraan yang rendah, dan infrastruktur yang terbatas diidentifikasi sebagai faktor utama yang berkontribusi terhadap tingginya angka kematian bayi di Indonesia Timur pada tahun 2022.

* Corresponding author: Fais Jefli
Politeknik Statistika STIS, Jakarta, Indonesia
Email: 212313072@stis.ac.id

1. Introduction

The infant mortality rate is one of the important indicators in measuring the health quality of mothers and children in a region. The high infant mortality rate remains a demographic problem that requires serious attention from the entire world. Globally, the infant mortality rate from 2010 to 2022 has decreased significantly, especially in the neonatal mortality rate (WHO, 2024).

According to BPS (2023), the definition of infant mortality rate (IMR) is the number of infant deaths under 1 year of age per 1,000 live births in a given year. In Indonesia, the infant mortality rate is 16.85 per 1,000 live births, which is still above the Sustainable Development Goals (SDGs) target, which calls for reducing the neonatal mortality rate to at least 12 per 1,000 live births. Although the infant mortality rate in Indonesia has fallen over the last decade, this trend has not been evenly distributed across all regions of Indonesia. Eastern Indonesia, such as Papua, West Papua, and Maluku, has an infant mortality rate that is still above the national average. This condition requires serious attention from both the national and local governments to continuously improve the quality of human resources in the future.

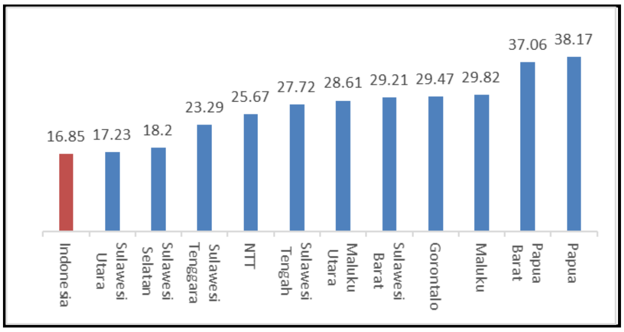

Figure 1. Comparison of Indonesia's IMR with provinces in Eastern Indonesia (*Source: BPS, 2023*)

According to the figure, both nationally and in Eastern Indonesia, the SDG 3.2 target has not yet been achieved, thus requiring government action to reduce infant mortality in the region. The high infant mortality rate is a demographic problem that requires considerable attention from the government, especially in Eastern Indonesia. Although the infant mortality rate in Eastern Indonesia has decreased over the last decade, it is still above the Indonesian average.

BPS (2023) states that the main factors affecting infant mortality are maternal conditions during pregnancy, childbirth, and newborn care. Considering previous studies on the same issue, additional factors affect this across regions. These factors are reviewed across several literature sources and grouped into three dimensions: the environmental, social, and basic access dimensions.

Environmental dimensions have a significant impact on infant health, both directly and indirectly. For example, extreme land surface temperature (LST) has been shown to increase the risk of neonatal mortality, especially in premature and newborn infants (Roos et al., 2021; Dimitrova et al., 2024). Exposure to green spaces, as measured using NDVI, has also been shown to reduce infant mortality by improving the immune system of infants (Zhang et al., 2024). In addition, air pollutants such as NO_2 and $PM_{2.5}$ contribute significantly to respiratory disorders and the risk of infant mortality during the early stages of life (Anita et al., 2023).

Infant mortality is also strongly influenced by social dimensions, such as poverty and maternal education. Households below the poverty line have a limited ability to meet basic nutritional needs and access health services (BPS, 2023). The level of maternal education, as measured by the Mean Years of Schooling (MYS) for women, correlates with greater knowledge and healthier behaviors in infant care (Vikram et al., 2020). Stunting, as defined by the WHO, is also closely related to infant mortality, and about 45% of under-five deaths worldwide are related to malnutrition (WHO, 2015).

Basic access dimensions such as health workers, healthcare facilities, and access to clean and safe drinking water are crucial determinants of infant survival rates. Areas with a high density of health workers have been shown to have lower infant mortality rates (WHO, 2016; BPS, 2023). Equal access to healthcare facilities such as community health centers and hospitals also reduces the risk of infant mortality, especially in emergency cases (UNICEF, 2021). Access to safe and clean drinking water is also an important factor, considering that consumption of contaminated water can increase the incidence of infectious diseases that directly impact infant mortality (WHO, 2022; BPS, 2023).

Previous studies analyzing the determinants of the Infant Mortality Rate (IMR) have generally focused only on social dimensions and on access to basic services, as derived from official statistics. Limitations in data availability have resulted in environmental factors that theoretically may affect infant health risks receiving limited attention in empirical studies. Therefore, a research gap exists regarding the unmeasured influence of environmental factors derived from alternative data sources, namely remote sensing data, on variations in IMR. In this study, remote sensing data were obtained via script-based processing on Google Earth Engine using various satellite imagery sources. Subsequently, these data were aggregated at the regency/municipality level using mean values, enabling their integration with official statistical data for IMR determinant analysis.

Furthermore, most previous studies have employed global statistical approaches that assume the relationship between independent variables and IMR is homogeneous across regions. In contrast, this study applies Geographically Weighted Regression (GWR) because the data exhibit spatial heterogeneity, meaning that the influence of each dimension on IMR may vary across regions. This condition indicates that the determinants of infant mortality are difficult to generalize. Through the integration of official statistics and remote sensing data, as well as the application of GWR analysis, this study is expected to explain variations in IMR more comprehensively and support more targeted decision-making.

Based on the problems described above, this research aims to: (1) describe the spatial distribution of infant mortality rates in Eastern Indonesia; (2) analyze multidimensional factors, including environmental, social, and basic access factors that affect infant mortality rates. The results of this study are expected to provide recommendations for relevant stakeholders to address the high infant mortality rate in Eastern Indonesia.

2. Methods

This research is a quantitative study covering 166 districts/cities in Eastern Indonesia with a research period of 2022. The independent variable in this study is infant mortality, while the dependent variables consist of indicators representing several dimensions: environmental, social, and basic access. Further details on each indicator in each dimension will be presented in the following section.

Table 1. Independent variables suspected to affect infant mortality rates in eastern Indonesia

Variable	Description	References	Unit	Hypothesis
Environmental Dimension				
LST	Land surface temperature.	Principi et al. (2025); Dimitrova et al. (2024)	Celcius	Positive
NDVI	Vegetation index.	Zhang et al. (2024)	Index	Negative
Emission Index	Composite index of NO2 and PM2.5.	Anita et al. (2023)	Index	Positive
Social Dimension				
Poverty	Percentage of poor population indicating the total proportion of people living below the poverty line.	Gatica-Domínguez et al. (2020); Anteneh et al. (2025)	Percent	Positive
Women Mean Years of Schooling	Average years of schooling for women.	Vikram et al. (2020); Arini et al. (2024)	Percent	Negative
Stunting	Prevalence of stunted children under five years old.	Tomori *et al.* (2024)	Percent	Positive
Basic Access Dimension				
Health Workers	Ratio of health workers per 1,000 population.	BPS (2023)	Ratio	Negative
Community Health Centers	Ratio of community health centers per 100,000 population.	UNICEF (2021)	Ratio	Negative
Access to Safe Drinking Water	Percentage of population with access to safe or improved drinking water.	WHO (2022)	Percent	Negative

Referring to Table 1, variables representing social dimensions and basic access were obtained from publications by the Badan Pusat Statistik (BPS) at the aggregate district/city level. In the meantime, variables reflecting environmental dimensions were derived from satellite imagery acquired from January 1, 2022, to December 31, 2022.

The environmental parameters used in this study include Land Surface Temperature (LST), the Normalized Difference Vegetation Index (NDVI), and a composite emission index. These three variables were derived from remote sensing data processing using scripts on the Google Earth Engine (GEE) platform. The study area was defined based on regency/municipality administrative boundaries obtained from Statistics Indonesia (BPS) and used as the spatial aggregation unit. LST was extracted from MODIS products, while NDVI was calculated using Sentinel-2 imagery. NDVI was computed based on the ratio between the difference and the sum of the reflectance values of the Near Infrared (NIR) and red bands, expressed as (NIR − Red) / (NIR + Red) (Strashok & Ziemiańska, 2022). Prior to the calculation process, the imagery underwent a cloud masking procedure to reduce observation disturbances.

Meanwhile, NO_2 data were obtained from the Sentinel-5P/TROPOMI product, whereas $PM_{2.5}$ concentrations were derived from the MERRA-2 dataset (Gelaro et al., 2017). To construct the air quality indicator, NO_2 and $PM_{2.5}$ values were first normalized using the min–max scaling method and subsequently averaged to generate a composite emission index. Furthermore, the mean value of each environmental variable for each regency/municipality was calculated using the zonal statistics method, yielding a single representative value for each administrative area. These values were then integrated with official statistical data of analyze the determinants of the Infant Mortality Rate (IMR).

This analysis uses an ordinary least squares (OLS) regression model as the global model. This global model will be used to demonstrate the effect of independent variables on dependent variables with regression parameter values that are fixed (constant) across all areas. In constructing the global model, it is necessary to ensure that the data and model meet the required conditions and assumptions. The data requirement that must be met is the non-existence of multicollinearity between independent variables. In addition, the regression model must also fulfill the classical assumptions of homoscedasticity and normality.

If the homoscedasticity assumption is violated, GWR is used. GWR is a local regression method used to explore spatial heterogeneity in spatial data. This model can construct regression equations for each location in the dataset (Tang, 2025). The GWR model can be expressed as follows (Caraka & Yasin, 2017).

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

In developing the GWR model, several hypothesis tests can be conducted, including testing the goodness of fit to determine whether the GWR model provides better results than the global model (OLS) and testing the model parameters partially to determine which independent variables affect the dependent variables.

3. Results

3.1 Overview of Infant Mortality Rates

High infant mortality rates may reflect challenges in environmental, health, and social dimensions. It is important to understand the geographical distribution of infant mortality rates to identify areas that require further attention in efforts to reduce it.

The map of IMR distribution in Eastern Indonesia shows the distribution of IMR per 1,000 live births, grouped into three categories: low (less than 20 infant deaths), moderate (20 to 40 infant deaths), and high (more than 40 infant deaths). In general, there are distinct variations between provinces in this region. Provinces such as Maluku and Sulawesi tend to fall into the moderate category, indicated by the orange color, although some areas are classified as low. On the other hand, areas in Papua dominate the high category, indicated by the darker colors on the map. These IMR patterns show that infant health conditions in Eastern Indonesia are unevenly distributed, with some regions still experiencing high IMRs.

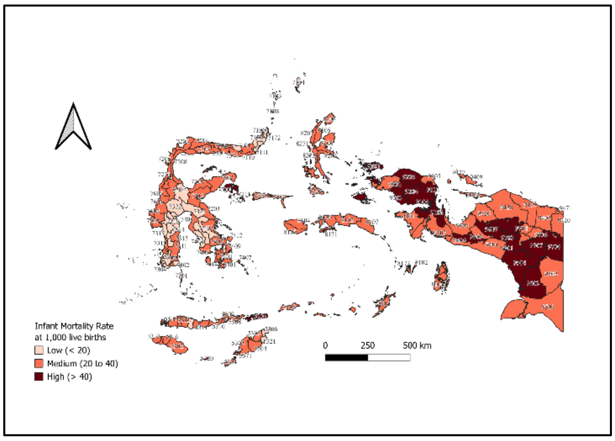

Figure 2. Map of IMR distribution in Eastern Indonesia

3.2 Global Model

Model building began with the formulation of a global model using multiple linear regression estimated via OLS at a significance level of 5%. Before estimation, multicollinearity testing was conducted using the Variance Inflation Factor (VIF). The results showed that all independent variables had VIF values < 5, indicating no signs of multicollinearity and that the OLS model was suitable for use.

The classical assumption test shows that the Jarque-Bera normality test resulted in a p-value (0.204) > α = 0.05, thus failing to reject H_0. With a 95% confidence level, the residuals are normally distributed. Furthermore, the homoscedasticity test with the Breusch-Pagan test resulted in a p-value (0.004) < α = 0.05, thus rejecting H_0. With that, heteroscedasticity in the data is evident, indicating spatial heterogeneity in infant mortality rates in Eastern Indonesia. For that reason, the GWR model can be used.

3.3 Local Model

The formulation of the GWR model begins with the development of a spatial weight matrix. This study utilizes an adaptive kernel function, of which the optimal Bandwidth is selected based on the smallest cross-validation (CV) value across various kernels; the results of which are presented in the following Table 2.

Table 2. Optimum bandwidth results for each adaptive Kernel Function

Kernel Function	AIC	BIC	*R-Square* (R^2)	*Bandwidth (bw)*
Gaussian	1031.5924	922.6075	0.7076	104
Bi-Square	1024.0672	930.5561	0.7268	162
Exponential	971.0847	1001.1877	0.8345	19
Tricube	1026.0668	929.2673	0.7222	162
Boxcar	1036.4226	912.4272	0.6923	162

Based on Table 2, the adaptive exponential kernel function is the most suitable kernel because it meets two of the three model selection criteria: it has the smallest AIC and the largest R-squared. Therefore, this kernel function is used in GWR modeling. Based on the GOF test, the p-value (<0.000) < α = 0.05, so H_0 is rejected. With a significant level of 5%, it can be concluded that the GWR model is better than the global model. As a result, local modeling (GWR) can be continued.

According to the summary of statistical parameters of the GWR model, it can be observed that the coefficients between regions show considerable variation. A coefficient of variation (CV)> 30% indicates spatial heterogeneity (Sallin et al., 2022), so the GWR model is considered capable of capturing this heterogeneity. Furthermore, several variables have coefficients that do not fit the theory, thus requiring a review of the significance of each parameter.

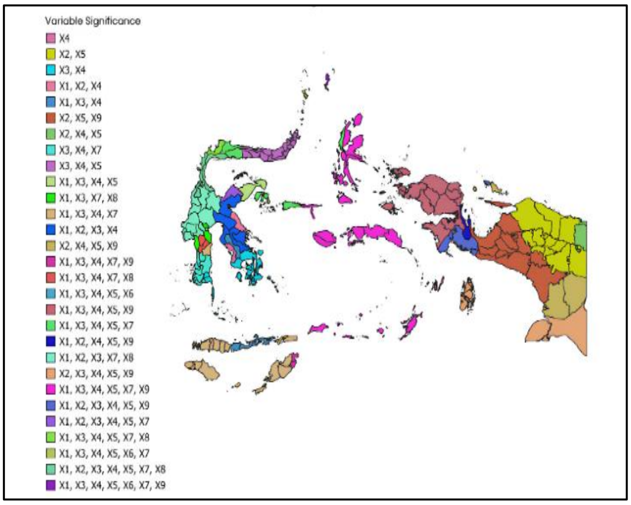

Figure 3. Local model significance map

Table 3. Summary of GWR Model Parameter Coefficient Estimates

Notation	Variable	Min	Median	Max	| CV | (%)
-	Intercept	-46.074	-3.563	28.8629	345.31
X_1	LST	-0.4255	1.0464	2.2111	53.82
X_2	NDVI	-4.5976	12.631	87.7053	102.13
X_3	Emission Index	-39.126	-27.838	6.8318	40.75
X_4	Poverty	0.1323	0.4182	0.663	33.06
X_5	Women's Mean Years of Schooling	-2.3401	-1.37	-0.1244	49.67
X_6	Stunting	-0.0959	0.0697	0.2033	81.61
X_7	Health Workers	-0.0017	0.0015	3.7707	93.51
X_8	Community Health Centers	-0.3873	-0.9729	0.1453	140.56
X_9	Access to Safe Drinking Water	-0.1337	-0.0377	0.0358	117.43

Looking at Figure 3, there are 29 combinations of regional groups that exhibit the same variable significance pattern at the 5% significance level. What is interesting is that the most significant variable is the Emissions Index, which is around 82% (136 out of 166 districts/cities), followed by the poverty variable at around 78% (129 out of 166 districts/cities). Meanwhile, the least significant variable is stunting, which is only around 1.8% (3 out of 166 districts/cities). This result indicates that stunting is not a major factor affecting Infant Mortality Rates in Eastern Indonesia.

4. Discussion

The GWR model with optimal bandwidth was used to examine the partial effect of each independent variable on infant mortality rates. The results of the analysis are presented in the form of a parameter coefficient distribution map, where blue areas represent positive effects and red areas represent negative effects.

According to the environmental dimension, the LST variable has a positive and significant effect in 2022, especially in the western and central regions of Eastern Indonesia, indicating that an increase in LST raises the IMR.

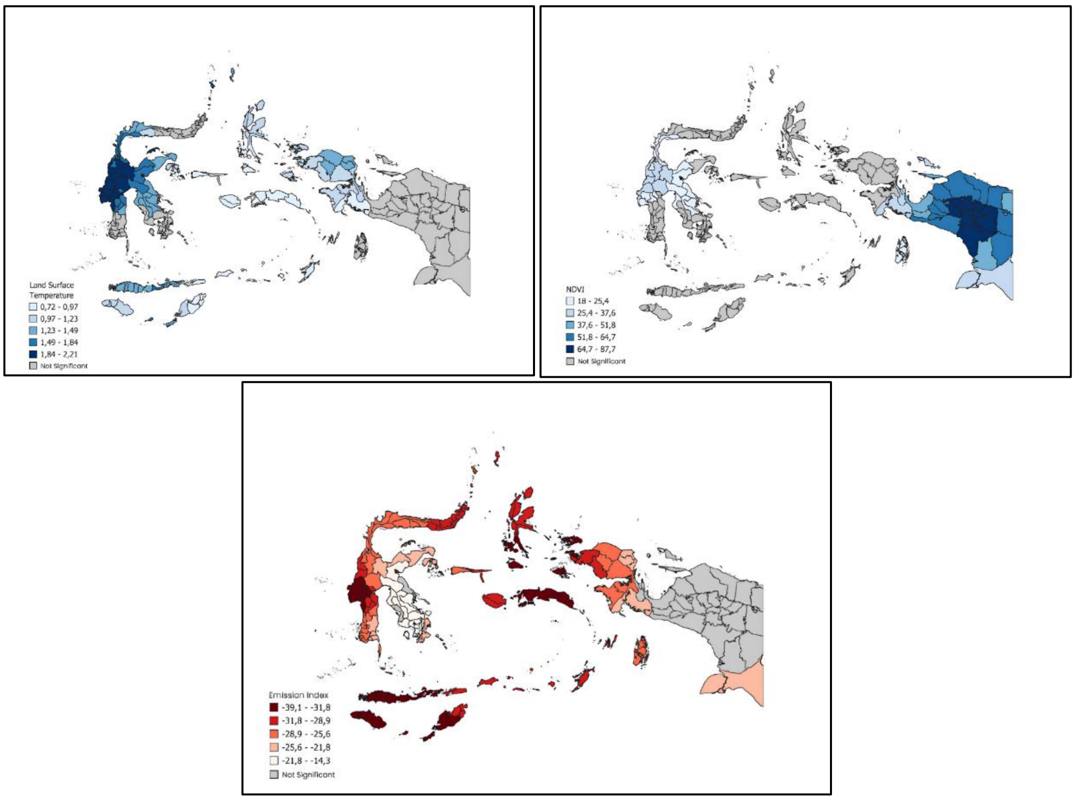

Figure 4. Map of environmental dimension coefficients

This is consistent with the research hypothesis and is supported by studies by Dimitrova et al. (2024) and Roos et al. (2021), which show that infant mortality risk tends to increase with higher temperatures. This is due to the anatomical and physiological limitations of infants in adapting to extreme temperatures, especially heat.

Additionally, exposure to hot temperatures can increase the risk of dehydration and thermal stress in infants (Principi et al., 2025). The NDVI variable shows a positive and significant effect, especially in Papua and Central Sulawesi, indicating that higher NDVI values increase the IMR. This result is not in line with the research hypothesis. This is evident in the fact that most of Eastern Indonesia has an NDVI value of around 0.78, which is classified as a densely forested area with a green and healthy environment (Lasaiba & Tetelepta, 2023). This means that high NDVI values show a lot of green areas and not many built-up areas like infrastructure, settlements, and public facilities, including health facilities (Hariani et al., 2024). This lack of access could increase the risk of infant mortality because basic services are hard for most people to get to.

The emission index variable had a significantly negative effect in regions other than Papua, meaning that higher emissions reduced the IMR. This discovery was not consistent with the research hypothesis. More specifically, NO_2 values ranged from 0.006 to 0.019 mmol/m^2, and PM2.5 values ranged from 4.511 to 16.542 μg/m^3, which are still considered harmless (BMKG, 2025a; BMKG, 2025b). These relatively safe conditions indicate that high emissions reflect a limitation of green areas. This shows that in Papua, high NDVI values tend to be associated with low emission levels due to the ability of vegetation to absorb emissions. This condition differs from many other regions with low NDVI and high emissions, which generally reflect larger built-up areas for infrastructure, roads, and other land uses. In addition, higher Gross Domestic Product (GDP) is associated with increased emissions, indicating that areas with higher emissions tend to experience more rapid infrastructure development (Karunia et al., 2023). This implies that there are areas with low NDVI and higher, but not dangerous, emissions, associated with lower infant mortality rates.

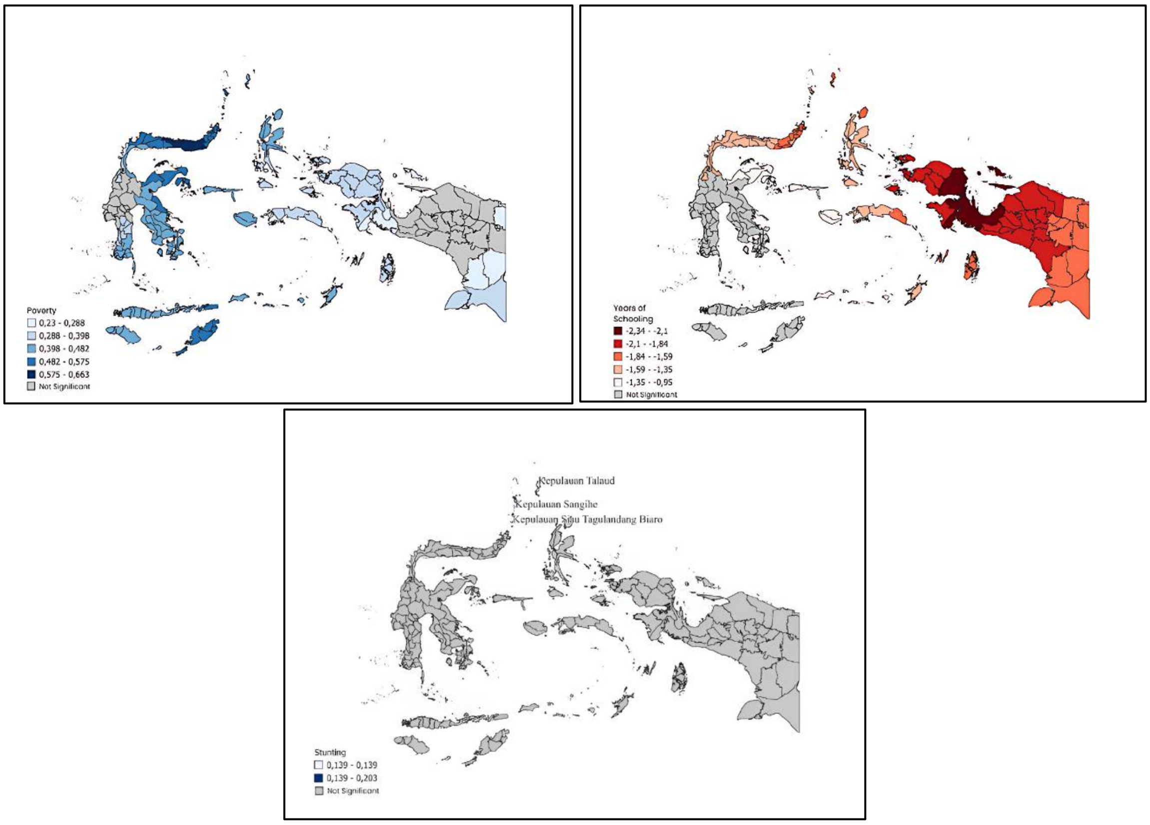

Figure 5. Map of social dimension coefficients

Based on the 2022 social dimension, the poverty variable had a positive and significant effect on the IMR, particularly in Northern Sulawesi, Maluku, and Nusa Tenggara. This finding is consistent with the research hypothesis that poverty increases the risk of infant malnutrition. Limited economic resources reduce access to nutritious food and diverse complementary feeding for infants. Gatica-Domínguez et al. (2021) found substantial socioeconomic inequalities in infant and young child feeding practices among children aged 6–23 months, with wealthier households demonstrating better dietary quality than poorer households. In addition, Anteneh et al. (2025) reported that poverty exacerbates inequalities in access to healthcare and increases the risk of infant mortality, particularly in low- and middle-income countries.

The female Mean Years of Schooling variable also has a significant negative effect in North Sulawesi, Maluku, and Papua, indicating that an increase in MYR decreases the IMR. This discovery is consistent with the research hypothesis supported by Vikram et al. (2020), who found that maternal education plays an important role in children's health behavior. Low female education can worsen the utilization of health services, thereby increasing the risk of infant mortality. The stunting variable has a significant positive effect in regions such as the northern Sulawesi islands, indicating that an increase in stunting raises the IMR. This is in line with the research hypothesis that chronic malnutrition in children increases the risk of infant mortality. Children who are stunted show stunted physical growth due to long-term malnutrition, which weakens their immune systems and makes them susceptible to disease (Rahman et al., 2019). The number of significant regions is relatively small because the relationship between stunting and infant mortality is not spatially consistent.

In contrast, the effect of stunting on IMR is indirect. Its impact is usually mediated by other factors such as the quality of health services, sanitation, and access to health facilities. When these mediation factors are more dominant or vary more strongly between regions than stunting itself, the direct relationship between stunting and infant mortality becomes weak or statistically insignificant (Gebre et al., 2021).

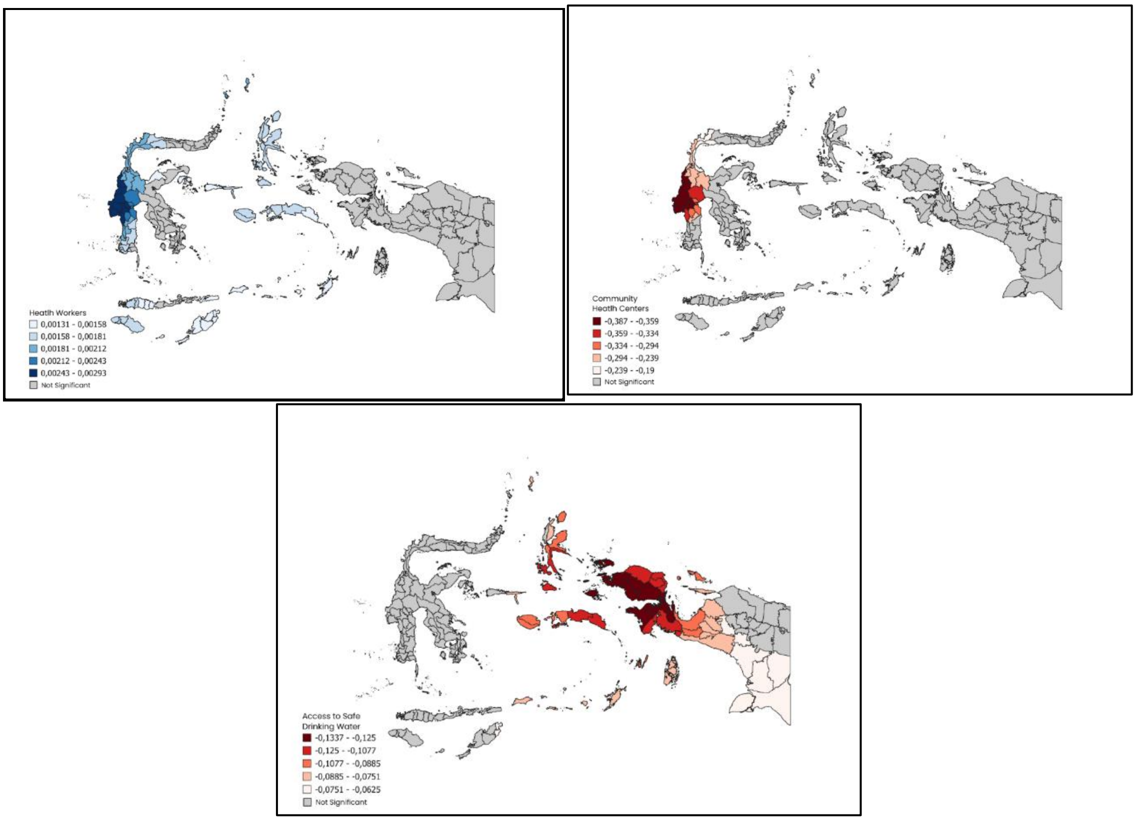

Figure 6. Map of basic access dimension coefficients

In terms of basic access in 2022, the health workers variable appears to have a significant positive effect on IMR, especially in Western Sulawesi, indicating that an increase in health workers raises IMR. This result is not in line with the research hypothesis. This may be due to the fact that many health workers in a significant area do not always reflect the quality of services or the effective use of health facilities there. In some regions, health workers must deal with excessive workloads, limited support facilities, or inappropriate task distribution, so that health service performance does not have an optimal impact on reducing infant mortality. Additionally, public participation in utilizing health services, such as pregnancy check-ups and immunizations, may still be low due to cultural influences, lack of knowledge, or cost constraints.

The health facilities variable shows a negative and significant effect on IMR, especially in western Sulawesi, indicating that an increase in health facilities reduces IMR. These results are consistent with a study conducted by UNICEF (2021), which shows that areas with low health facility coverage have higher infant mortality rates. Newborns are highly dependent on the quality and availability of basic health services, both physiologically and systemically, especially health facilities, which serve as the primary providers of maternal and child health services, childbirth, immunization, and initial treatment of complications. For this reason, the greater the number of health facilities in a region, the greater the opportunity to identify and address threats to newborn health promptly. The variable of access to drinkable water shows a significant negative effect on IMR, especially in western Papua, indicating that increased access to drinkable water decreases IMR. These results are in line with environmental health theory and hypotheses, which state that drinkable and clean water can help infants avoid infectious diseases such as diarrhea, sepsis, and gastrointestinal diseases, which are the leading causes of infant mortality in developing countries. Studies by UNICEF (2022), WHO (2023), and Lengkong et al. (2020) reinforce these results, finding a significant correlation between access to safe drinking water and basic hygiene practices and a significant reduction in IMR.

5. Conclusions

Analysis results indicate that IMR in Eastern Indonesia shows spatial heterogeneity. This discovery suggests that factors affecting IMR differ across regions. This is supported by model fit test results, which showed that GWR outperformed global regression (OLS), indicating that this model is better able of explain spatial variations in IMR.

The results of the local coefficient analysis indicate that the environmental dimensions of this case study have generally not been a major factor in explaining the variation in IMR rises in Eastern Indonesia. Among the environmental variables used, only land surface temperature has a consistent and significant effect on IMR growth. Meanwhile, the NDVI and emission index variables did not show a strong correlation with environmental conditions but instead reflected infrastructure inequality in the region. By contrast, social factors and access to basic services have been shown to play a more significant role in influencing IMR variation between regions. Limited access to health care, low levels of welfare, and disparities in infrastructure development appear to be the main factors contributing to high IMRs, especially in disadvantaged regions such as Papua and surrounding areas.

For future research, it is recommended to expand the use of environmental variables that may influence the Infant Mortality Rate (IMR), particularly by developing indices that are more representative of environmental health conditions. In addition, the analysis could be further enhanced of using panel data, enabling a more comprehensive assessment of the temporal dynamics of explanatory variables, for example, through the application of Geographically Weighted Regression Panel (GWR-Panel). For policymakers and other stakeholders, efforts to reduce infant mortality, particularly in Eastern Indonesia, should focus on ensuring a more equitable distribution of health infrastructure, improving the quality and accessibility of basic healthcare services, and enhancing the socioeconomic conditions of communities in order to reduce regional health disparities.

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