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Identification Of Infant Mortality Rate Factors Using Spatial Autoregressive Moving Average

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Abstract
Introduction: Infant mortality rate (IMR) is one of the indicator of the success for maternal and child health programs. Infant mortality rates affected by biological, environmental, socioeconomic factors and quality of healthcare services. This study aimed to analyze the factors affecting infant mortality rates in the East Java Province using a spatial regression model.
Methods: The research units were all 38 districts and cities in East Java Province. Secondary data from the 2023' Health Profile of East Java Province was used in this study, which included the number of infant deaths and the biological, environmental, socioeconomic factors, the availability and quality of health services. In this study, spatial modelling was conducted using an area approach and spatial influence using the Spatial Autoregressive Moving Average (SARMA) method with Queen Contiguity spatial weights.
Results: Based on R^2 and AIC values, the Spatial Autoregressive model was preferable to Ordinary Least Squares. The obtained model showed that low birth weight and the percentage of the population that can access good sanitation were the significant factors influencing infant mortality in this study. The other factors: percentage of deliveries by health workers, obstetric complications handled, percentage of poor people, infants receiving vitamin A, and infants receiving exclusive breastfeeding had no significant effect on Infant Mortality Rates.
Conclusion: Factors that had significant effect on infant mortality rates in this study were low birth weight and percentage of residents who had access to proper sanitation.

Keywords: infant mortality rate, ordinary least squares, spatial autoregressive moving average, sanitation, low birth weight.

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Introduction

One of the most serious problems encountered in developing countries, including Indonesia, is the infant mortality rate (IMR). The infant mortality rate in developing countries is greater than that in developed countries due to the complex interactions between socio-economic, healthcare, and environmental factors.[1] IMR is the number of infant deaths (0-11 months) per 1000 live births within one year. [2,3] Infant mortality rate is an important indicator that reflects the health status of a community. Newborn infants are particularly sensitive to the conditions of the environment where their parents live, such as poor sanitation and inadequate access to clean drinking water; this is closely related to the social status of their parents. According to the 2020 Population Census Long Form data, the IMR decreased significantly from 26 deaths per 1000 live births from the 2010 Population Census results to 16,85 deaths per 1000 live births from the SP2020 Long Form results.[4] This rate is relatively high than other developing countries such as Malaysia, which is already below 10 deaths per 1000 infant births, [5] Thailand 7,30 deaths per 1000 infant deaths, Brunei Darussalam 8,98 per 1.000 infant deaths, etc. [6]

Based on the National Medium-Term Development Plan (RPJMN) 2020-2024, the IMR is targeted to be 16,00 per 1000 live births by 2024.[7] Meanwhile, and according to the Sustainable Development Goals (SDGs), the IMR in 2030 is expected to reach 12 per 1000 live births.[8,9] By improving health services such as investments in community health centers (CHCs) and sanitation facilities and reducing the risk of infant mortality, it is believed that the SDGs target will be achieved. Therefore, one way to reduce the occurrence of IMR is to prevent the factors that affect IMR.[10] According to the World Health Organization, the highest rate of infant mortality occurs during the neonatal period, especially in the first week.[11] Meanwhile, low birth weight and prematurity are the main causes of neonatal mortality, and the main causes of death during the post-neonatal period are diarrhea and respiratory infections. According to recent estimates, about 120-156 million cases of acute respiratory infections, mainly pneumonia and bronchitis, occur each year with about 1.4 million deaths.[12] Other factors such as socioeconomic class, malnutrition, maternal age, breastfeeding, delivery distance, place of delivery, and type of delivery may also contribute to infant mortality. According to data collected from the East Java Provincial Health Office, the infant mortality rate in 2023 has increased from the previous year, from 6,4/1000 live births to 7,8/1000 live births.[13] Although all districts/municipalities in East Java have an IMR below 20/1000 live births, interventions to reduce infant mortality must be continued.[14]

Many studies have used general statistical methods, but there are still limited studies that use more detailed spatial analysis, such as geographic mapping or spatial cluster analysis, to understand the distribution of infant mortality and the main determinants that affect the infant mortality rate, such as access to maternal health services, socioeconomic status, and environmental conditions. Spatial aspects in efforts to reduce infant mortality are very important because they can provide a more detailed picture of the factors that influence the distribution of infant mortality in an area.[15] Identifying geographic patterns and area-based risks are important reasons why spatial aspects are needed in infant mortality reduction interventions. Spatial data allow researchers to identify patterns or clusters of infant mortality in an area.[16] For example, if an area has a high infant mortality rate, it can be identified whether the surrounding areas also have high infant mortality cases or vice versa.[17] In addition, spatial aspects can help identify high-risk areas. This can make it easier for governments and health organizations to determine preventive measures and resources that are appropriate to the geographical conditions of the area.[18–20]

Spatial regression analysis is an analysis that evaluates the relationship between a dependent variable and several independent variables, taking into account the spatial aspects of a region.[21] The spatial regression method is the development of a simple regression model to obtain information on observations affected by space and location. The characteristic of spatial regression is the existence of a weighting matrix, which is a marker of the relationship between a region and other regions.[22] To determine the value of the elements of the spatial weight matrix depends on the definition of neighbourhood of each observation and requires a map to see the boundaries of the region. [23–25] The closer the region or location, the higher the weight value of the corresponding element.

Spatial Autoregressive Moving Average (SARMA) is a spatial regression model used to understand the relationship between variables by considering the spatial weights between neighbouring regions. SARMA is a combination of two spatial regressions, namely the Spatial Autoregressive Model (SAR), where the spatial model occurs due to the influence of spatial lag on the dependent variable, [26] and the Spatial Error Model (SEM), a spatial regression that occurs due to the error value at a location correlated with the error value in the surrounding location.[27] If the data analyzed produces lag dependencies and error dependencies, the data can be modelled using SARMA. According to Dogan and Taspinar (2013), the use of The SARMA model is suitable for analyzing cross-sectional data by using a spatial weight matrix as a form of relationship between regions.[28] The SARMA model in this study will be used to determine the relationship between spatial dependency and factors that affect infant mortality and can be used as a reference in further policy and strengthen existing research in Indonesia.

Methods

Study Design

The research units were districts and cities in East Java Province, with a total of 38 districts and cities. East Java was chosen as the study area because of it's relatively high infant mortality rate, especially in the areas with limited health access or rural areas. The data used in this study are secondary data obtained from the 2023' Health Profile of East Java Province. Data use include the number of infant deaths and the determinants of infant mortality in East Java Province in 2023.

The conceptual framework for analyzing infant mortality according to WHO is the result of the interaction of biological, environmental, socioeconomic factors, the availability and quality of health services. [29] The percentage of infants with low birth weight, percentage of infants receiving vitamin A, and percentage of infants exclusively breastfed represent the biological factors of mothers and infants. Infants with low birth weight are at a higher risk of mortality owing to complications such as respiratory distress and infections. [30] Vitamin A is essential for maintaining immune function, which is critical for preventing infections that can lead to mortality in infants. [31] Exclusive breastfeeding significantly lowers the risk of gastrointestinal and respiratory infections, which are leading causes of mortality in children under five. [32] The percentage of families that are able to access proper sanitation represents the environmental factors that reduce infant mortality. The percentage of poor people represents the socioeconomic condition of the community. The percentage of deliveries by health workers and handling of obstetric complications indicate the ease with which the community can receive appropriate health services.

Based on the conceptual framework explained, this research variable consists of response variables (y) and predictor variables (X). The response variable was infant mortality rate. The predictor variables are presented in Table 1.

Step of Analysis

The steps used in the analysis to identify factors that influence infant mortality rates were as follows.

1. The mapping of the distribution of infant mortality rate in East Java Province was evaluated by exploring thematic map data to identify the distribution patterns and dependencies of each variable and determine the relationship patterns between variables X and Y. The software used is ArcGIS and RStudio
2. Modelling the variables infant mortality rate and its influencing factors in the following ways:
   a) Analyze using the OLS method, which incorporates parameter and hypothesis testing of parameter significance. OLS will be used as a benchmark to compare whether spatial regression is more capable of solving the infant mortality problem in this study
   b) Testing spatial effects, that is, testing for spatial dependence or autocorrelation with Moran's I, for each variable. Moran's I is only used to identify spatial dependencies, while spatial effects are tested using the Langrange multiplier test
   c) Perform modelling with the SARMA method which comprises

parameter estimation, hypothesis testing, or parameter significance

d) Identification of the best model using the R^2 and AIC. This study focuses on exploring the relationship between variables rather than prediction to identify the best model using only R^2 and AIC.

Moreover, a flowchart, like the one in Figure 2 below, can be used to illustrate the data analysis stages mentioned above

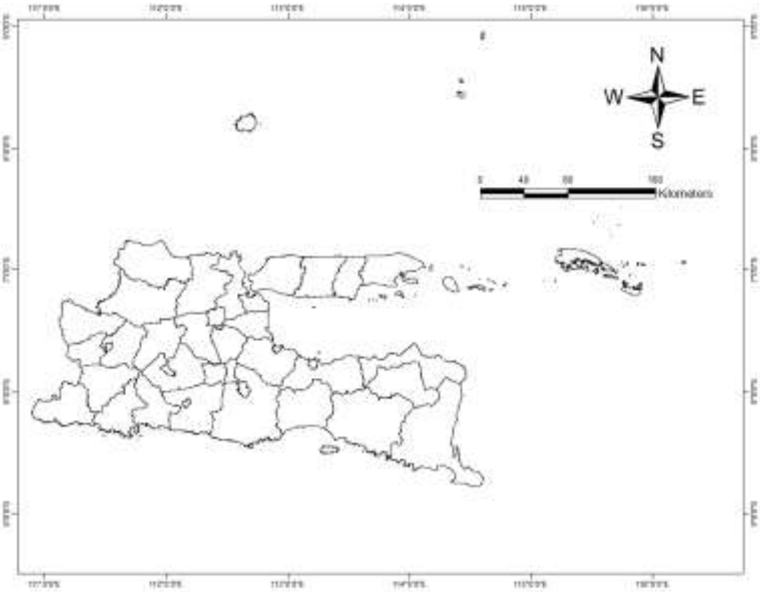


Figure 1. Geographical Map of East Java Province

Table 1. Variables Description

Variable	Description	Variable	Description
y	Infant mortality rate	X_4	Percentage of low birth weight babies
X_1	Percentage of childbirth by a health worker	X_5	Percentage of infant receiving vitamin A
X_2	Percentage of obstetric complications handled	X_6	Percentage of infant receiving exclusive breastfeeding
X_3	Percentage of poor people	X_7	Percentage of families that are able to access proper sanitation

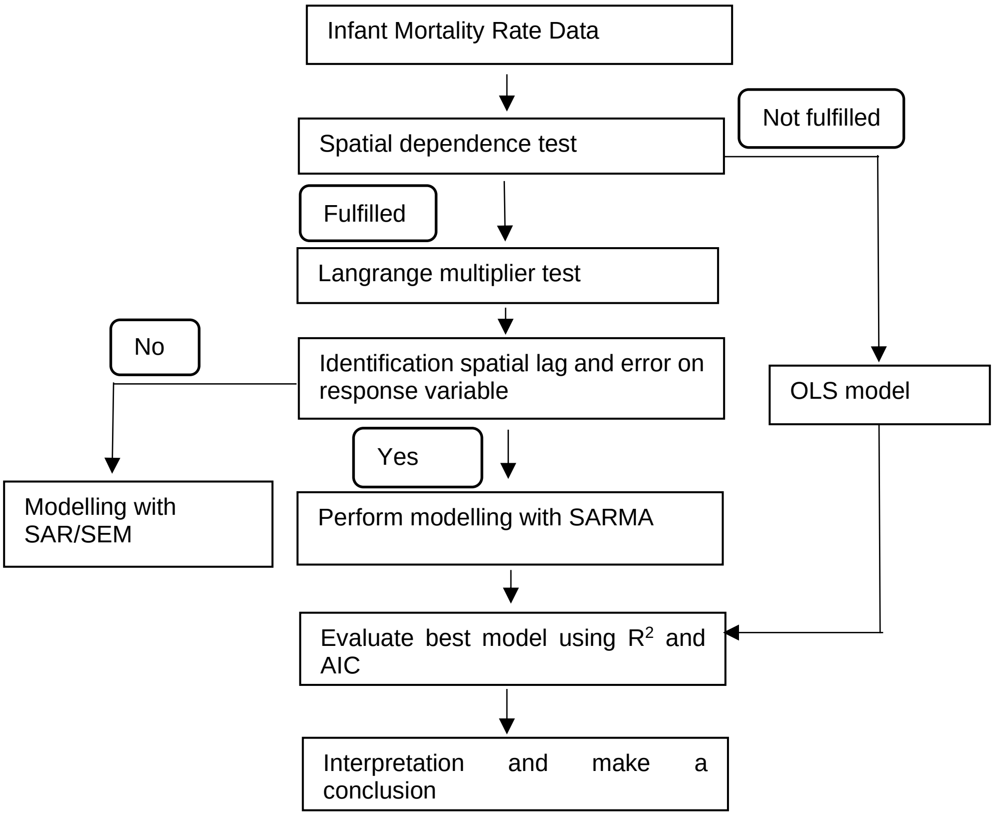


Figure 2. Flowchart of Analysis Stages

Results

Infant Mortality Rate

Based on the results of data collected (registration) by the East Java Provincial Health Office, the infant mortality rate in East Java Province in 2023 was 7,80/1000 births. The descriptive statistics of all the variables are described in Table 2.

Figure 3 shows the spatial distribution of infant mortality rates in the East Java Province. The method used to cluster districts on the map was a natural break. The district with the highest mortality rate is Bondowoso, with an infant mortality rate of 15,65/1000 births, while the lowest infant mortality rate is in Sumenep district with 2,11/1000 births. The differences between Sumenep and Bondowoso districts in infant mortality rates are likely influenced by a combination of factors, such as access to health services, community education levels, socio-economic conditions, and the quality and distribution of medical personnel in the two areas.

Figure 4 shows the spatial distribution of the factors causing infant mortality in East Java Province. Figure 4(a) shows that areas with high infant mortality rates tended to have a low percentage of deliveries by health workers. However, in this study, there was an anomaly in which areas with high infant mortality rates were followed by high delivery by health workers. Although deliveries are performed by health workers, other factors, such as the quality of health services, limited medical facilities, the mother's medical condition, access to follow-up care, and socioeconomic factors, can still lead to high infant mortality rates. Therefore, efforts to reduce infant mortality should include improving the quality of medical services, equitable distribution of health facilities, and strengthening referral systems and postnatal care. [33] Figure 4(b) explains that high obstetric complications are followed by increased infant mortality. Obstetric complications such as preeclampsia, gestational diabetes, premature birth, maternal infection, and haemorrhage during pregnancy can affect the baby's condition both in the womb and during the delivery process. [34] Figure 4(c) shows that an increase in the percentage of poor people leads to an increase in infant mortality rate. However, the opposite result was obtained in this study, where areas with a high percentage of poor people had a low infant mortality rate. This is possible if many people use their health insurance for childbirth and other health consultations. Figure 4(d) shows that areas with a high percentage of low birth weight tend to have high infant mortality rates. When the mother's nutritional condition is not optimal, it can cause the baby to have a low birth weight because the baby suffers from malnutrition, and if not immediately given assistance, it can cause death for the baby. [35]

Figure 4(e) shows that the percentage of infants receiving vitamin A was relatively distributed across the East Java Province. One of the functions of vitamin A is to boost an infant's immune system, which can help infants fight infections or other deadly diseases. Vitamin A deficiency makes infants more susceptible to diseases such as diarrhea, measles, and acute respiratory infections, which are the cause of high infant mortality rates in developing countries. [36] Another study reported a 9% reduction in under-five mortality from Vitamin A supplementation based on well-concealed trials, translating to a decrease from 28 to 25 deaths per 1000 live births, suggesting a quantitatively insignificant impact on child mortality. [37] Compared to the distribution of infant mortality, areas with a high percentage of vitamin A administration can reduce infant mortality. Figure 4(f) shows that regions with a high percentage of exclusive breastfeeding tended to have low infant mortality rates. In addition to improving infant nutrition, exclusive breastfeeding also plays a role in improving the immune system and reducing the risk of transmission of dangerous diseases to infants. [38] World health organizations, such as the WHO and UNICEF, recommend exclusive breastfeeding for the first six months of life as an effective measure to support infant survival and reduce infant mortality worldwide. Figure 4(g) shows that areas with access to proper sanitation can reduce the risk of disease spread. Compared to the distribution of infant mortality, areas with access to proper sanitation can reduce infant mortality. [39]

Spatial Regression Modelling

The first step before modelling using spatial regression is the spatial dependency test to identify the dependency relationship between locations and each variable. The test used to identify spatial dependency is Moran's I test, with the null hypothesis that there is no spatial dependency between locations, and the alternative hypothesis is that there is spatial dependency between locations. Table 3 presents the results.

The results of the spatial dependency test in Table 3 show that H_0 is rejected if it indicates dependencies between districts/cities. In the results of the Moran's I test that has been carried out, there are 4 variables that have spatial dependencies with an alpha significance level of 10%, which are IMR, percentage of births assisted by health workers, percentage of poor people and percentage of infants receiving exclusive breastfeeding. After conducting the spatial dependency test, the test continued to identify the existence of spatial effects using the Lagrange Multiplier (LM) test, in which the spatial weighting matrix used is queen contiguity, where for each district/city that intersects a side and corner, it is given a weight of 1. The results of the spatial identification test using the LM lag, Robust LM lag, LM error and Robust LM error are presented in Table 4.

Table 4 shows that:

a) The *p-value of* the LM lag is $6{,}894 \times 10^{-3}$, smaller than α = 10%, which means there is a spatial lag dependency so that it can be continued using SAR.
b) An LM error *p-value* of 0.086 is smaller than α = 10%, which means that there is a spatial dependency of error so that it can be continued using the SEM model.
c) The LM sarma *p-value is* $1{,}637 \times 10^{-4}$, smaller than α = 10%, which means there is a spatial dependency of lag and error so that modelling can be performed using SARMA.

Based on LM testing, it was found that there is a spatial dependency of lag and error; therefore, the model used is the Spatial Autoregressive Moving Average. The parameter estimation results are presented in Table 5.

Based on the parameter estimation results of the SARMA model in Table 5, the variables with a *p-value* less than the significance level α = 10% are the percentage of low birth weight and the percentage of the population accessing proper sanitation. This explains why these two variables were not significant in the model. To overcome this, re-modelling was carried out using the backward elimination method, which eliminates insignificant variables gradually, both simultaneously and partially.

Based on Table 6, all variables have a p-value less than the significance level α = 10%. X_4 has a positive relationship with the response variable, which means that every increase in the percentage of low birth weight babies in a district or city causes an increase in IMR in East Java Province, and every increase in the percentage of residents who are able to access proper sanitation will reduce infant mortality. The significant variables in Table 5 form a SARMA model, as shown in the following equation:

$$\mathrm{y}_i = 0,761\sum_{j=1,i\neq j}^{38} w_{ij}\sqrt{\mathrm{y}_j} + 9,993 + 0,303\mathrm{X}_{7i} - 0,107\mathrm{X}_{10i} - 0,729\sum_{j=1,i\neq j}^{38} w_{ij}u_j$$

y_i denotes the estimated infant mortality rate in the *i^th^* district/city in East Java Province. y_i denotes the infant mortality rate in the i^{th} district/city in East Java Province. w_{ij} is the spatial weight matrix. X_{4i} is the percentage of low birth weight babies in the i^{th} district/city. X_{7i} is the percentage of people who are able to access proper sanitation in the i^{th} district/city. Based on the equation obtained, it can be interpreted that the addition of one per cent of low birth weight infants causes an increase of 0,303 infant deaths (per 1000 births), and the addition of one per cent of citizens who are able to access proper sanitation will reduce 0.107 infant deaths (per 1000 births). The coefficient ρ = 0,761 indicates that if a district/municipality is surrounded by other districts/municipalities, it has the effect of each district/municipality having a district/municipality of 0,761. A positive ρ indicates that if the value of a variable is high in one location, it tends to be followed by a high value in the neighbouring location, and if ρ is negative, the value of a variable is high in one location tends to be followed by a low value in the neighbouring location. The coefficient λ = -0,729 indicates that the error of neighbouring districts is -0,729.

From the SARMA equation obtained, each district/city has a different equation. This is because of the existence of a weighting matrix that reflects the spatial relationship between one district/city and other areas that are the object of observation. Suppose that the observed area is the Banyuwangi Regency. Banyuwangi Regency has boundaries with Bondowoso Regency, Jember Regency and Situbondo Regency.

$$\begin{aligned}\hat{\mathrm{y}}_{Banyuwangi} &= 0,761(w_{BanyuwangiBondowoso}\mathrm{y}_{Bondowoso} + w_{BanyuwangiJember}\mathrm{y}_{Jember} + w_{BanyuwangiSitubondo}\mathrm{y}_{Situbondo}) + 9,993\\ &+0,303\mathrm{X}_{7\,Banyuwangi} - 0,107\mathrm{X}_{10\,Banyuwangi}\\ &-0,729(w_{BanyuwangiBondowoso}u_{Bondowoso} + w_{BanyuwangiJember}u_{Jember}\,w_{BanyuwangiSitubondo}u_{Situbondo})\end{aligned}$$

Based on the SARMA model that has been obtained, Banyuwangi Regency gets an influence from Bondowoso Regency, Jember Regency and Situbondo Regency with each of these regions amounting to 0,761. The error scores from the Bondowoso Regency, Jember Regency, and Situbondo Regency affect the SARMA model in Banyuwangi Regency by -0.729. This can be interpreted as follows: the infant mortality rate in Banyuwangi Regency will decrease by 0.729 if there is a one-unit increase in the error factor in Bondowoso Regency, Jember Regency, and Situbondo Regency.

Best Model Selection

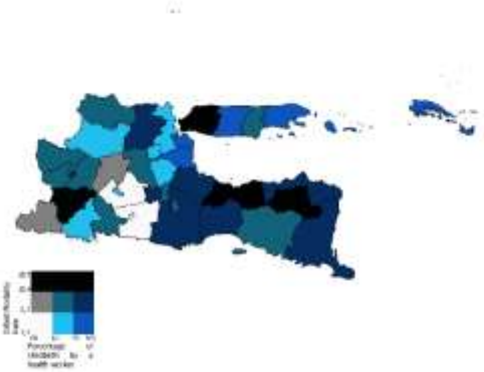
The best model selection was determined based on the maximum R^2 value and minimum AIC value. The R^2 and AIC values of the analysis performed using the OLS and SARMA methods are shown in Table 6.

The SARMA model has an R^2 value of 64.582%, which means that the model can explain the diversity of infant mortality rates by 64.582%, and the remaining 35.418% can be explained by other variables outside the model in the residual value. The SARMA model has a greater R^2 value and a smaller AIC value, so it can be concluded that the SARMA model is better used in modelling the factors that influence infant mortality in East Java Province than the OLS regression model.

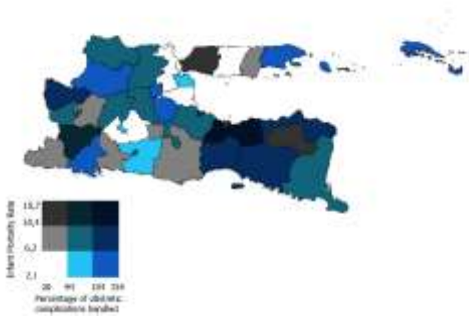
Table 2. Descriptive Statistics of IMR and Its Influencing Factors

Variable	Maximum	Minimum	Average
Y	15.66	2.11	7.79
X_1	105	80	72.47
X_2	154	20	89,78
X_3	21.76	3.31	5.42
X_4	15.60	1.60	10.29
X_5	148.50	38.90	97.95
X_6	137.20	34.70	93.26
X_7	100	69.74	7.79

Figure 3. Infant Mortality Rate in East Java Province 2023



(a)



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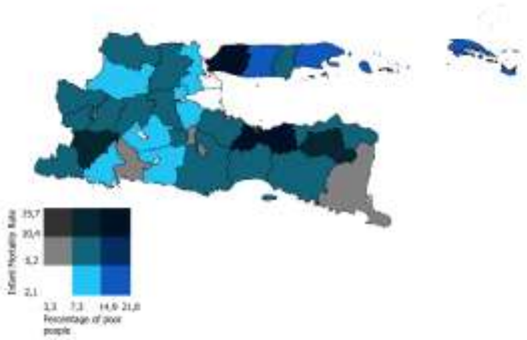

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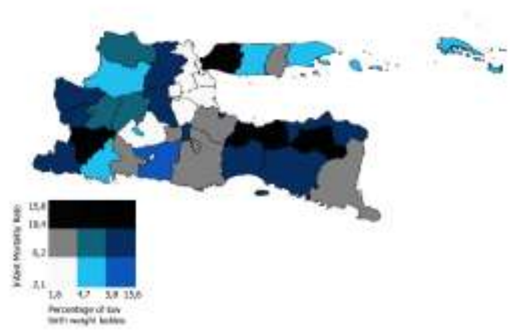
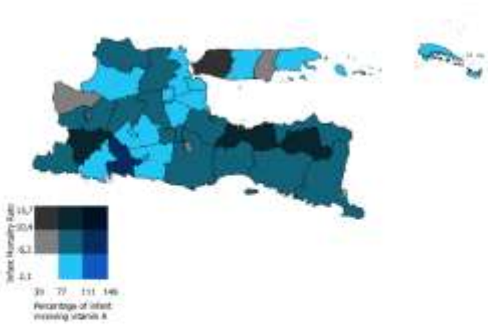
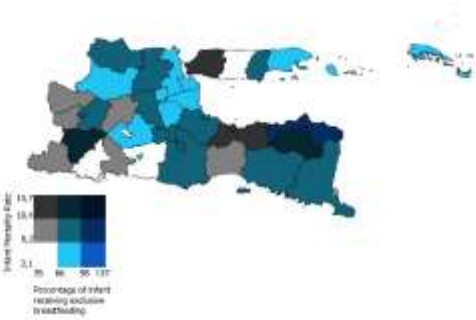


(d)



(e)



(f)

(g)

Figure 4. Percentage of childbirth by a health worker (a), Percentage of obstetric complications handled (b), Percentage of poor population (c), Percentage of low birth weight babies (d), Percentage of infant receiving vitamin A (e), Percentage of infant receiving exclusive breastfeeding (f), Percentage of families who have access to proper sanitation (g)

Table 3. Results of Moran's I Test

Code	Variables	Moran's I	$\lvert Z_{score} \rvert$
Y	Infant mortality rate	0.406	3.313*
X_1	Percentage of deliveries by healthcare professionals	0.343	2.838*
X_2	Percentage of obstetric complications	-0.025	0.015
X_3	Percentage of poor population	0.398	3.261*
X_4	Percentage of low birth weight babies	0.071	0.754
X_5	Percentage of infant receiving vitamin A	0.030	0.439
X_6	Percentage of infants receiving exclusive breastfeeding	0.172	1.529*
X_7	Percentage of access proper sanitation	-0.053	0.196

*) significance α = 10%
$Z_{0,1} = 1,28$

Table 4. Result of Langrange Multiplier Test

Test	Score	p-value	Criterion
LM Lag	7.300	$6.894*10^{-3*}$	Reject H_0
Robust LM Lag	14.492	$1.408*10^{-4*}$	Reject H_0
LM Error	2.944	0.086*	Reject H_0
Robust LM Error	10.125	$1.455*10^{-3*}$	Reject H_0
LM SARMA	17.435	$1.637*10^{-4*}$	Reject H_0

*) significance α = 10%
$Z_{0,1}$=1,28

Table 5. Parameter Estimation of SARMA

Coefficients	Estimation	*Std. Error*	p-*value*
λ	-0.784	0.136	$8,234*10^{-9}$
ρ	0.718	0.101	$1,494*10^{-12}$
Constanta	2.912	7.584	0,701
X_1	0.072	0.055	0,196
X_2	0.017	0.019	0,373
X_3	-0.032	0.089	0,718
X_4	0.368	0.148	**0,013**
X_5	-0.013	0.023	0,569
X_6	-0.024	0.021	0,252
X_7	-0.085	0.051	**0,092**

Table 6. Parameter Estimation of SARMA Backward Elimination

Coefficients	**Estimation**	***Std. Error***	**p-*value***
λ	-0.729	0.160	$\mathbf{5.222*10^{-6}}$
ρ	0.761	0.095	$\mathbf{1.332*10^{-15}}$
Constanta	9.993	4.557	0.028
X_4	0.303	0.146	**0.038**
X_7	-0.107	0.044	**0.016**

Table 6. Best Model Selection

Model	$\mathbf{R^2}$	**AIC**
OLS	19.189%	211.4805
SARMA	64.582%	193.1519

Discussion

Characteristics of Infant Mortality Rates in East Java Province

The distribution of districts/cities by infant mortality rate and its influencing factors tends to be clustered. Districts/cities around Bondowoso Regency, commonly called the horseshoe region of East Java, tend to have high infant mortality rates, while districts/cities around Surabaya tend to have low infant mortality rates. This indicates that infant mortality does not only come from one factor, but there are several other determinant factors that drive the high infant mortality rate in East Java Province. For example, in Surabaya and the surrounding areas, the percentage of low birth weight babies and families with access to good sanitation are both relatively low. This indicates that, generally, the development of community infrastructure is centralized in one area so that nearby areas will follow the advancement of the area.

In 2023, East Java Province set a target for reducing the IMR to below 20 per 1,000 live births. This target is part of the efforts to improve maternal and child health in East Java Province. [40] In line with the target of the National Medium-Term Development Plan, reducing infant mortality is one of the priorities that must be resolved immediately, given its importance in achieving the Sustainable Development Goals target of the third goal of 'Good Health and Well-being'.[8] With the increasing number of studies on the spatial aspects of IMR reduction, it is expected that clustering of priority areas in infant mortality reduction interventions will emerge.

To achieve these targets, relevant parties continue to carry out several interventions, including increasing access to maternal and child health services, maternal and infant health programs, and technology-based innovations. Improving access to maternal health services can be implemented through activities such as maternal health services, tetanus immunization services for women of childbearing age and pregnant women, the provision of blood supplement tablets, maternity and postpartum health services, childbirth planning and prevention of complications (P4K), family planning services, and HIV and hepatitis B testing. [41] According to Minister of Health Regulation No. 25/2014, efforts to improve child health can be made through fetal health services in pregnancy, newborn health, infants, toddlers, preschoolers, and child health protection. In addition to the role of the government and related health workers, reducing infant mortality is also strongly influenced by the role of the family. [42] A family's role can be accomplished through the family approach. The implementation of this family approach has three aspects that must be held or developed: instruments used at the family level, communication forums developed for contact with families, and the involvement of personnel from the community as partners of health centres. [43]

The spatial aspects play an important role in the management of health cases. From a policy intervention perspective, spatial aspects can provide a deeper understanding of the geographical distribution of a health case. [44] In this study, spatial analysis was able to focus interventions on the districts most in need, understand the factors that affect health contextually, and ensure more efficient resource readiness. As an example of an intervention that can be taken is the equalization of health facilities, the quality of health facilities in neighboring areas is not significantly different. The combination of statistical methods and more sophisticated computerized software, such as geographic information systems, can provide more detailed references to health authorities in a district. [45,46] This technology can provide visualizations that are more easily understood by policymakers, so that the results of the analysis can be directly applied to appropriate policies. Future research is expected to develop statistical methods and review the factors thought to influence infant mortality in East Java Province. In addition, researchers are encouraged to use spatially based nonparametric methods to overcome nonlinear relationship patterns between the predictor and response variables and overcome spatial dependencies. Nonparametric tests can be used to compare IMR across different geographic areas or demographic groups (e.g., urban vs. rural, high vs. low socioeconomic status).

Conclusion

Factors that were found to have a significant effect on infant mortality rates in this study were low birth weight and percentage of residents who had access to proper sanitation. The other factors of percentage of deliveries by health workers, obstetric complications handled, percentage of poor people, percentage of infants receiving vitamin A and percentage of infants receiving exclusive breastfeeding had an insignificant effect on IMR. Based on the conceptual framework of infant mortality, biological and environmental factors have a significant influence on infant mortality in East Java. Intervention steps that can be taken to reduce the rate of low birth weight include providing optimal nutrition and routine monitoring on pregnant mothers' health conditions. Improving access to proper sanitation requires a holistic approach involving government, community, private sector, and non-governmental organizations.

Ethics approval
Not applicable

Availability of data and materials
Available

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Author Contribution
FDC: Conceptualization, Methodology, Writing – original draft; HFAS: writing–review, validation, supervision. All authors have read and approved the final manuscript.

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