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Bayesian Spatio-Temporal Conditional Autoregressive Modeling of Stunting Risk Factors in East Java

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ABSTRACT

This study analyzes stunting cases in East Java Province using district/city-level panel data covering the period 2022-2024. The data were obtained from the Indonesian Nutritional Status Survey (SSGI), the Indonesian Health Survey (SKI), and official statistical sources, consisting of stunting cases and several health, socioeconomic, and environmental indicators across 38 districts and municipalities. The study applies a Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) model with the Integrated Nested Laplace Approximation (INLA) approach to account for spatial dependence among neighboring regions and temporal variation over time. The results show that stunting cases in East Java exhibit significant spatial and temporal dependence, supported by significant positive spatial autocorrelation across all observation years. Model evaluation yields a Deviance Information Criterion (DIC) value of 1477,267 and a Watanabe-Akaike Information Criterion (WAIC) value of 1442,479. The estimation results indicate that all examined covariates, including low birth weight, complete basic immunization, exclusive breastfeeding, proportion of poor population, access to improved drinking water, and access to improved sanitation, are statistically significant in explaining variations in stunting cases after controlling for spatial and temporal effects. Relative risk mapping reveals clear spatial heterogeneity, with higher-risk clusters concentrated in districts such as Jember, Lumajang, and Probolinggo, while lower-risk areas are mainly observed in urban regions such as Surabaya, Mojokerto, and Madiun. Overall, the findings suggest that stunting distribution in East Java is shaped by both spatial and temporal structures, highlighting the importance of geographically targeted intervention strategies at the district/city level.

1. Introduction

Stunting remains a significant chronic nutritional problem in Indonesia and continues to pose serious challenges to public health [1] [2]. This condition negatively affects child growth and cognitive development and may reduce human capital productivity and socioeconomic well-being in the long term [3] [4]. In East Java Province, data from the Indonesian Nutritional Status Survey (SSGI) and the Indonesian Health Survey (SKI) indicate that stunting prevalence declined from 19.2% in 2022 to 17.7% in 2023 and further declined to 14.7% in 2024. However, this decline has not been evenly distributed across districts and municipalities. Several regions, including Jember (30.4%), Lumajang (23.4%), Malang (23.3%), and Batu City (24.5%), continue to report relatively high prevalence rates, whereas Lamongan (6.9%), Trenggalek (6.7%), and Surabaya (8.5%) exhibit substantially lower rates [5] [6] [7]. These disparities indicate the presence of spatial variation and temporal dynamics in stunting prevalence, thereby necessitating spatial-temporal analytical approaches to support more targeted intervention policies [8].

Several previous studies have employed Bayesian spatial approaches to analyze stunting risk factors in Indonesia. Aswi and Sukarna [9] applied Bayesian Spatial Conditional Autoregressive (CAR and BYM) models in South Sulawesi and found that access to sanitation, exclusive breastfeeding, and household economic conditions had significant effects, with the presence of spatial autocorrelation among districts and municipalities. A national-scale study by Hasibuan et al. [10] utilized a Bayesian

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Spatial CAR-BYM model with the Integrated Nested Laplace Approximation (INLA) approach across 514 districts and municipalities, demonstrating that food security, access to improved drinking water, and per capita expenditure were dominant factors, accompanied by strong spatial dependence patterns. Meanwhile, Aswi et al. [11] developed a Bayesian Spatio-Temporal Localized CAR model and revealed that adverse socioeconomic conditions and low birth weight had significant effects on stunting, while successfully mapping high-risk clusters in East Nusa Tenggara and West Sulawesi. These studies demonstrate that Bayesian spatial and spatio-temporal approaches are effective for identifying regional heterogeneity and spatial dependence in stunting cases. However, most previous analyses were conducted at the provincial or national level and did not specifically examine spatio-temporal dynamics at the district/city level in East Java Province.

Building upon previous Bayesian spatial studies, this study applies a Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) model with the Integrated Nested Laplace Approximation (INLA) approach to analyze stunting cases in East Java. The BST-CAR model integrates spatial and temporal components, enabling the analysis to capture interregional dependencies and changes in stunting cases over time more effectively. Previous studies have shown that Bayesian spatio-temporal models are effective for capturing spatial dependence, temporal dynamics, and regional heterogeneity in public health data [11] [12]. Compared with conventional Markov Chain Monte Carlo (MCMC) estimation, the INLA approach provides faster and more stable posterior estimation for complex hierarchical spatial models [13]. By focusing on district/city-level data in East Java during the 2022–2024 period, this study is expected to provide more comprehensive evidence to support district/city-level stunting intervention planning.

2. Methods

2.1. Data and Variables

This study utilizes secondary data for the period 2022-2024, covering 38 districts and municipalities in East Java. The data were obtained from the Indonesian Nutritional Status Survey (SSGI), the Indonesian Health Survey (SKI), the East Java Provincial Health Office, and publications from Statistics Indonesia (BPS). The dependent variable (y) represents the number of stunting cases among children under five years of age at the district/city level, while the independent variables (x) include health, socio-economic, and environmental indicators. A summary of the research variables is presented in Table 1.

Table 1. Research Variables

Symbol	Variable
y	Stunting Cases
x_1	Low Birth Weight (LBW)
x_2	Complete Basic Immunization
x_3	Exclusive Breastfeeding
x_4	Poor Population
x_5	Access to Improved Drinking Water
x_6	Access to Improved Sanitation

2.2. Research Flow

The data structure in this study is panel data consisting of 38 districts and municipalities in East Java observed during the 2022-2024 period. Each observation contains the number of stunting cases along with the corresponding health, socioeconomic, and environmental variables by region and year. The analysis was conducted using a Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) approach with parameter estimation using the Integrated Nested Laplace Approximation (INLA)

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method. The research workflow consists of data collection, data preprocessing, construction of the spatial weight matrix using the queen contiguity method, spatial autocorrelation testing, likelihood distribution selection, prior specification, parameter estimation using INLA, model evaluation and comparison, identification of significant factors, relative risk estimation, and interpretation of the spatio-temporal results. The overall research framework is presented in Figure 1.

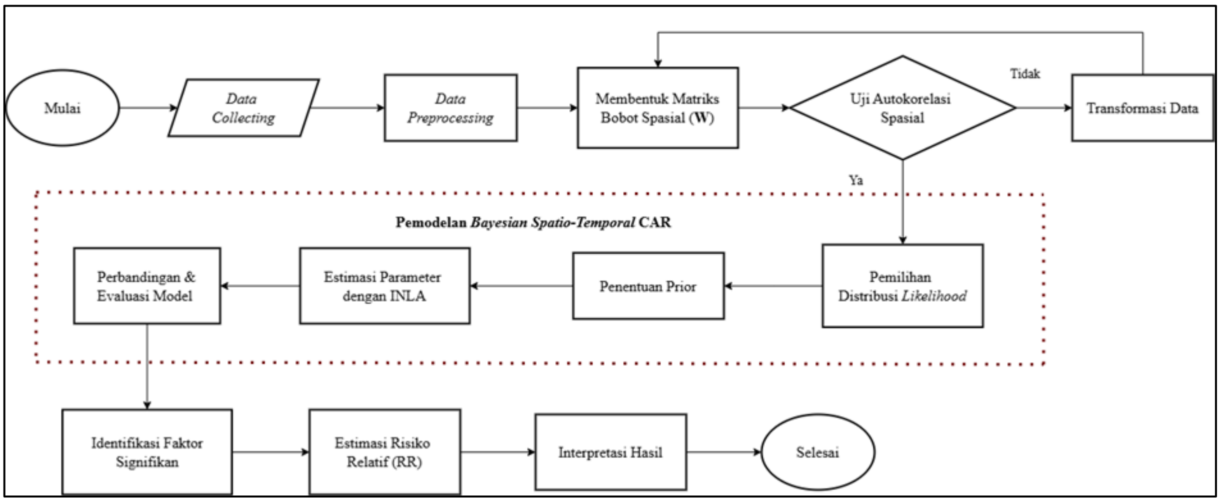

Figure 1. Research Flow

2.3. Spatial Weight Matrix and Spatial Autocorrelation

Spatial analysis is the process of processing, modeling, and interpreting data associated with geographic locations to understand relationships among objects or phenomena within a given region [14]. One of the main components of spatial analysis is the spatial weight matrix, which is used to represent the degree of connectivity among regions based on proximity or neighborhood relationships within the study area [15]. The spatial weight matrix (W) represents spatial dependence among regions based on distance or neighborhood structure. Each element, wij, indicates the relationship between region i and region j, where $wij = 1$ if the two regions are neighbors and $wij = 0$ otherwise. The matrix W is a square matrix of size $n \times n$, where n denotes the number of regions under analysis [16]. This matrix is subsequently used to calculate Moran's Index to assess the level of spatial autocorrelation of a variable across the analyzed regions. Moran's Index is employed to measure the spatial association of a phenomenon, describing the pattern of spatial autocorrelation among regions [17]. The formula is presented as follows [18]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})^2} \tag{1}$$

where I denotes Moran's Index, n represents the number of spatial units, w_{ij} is the spatial weight between the regions i and j, x_i and x_j denote the observed values of the variable in regions i and j, respectively, and $\bar{x}$ is the mean value of the observed variable across all regions.

2.4. Bayesian Spatio-Temporal CAR Model

Although Moran's Index can identify spatial autocorrelation patterns, it is descriptive in nature and does not directly estimate regional risk levels. Therefore, a Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) model is employed to simultaneously account for spatial and temporal dependencies in stunting cases [13]. In this study, the spatial component is modeled using the Besag-York-Mollié modified (BYM2) approach, while the temporal component is modeled using a first-order random walk (RW1) structure. Since the response variable represents the number of stunting cases, a Poisson likelihood is adopted [13]. The model is formulated as follows [19]:

$$Y_{ij} \sim Poisson(E_{ij}\theta_{ij}) \tag{2}$$

with

$$\log(\theta_{ij}) = \alpha + \sum_{k=1}^{p} \beta_k X_{k,ij} + u_i + v_i + \gamma_j + \delta_{ij} \tag{3}$$

where Y_{ij} denotes the number of stunting cases in the region i at time j, E_{ij} represents the expected number of cases, and θ_{ij} denotes the relative risk. Furthermore, α is the intercept, $X_{k,ij}$ denotes the k-th covariate with the regression coefficient β_k, u_i and v_i represent the structured and unstructured spatial effects under the BYM2 specification, γ_j denotes the temporal effect following an RW1 process, and δ_{ij} represents the spatio-temporal interaction effect.

2.5. Integrated Nested Laplace Approximation (INLA)

Parameter estimation in this study is conducted using the Integrated Nested Laplace Approximation (INLA) approach. INLA is a Bayesian method used to estimate parameters in Latent Gaussian Models (LGMs). These models are formulated with fixed effects and Gaussian latent random effects. INLA is chosen because it is capable of computing posterior distributions rapidly and efficiently, particularly for complex models such as spatial, temporal, or hierarchical structures [13]. The general formulation of this method is presented in the following equation [20]:

$$\pi(z_i|y) = \int \pi(z_i|\theta, y)\pi(\theta|y)d\theta \tag{4}$$

where $\pi(z_i|y)$ denotes the marginal posterior distribution of the latent parameter z_i, given the observed data y, $\pi(z_i|\theta, y)$ represents the conditional posterior distribution given the hyperparameter θ, and $\pi(\theta|y)$ denotes the posterior distribution of the hyperparameters.

2.6. Relative Risk Estimation

Based on the estimation results of the BST-CAR model, the relative risk (RR) is obtained through an exponential transformation of the estimated spatial effect component. Relative risk is an important indicator in disease mapping to identify areas with different levels of vulnerability to stunting. The RR value reflects the relative level of stunting risk in a region compared to the average risk across East Java Province after accounting for spatial and temporal dependencies. The interpretation of RR values is as follows [21]:

i. $RR = 1$: The stunting level in the area is equal to the average of East Java Province.
ii. $RR < 1$: The stunting risk level is lower than the average of East Java Province.
iii. $RR > 1$: The stunting risk level is higher than the average of East Java Province.

2.7. Model Evaluation

Model selection was conducted using two Bayesian evaluation criteria, namely the Deviance Information Criterion (DIC) and the Watanabe-Akaike Information Criterion (WAIC). Both criteria are used to assess the trade-off between model fit and model complexity, where models with lower DIC and WAIC values are considered more appropriate [22]. The Deviance Information Criterion (DIC) is a Bayesian model evaluation measure that combines the goodness of fit to the data with the effective number of parameters, thereby enabling comparison among models with differing levels of complexity [23]. The DIC is formulated as follows [24]:

$$DIC = D(\hat{\theta}) + 2_{pD} \tag{5}$$

where $D(\hat{\theta})$ denotes the deviance, evaluated at the posterior mean of the parameters, and pD represents the effective number of parameters reflecting model complexity [24]. Meanwhile, the Watanabe- Akaike Information Criterion (WAIC) is used to evaluate the predictive performance of Bayesian models on new data by taking into account the entire posterior distribution. The WAIC is formulated as follows [25]:

$$WAIC = -2(lppd - pWAIC) \tag{6}$$

where $lppd$ (log pointwise predictive density) measures the goodness-of-fit of the model to the observed data, while $pWAIC$ represents the model complexity penalty calculated from the posterior variance of the log-likelihood. This characteristic makes WAIC more suitable for evaluating predictive performance in the Bayesian framework compared to criteria based solely on point estimation.

3. Results and Discussions

This section reports the findings of the analysis on stunting risk factors in East Java Province obtained using a Bayesian spatio-temporal Conditional Autoregressive (CAR) model. The analysis focuses on identifying spatio-temporal patterns of stunting cases, estimating the effects of risk factors, and mapping relative risk across districts and municipalities during the 2022-2024 period.

3.1. Spatio-Temporal Distribution of Stunting Prevalence in East Java

Based on data obtained from the Indonesian Nutritional Status Survey (SSGI), the Indonesian Health Survey (SKI), and the East Java Provincial Health Office, stunting prevalence in East Java Province during the 20222024 period exhibited substantial spatial and temporal variation. These variations can be observed through thematic maps illustrating differences in prevalence levels among districts and municipalities as well as changes in spatial distribution patterns over time.

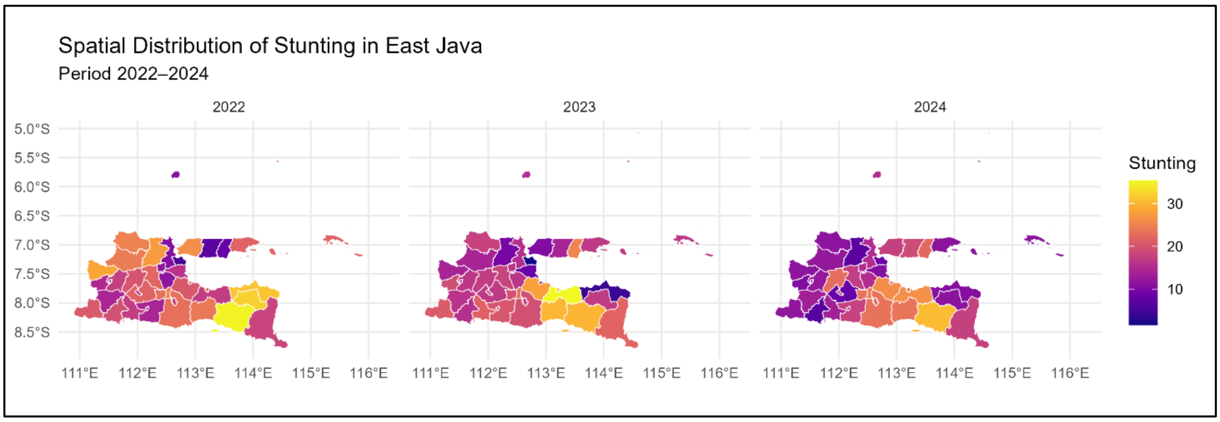

Figure 2. Spatial Distribution of Stunting Prevalence in East Java Province (2022-2024)

As presented in Figure 2, stunting prevalence in East Java Province exhibited pronounced spatial variation across districts and municipalities during the 2022-2024 period. Several areas consistently displayed relatively high prevalence levels, particularly in the Tapal Kuda region and its surrounding areas. Jember Regency, Lumajang Regency, and Probolinggo City were among the regions with persistently high stunting prevalence throughout most of the observation period, with values remaining above the provincial average. In contrast, several urban areas and regions in northern East Java tended to exhibit lower prevalence levels. Surabaya City consistently recorded the lowest prevalence during the 2022–2024 period, followed by Mojokerto City and Madiun City, which also showed relatively lower prevalence compared to surrounding districts.

From a temporal perspective, changes in stunting prevalence across years were not uniform among regions. Several districts, including Trenggalek Regency, Kediri Regency, and Lamongan Regency, experienced noticeable declines in prevalence from 2022 to 2024. However, other regions such as Malang Regency, Pasuruan Regency, and Batu City maintained relatively high prevalence levels or exhibited fluctuations during the observation period. The clustering of regions with similar prevalence levels in geographically adjacent areas suggests that the distribution of stunting prevalence in East Java was not random. These findings indicate the presence of both spatial and temporal dependence in stunting prevalence, thereby supporting the application of a Bayesian spatio-temporal modeling approach in subsequent analyses.

3.2. Multicollinearity Testing

Before estimating the Bayesian spatio-temporal CAR model, multicollinearity testing was conducted to examine the linear relationships among the independent variables. Pearson correlation analysis and the Variance Inflation Factor (VIF) were employed to assess the presence of multicollinearity. Figure 3 presents the Pearson correlation matrix among the independent variables. Overall, the correlation coefficients were relatively low to moderate, indicating the absence of strong linear relationships among predictors. The highest correlation was observed between the poor population (x_5) and access to improved sanitation (x_7) with a coefficient of -0,61, which remained below the commonly used threshold of |0,70| for serious multicollinearity.

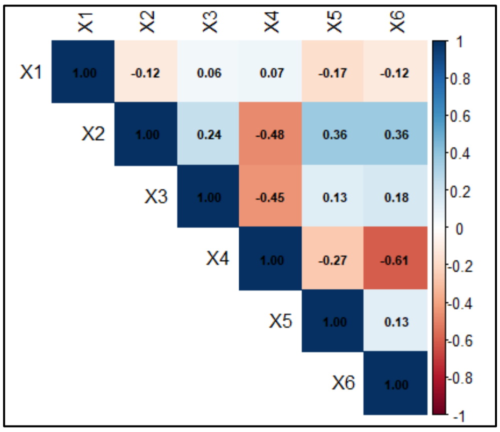

Figure 3. Pearson Correlation Matrix of Independent Variables

In addition to the Pearson correlation analysis, multicollinearity was further evaluated using the Variance Inflation Factor (VIF). The VIF results are presented in Table 2.

Table 2. Variance Inflation Factor (VIF) Values

Variable	VIF
x_1	1,05
x_2	1,43
x_3	1,29
x_4	2,19
x_5	1,20
x_6	1,66

Based on Table 2, all VIF values were substantially below the threshold value of 10, indicating that multicollinearity was not a serious issue in the model. Therefore, the selected explanatory variables were considered suitable for subsequent Bayesian spatio-temporal analysis.

3.3. Spatial Autocorrelation Testing Using Moran's Index

To examine whether the identified spatial patterns of stunting prevalence are statistically significant, spatial autocorrelation testing was conducted using Moran's Index. This analysis employed a queen contiguity spatial weight matrix, in which districts and municipalities are defined as neighbors when they share a common boundary or vertex. The test was performed separately for each year of observation to assess the consistency of spatial patterns over time.

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Table 3. Results of Spatial Autocorrelation Testing for Stunting Prevalence in East Java

Year	Moran's I	P-value	Interpretation
2022	0,245	0,0187	Significant
2023	0,323	0,0033	Significant
2024	0,391	0,0007	Significant

Based on Table 3, Moran's Index values for all observation periods indicate significant positive spatial autocorrelation. This finding suggests that the distribution of stunting prevalence in East Java is not random, but rather exhibits spatial clustering across regions. The increasing Moran's I values from 2022 to 2024 indicate that spatial dependence among districts and municipalities with similar levels of stunting prevalence tends to become stronger over time. These results confirm that stunting prevalence in East Java is influenced by spatial factors, thereby violating the assumption of independence across regions. Accordingly, a BST-CAR approach is employed in subsequent analyses to capture spatial dependence as well as the temporal dynamics of stunting prevalence in a more comprehensive manner.

3.4. Bayesian Spatio-Temporal Conditional Autoregressive (CAR) Model

After identifying significant spatial autocorrelation in stunting cases in East Java Province, the analysis was continued using a Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) model. This model was used to estimate stunting risk factors while accounting for spatial dependence among districts and municipalities and temporal dynamics over the 2022-2024 period. Parameter estimation was performed using the Integrated Nested Laplace Approximation (INLA) method for computational efficiency and stability. The model is specified through a hierarchical regression framework involving fixed effects and spatial-temporal random effects. Region-specific relative risks (RR) are derived from the posterior distribution of the latent field, representing spatial and temporal variation in stunting risk after adjusting for covariates. The results are presented in terms of posterior parameter inference and spatial-temporal mapping of relative risk.

a. Model Performance Evaluation

The performance of the Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) model was evaluated using the Deviance Information Criterion (DIC) and the Watanabe-Akaike Information Criterion (WAIC). Both criteria are commonly used in Bayesian hierarchical modeling to assess the trade-off between model fit and complexity, where lower values indicate better predictive performance. Table 4 presents the model evaluation results.

Table 4. Evaluation Criteria Values of the Bayesian Spatio-Temporal CAR Model

Criterion	Value
DIC	1477,267
WAIC	1442,479

Based on Table 4, the obtained DIC and WAIC values indicate that the Bayesian Spatio-Temporal CAR model provides an adequate fit for modeling the number of stunting cases across districts and municipalities in East Java Province. The results suggest that the model is capable of capturing spatial and temporal dependence in the distribution of stunting cases while maintaining a reasonable level of model complexity. Overall, these findings confirm that the BST-CAR model is appropriate for analyzing spatial and temporal variations in stunting case counts, as well as for identifying associated risk factors and estimating region-specific relative risks.

b. Risk Factors Influencing Stunting

The estimation of the effects of stunting risk factors was conducted through the fixed-effects parameters in the Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) model. Parameter significance was determined based on the 95% credible interval (CI), where a variable was considered statistically significant if the interval did not include zero. The results of the fixed-effects parameter estimates are presented in Table 5.

Table 5. Fixed-Effects Parameter Estimates of the Bayesian Spatio-Temporal CAR Model

Variable	Mean	95% CI	Interpretation
Low Birth Weight (LBW) (x_1)	-0,0398	[-0,0424 ; -0,0373]	Significant
Complete Basic Immunization (x_2)	0,0104	[0,0101 ; 0,0108]	Significant
Exclusive Breastfeeding (x_3)	0,0047	[0,0045 ; 0,0049]	Significant
Poor Population (x_4)	-0,0384	[-0,0534 ; -0,0243]	Significant
Access to Improved Drinking Water (x_5)	0,0248	[0,0232 ; 0,0263]	Significant
Access to Improved Sanitation (x_6)	-0,0205	[-0,0218 ; -0,0192]	Significant

Based on Table 5, all explanatory variables are statistically significant at the 95% credible interval level, indicating that each variable contributes to explaining the variation in stunting cases across districts and municipalities in East Java Province after accounting for spatial and temporal effects. The results show that all variables are associated with stunting cases, with variations in the direction and magnitude of the effects across covariates. These differences reflect the complex relationships between nutritional, health, and socioeconomic factors in explaining stunting distribution at the regional level. Low birth weight (x_1) and access to improved sanitation (x_6) show associations with lower stunting cases, while complete basic immunization (x_2), exclusive breastfeeding (x_3), poor population (x_4), and access to improved drinking water (x_5) are associated with higher stunting cases after controlling for spatial and temporal dependencies. Overall, these findings suggest that stunting cases in East Java Province are influenced by a combination of health-related and socioeconomic factors, with spatial and temporal structures playing an important role in shaping the observed relationships across regions.

c. Relative Risk of Stunting

The Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) model was used to estimate the relative risk (RR) of stunting cases across districts and cities in East Java Province. The RR values represent the spatial-temporal variation of stunting risk after adjusting for covariates and spatial dependence effects in the model. The estimated RR values were categorized into low risk (RR < 0,95), moderate risk (0,95 ≤ RR ≤ 1,05), and high risk (RR > 1,05). The complete RR values for each district/city are presented in Table 6.

Table 6. Relative Risk of Stunting Cases by District/City in East Java Province

No.	District/City	RR	No.	District/City	RR
1	Pacitan	0,9925	20	Magetan	1,3350
2	Ponorogo	0,8256	21	Ngawi	1,4851
3	Trenggalek	0,7825	22	Bojonegoro	0,8068
4	Tulungagung	0,9872	23	Tuban	1,0264
5	Blitar	0,9913	24	Lamongan	0,9957
6	Kediri	0,8684	25	Gresik	0,8023
7	Malang	1,2465	26	Bangkalan	0,7904
8	Lumajang	1,4594	27	Sampang	0,7699

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No.	**District/City**	**RR**	**No.**	**District/City**	**RR**
9	Jember	1,7995	28	Pamekasan	1,0628
10	Banyuwangi	1,0955	29	Sumenep	0,9236
11	Bondowoso	1,1259	30	Kota Kediri	0,9554
12	Situbondo	0,8612	31	Kota Blitar	0,7934
13	Probolinggo	1,4936	32	Kota Malang	1,0995
14	Pasuruan	1,4095	33	Kota Probolinggo	1,4746
15	Sidoarjo	0,6662	34	Kota Pasuruan	0,9719
16	Mojokerto	0,8138	35	Kota Mojokerto	0,5880
17	Jombang	1,0924	36	Kota Madiun	0,6470
18	Nganjuk	0,5261	37	Kota Surabaya	0,2761
19	Madiun	0,7349	38	Kota Batu	1,3803

Based on Table 6, the relative risk of stunting varies across districts and cities in East Java Province. The highest RR is observed in Jember Regency (RR = 1,7995), followed by Probolinggo Regency, Ngawi Regency, Kota Probolinggo, and Lumajang Regency, indicating higher-than-average risk in these areas. These high-risk regions tend to form a spatial cluster in the southern and eastern parts of East Java Province. In contrast, the lowest RR values are observed in urban areas such as Kota Surabaya, Kota Mojokerto, Kota Madiun, and Sidoarjo Regency, indicating lower relative risk compared to the provincial average. Most remaining districts fall into the moderate-risk category, indicating relatively balanced risk distribution across the province.

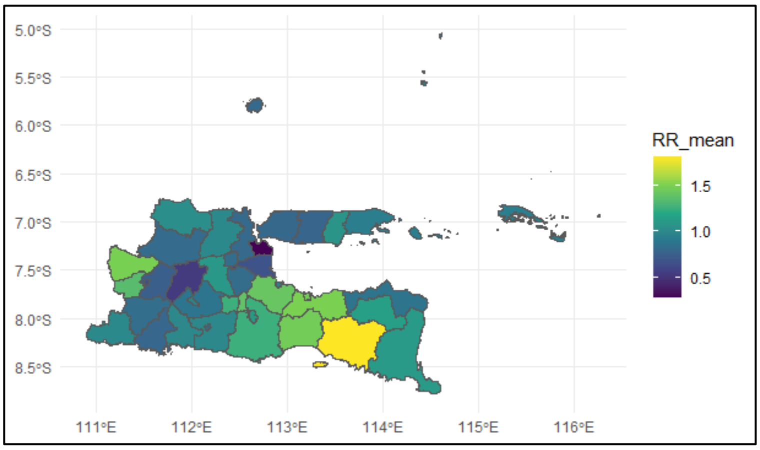

Figure 4. Spatial Distribution of Relative Risk of Stunting Cases in East Java Province

The spatial pattern shown in Figure 4 indicates a clear clustering of high-risk areas in rural regions, while lower-risk areas are predominantly concentrated in urban and more developed regions. The relative risk (RR) map does not directly correspond to the observed stunting case distribution, as it reflects the underlying risk after adjusting for population size, covariates, and spatial dependence within the BST-CAR model, resulting in a smoothed risk surface that captures latent spatial heterogeneity rather than raw case counts. This distinction highlights that high observed case numbers do not necessarily imply high relative risk. Overall, the spatial distribution of RR reveals substantial heterogeneity in stunting risk across East Java Province. These findings demonstrate that the RR map provides a model-based risk perspective that complements the observed distribution and is more appropriate for identifying priority areas for geographically targeted interventions.

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4. Conclusion

This study demonstrates that stunting cases in East Java Province during the 2022-2024 period exhibit significant spatial and temporal patterns, indicating that their distribution across districts and municipalities is not random. The Bayesian Spatio-Temporal Conditional Autoregressive (BST-CAR) model with INLA successfully captures spatial dependence and temporal dynamics, providing stable estimates of relative risk across space and time. The model evaluation results show a Deviance Information Criterion (DIC) value of 1477,267 and a Watanabe-Akaike Information Criterion (WAIC) value of 1442,479. The analysis indicates that all examined covariates, including low birth weight, complete basic immunization, exclusive breastfeeding, proportion of poor population, access to improved drinking water, and access to improved sanitation, are statistically significant in explaining variations in stunting cases across districts and cities after accounting for spatial and temporal effects. Relative risk mapping reveals clear spatial heterogeneity, with higher-risk clusters concentrated in several districts such as Jember, Lumajang, and Probolinggo, while lower-risk areas are predominantly found in urban regions such as Surabaya, Mojokerto, and Madiun. These findings highlight the importance of geographically targeted intervention strategies to reduce regional disparities in stunting. The main limitation of this study is the relatively short observation period (2022-2024) and the use of aggregated district-level secondary data, which may not fully capture long-term temporal trends and finer spatial heterogeneity. Future research is recommended to extend the temporal coverage to a longer period, incorporate additional relevant health, environmental, and socioeconomic variables, and explore more detailed spatial scales or alternative spatio-temporal modeling frameworks to improve the robustness and policy relevance of the findings.

References

[1] A. Fariza, R. Asmara, and G. N. Istiqomah, “Visualisasi Spasial Temporal Tingkat Risiko Stunting di Jawa Timur Menggunakan Metode Fuzzy Spatial Temporal Visualization of Stunting Risk Level in East Java Using Fuzzy Method,” *Jurnal Teknologi dan Informasi (JATI)*, vol. 13, no. 1, pp. 83–95, 2023, doi: 10.34010/jati.v13i1.

[2] Trimono, Amri Muhaimin, P. C. Ekacitta, and A. E. Ardiani, “Spatial Autocorrelation Analysis of East Java Stunting Prevalence Cases in 2023,” *Journal of Advances in Information and Industrial Technology*, vol. 7, no. 1, pp. 83–94, 2025, doi: 10.52435/jaiit.v7i1.689.

[3] E. S. Sakti, M. R. Makful, and R. Dewi, “Analisis Spasial Prioritas Penanganan Stunting Di Provinsi Aceh Tahun 2021,” *Jurnal Mutiara Kesehatan Masyarakat*, vol. 8, no. 1, pp. 10–23, 2023, doi: 10.51544/jmkm.v8i1.3856.

[4] K. T. Nastiti, Z. J. Luthfi, K. Ummah, I. I. Brilliant, and E. P. Setiawan, “Faktor-Faktor Penentu Prevalensi Stunting di Nusa Tenggara Barat: Analisis Spasial dengan Modifikasi Ketetanggaan,” *Jambura Journal of Probability and Statistics*, vol. 6, no. 1, pp. 1–6, 2025, doi: 10.37905/jjps.v6i1.24714.

[5] Kementerian Kesehatan Republik Indonesia, “Hasil Survei Status Gizi Indonesia (SSGI) 2022.”

[6] Kementerian Kesehatan Republik Indonesia, “Survei Kesehatan Indonesia 2023 Dalam Angka,” 2023.

[7] Kementerian Kesehatan Republik Indonesia, “Survei Status Gizi Indonesia (SSGI) 2024.”

[8] F. Vianti, H. Khaulasari, Y. Farida, C. Swantika, and H. Efendi, “Model Geographically Weighted Regression Menggunakan Adaptive Gaussian Kernel untuk Pemetaan Faktor Penyebab Stunting,” *Euler : Jurnal Ilmiah Matematika, Sains dan Teknologi*, vol. 12, no. 2, pp. 190–199, Dec. 2024, doi: 10.37905/euler.v12i2.28072.

[9] A. Aswi and S. Sukarna, “Pemodelan Spasial Bayesian dalam Menentukan Faktor yang Mempengaruhi Kejadian Stunting di Provinsi Sulawesi Selatan,” *Journal of Mathematics Computations and Statistics*, vol. 5, no. 1, p. 1, 2022, doi: 10.35580/jmathcos.v5i1.33499.

[10] A. S. Hasibuan, R. Nagari, and R. A. Nisa, “Analisis Prevalensi Stunting Menggunakan Model Spasial Bayes dengan Conditional Autoregressive,” *Seminar Nasional Official Statistics*, vol. 2024, no. 1, pp. 1003–1010, 2024, doi: 10.34123/semnasoffstat.v2024i1.2095.

[11] A. Aswi, S. Rahardiantoro, A. Kurnia, B. Sartono, D. Handayani, and N. Nurwan, “Bayesian spatio-temporal conditional autoregressive localized modeling techniques for socioeconomic factors and stunting in Indonesia,” *MethodsX*, vol. 15, no. June, p. 103464, 2025, doi: 10.1016/j.mex.2025.103464.

[12] V. Uwiringiyimana, F. Osei, S. Amer, and A. Veldkamp, “Bayesian geostatistical modelling of stunting in Rwanda: risk factors and spatially explicit residual stunting burden,” *BMC Public Health*, vol. 22, no. 1, pp. 1–14, 2022, doi: 10.1186/s12889-022-12552-y.

[13] J. Van Niekerk, E. Krainski, D. Rustand, and H. Rue, “A new avenue for Bayesian inference with INLA,” *Comput. Stat. Data Anal.*, vol. 181, May 2023, doi: 10.1016/j.csda.2023.107692.

[14] P. C. Latue, “Analisis Spasial Temporal Perubahan Tutupan Lahan di Pulau Ternate Provinsi Maluku Utara Citra Satelit Resolusi Tinggi,” *Buana Jurnal Geografi, Ekologi dan Kebencanaan*, vol. 1, no. 1, pp. 31–38, 2023, doi: 10.56211/buana.v1i1.339.

[15] M. Li, M. Cui, and D. Levinson, “Interaction between Development Intensity: An Evaluation of Alternative Spatial Weight Matrices,” *Urban Science*, vol. 7, no. 1, p. 22, Feb. 2023, doi: 10.3390/urbansci7010022.

[16] A. Kusuma Nur Ichsan, Y. Rahmawati, and F. N. Anggraeni, “Spatial Spillover Effect of East Java Economic Growth,” *East Java Economic Journal*, vol. 6, no. 1, pp. 1–24, 2022, doi: 10.53572/ejavec.v6i1.73.

[17] R. Mailanda, D. Kusnandar, and N. M. Huda, “Analisis Autokorelasi Spasial Kasus Positif Covid-19 Menggunakan Indeks Moran dan Lisa,” *Buletin Ilmiah Math. Stat. dan Terapannya (Bimaster)*, vol. 11, no. 3, pp. 483–492, 2022.

[18] R. Mastory, A. Aswi, M. Fahmuddin, and L. R. Rahmanda, “Bayesian Spatio-Temporal Conditional Autoregressive Modelling of Factors Affecting Pneumonia Cases in Indonesia,” *Jurnal MSA (Matematika dan Statistika serta Aplikasinya)*, vol. 13, no. 2, pp. 162–171, Nov. 2025, doi: 10.24252/msa.v13i2.56315.

[19] R. Mastory, “Pemodelan Bayesian Spatio Temporal Conditional Autoregressive (BST CAR) Terhadap Faktor yang Mempengaruhi Kasus Pneumonia Di Indonesia,” 2024.

[20] P. Moraga, C. Dean, J. Inoue, P. Morawiecki, S. R. Noureen, and F. Wang, “Bayesian spatial modelling of geostatistical data using INLA and SPDE methods: A case study predicting malaria risk in Mozambique,” *Spat. Spatiotemporal Epidemiol.*, vol. 39, 2021, doi: 10.1016/j.sste.2021.100440.

[21] A. Aswi, A. Mauliyana, M. A. Tiro, and M. N. Bustan, “Relative Risk of Coronavirus Disease (Covid-19) in South Sulawesi Province, Indonesia: Bayesian Spatial Modeling,” *Media Statistika*, vol. 14, no. 2, pp. 158–169, 2022, doi: 10.14710/medstat.14.2.158-169.

[22] Sukarna, M. S. Wahyuni, and R. Syam, “Comparison of Bayesian Spatio-temporal Models of Tuberculosis in Makassar, Indonesia,” *J. Phys. Conf. Ser.*, vol. 2123, no. 1, 2021, doi: 10.1088/1742-6596/2123/1/012048.

[23] G. Pompilio, A. Migliore, and D. Integlia, “Systematic literature review and bayesian network meta-analysis of episodic cluster headache drugs,” *Eur. Rev. Med. Pharmacol. Sci.*, vol. 25, no. 3, pp. 1631–1640, 2021, doi: 10.26355/eurrev_202102_24874.

[24] N. I. Shafira and J. M. Harits, “Pemodelan Regresi Binominal, Dengan Inla: Studi Kasus Faktor Risiko Penyakit Diabetes,” *Jurnal Riset Ilmiah*, vol. 2, no. 1, pp. 137–146, 2025.

[25] M. N. Abdullah, N. Iriawan, and I. Irhamah, “Pendekatan Bayesian untuk Analisis Survival pada Kasus Demam Berdarah Dengue Pasien RSUD Dr. Soetomo Surabaya,” *Jurnal Sains dan Seni ITS*, vol. 9, no. 2, 2021, doi: 10.12962/j23373520.v9i2.54448.

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