

# Bayesian spatial Durbin modelling of stunting prevalence across Indonesian districts

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## Abstract

Stunting remains a significant public health concern in Indonesia, characterized by wide regional disparities and persistent prevalence in rural and underserved communities. This study applies the Bayesian Spatial Durbin Model (BSDM) to analyze the spatial distribution and interregional dynamics of childhood stunting across 31 provinces in Indonesia. District level data on stunting prevalence were obtained from the community-based health survey RISKESDAS survey of 2023, focusing on three programmatically salient covariates: the proportion of households with adequate housing, the proportion of children under five who received complete basic immunization and the proportion of infants aged 0-5 months who were exclusively breastfed. The BSDM quantifies direct and spatial spill-over effects while accounting for spatial autocorrelation and parameter uncertainty. Results indicate that adequate housing and complete immunization are associated with lower stunting prevalence and that exclusive breastfeeding are directionally protective. The study finds that spatially coordinated investments in housing quality, immunization outreach and infant feeding support accelerated stunting reduction.

**Key words:** stunting, Bayesian Spatial Durbin Model, childhood stunting, adequate housing, complete basic immunization, Indonesia.

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## Introduction

Childhood stunting remains a major public health challenge in Indonesia, with prevalence rates showing considerable geographic variation. Provinces such as Papua still report stunting levels above 40%, while urbanized provinces like Java record much lower rates (Ayuningtyas *et al.*, 2022). These disparities highlight that child nutrition outcomes are shaped not only by individual factors but also by structural and geographic contexts.

Based on prior evidence, this study focuses on three actionable determinants of stunting. Adequate housing represents the structural environment that protects children from pathogen exposure and unsafe living conditions (Beal *et al.*, 2018; Mulyaningsih *et al.*, 2021). Complete basic immunization prevents common childhood infections that contribute to faltering growth (Dorsey *et al.*, 2018). Exclusive breastfeeding in the first 0–5 months ensures optimal early nutrition and immune protection, supporting healthy linear growth (Aswi *et al.*, 2024). However, most conventional analyses fail to account for spatial dependence and interregional spill-over effects, which may bias parameter estimates and obscure the true dynamics of stunting distribution. Regions do not exist in isolation, adjacent areas often share similar infrastructures, health service capacities and environmental vulnerabilities (Dorsey *et al.*, 2018; Batool *et al.*, 2023). Meanwhile, recent advances in spatial epidemiology highlight the need for models that explicitly account for geographic interdependence. Several studies have applied spatial autoregressive models to identify clustering and spatial spill-

overs in child under-nutrition and related health indicators (Kalinda *et al.*, 2023; Kuse & Debeko, 2023). For instance, Zhu *et al.* (2020) and Lacombe *et al.* (2014) demonstrated the methodological superiority of Bayesian Spatial Durbin Model (BSDM) in dealing with spatial heteroskedasticity and uncertainty. More recently, Batool *et al.* (2023) used spatial lag models to assess drivers of stunting in Pakistan related to Water, Sanitation and Hygiene (WASH), while Yanuar *et al.* (2024) introduced a spatial Durbin framework for modelling tuberculosis distribution in Indonesia. To address these gaps, we applied a BSDM to the district-level stunting prevalence provided by the Ministry of Health's nationwide, community-based health survey (RISKESDAS) of 2023. We estimated both direct and spill-over effects of the three determinants, incorporating spatial autocorrelation and parameter uncertainty through Markov Chain Monte Carlo (MCMC). This study contributes to the literature by providing geographically nuanced evidence on structural and behavioural factors of stunting and by demonstrating the utility of BSDM for informing coordinated, district-level nutrition interventions.

## Materials and Methods

### Study area and data sources

The outcome variable is stunting prevalence (%), defined as the proportion of children under five with height-for-age Z-score <

-2 SD according to World Health Organization (WHO) standards. District level data were obtained from RISKESDAS 2023. We included three explanatory variables, all harmonized to the district level and aligned to 2023 administrative boundaries.

**Adequate housing (%)**: proportion of households meeting Statistics Indonesia (BPS) adequacy criteria, including permanent floor/wall/roof materials and a minimum floor area of  $\geq 7.2$  m<sup>2</sup> per person. This indicator reflects structural living conditions relevant to child health.

**Complete basic immunization (%)**: proportion of children under five who received the complete national basic immunization schedule based on RISKESDAS 2023 records. This serves as a proxy for preventive health service coverage.

**Exclusive breastfeeding (0-5 months, %)**: proportion of infants aged 0–5 months who were exclusively breastfed at the time of survey as measured in RISKESDAS 2023. This variable captures optimal early life feeding practice.

All variables were inspected for missing values and underwent

standardization (z-scores) before estimation in the BSDM to facilitate interpretation of direct and spatial spill-over effects. No additional socioeconomic or environmental covariates were included, ensuring focus on these three programmatically relevant factors.

In 2023, the national prevalence of stunting among children under five varied substantially across Indonesia. Central Papua recorded the highest prevalence (39.4%), while Jambi had the lowest (13.5%) as shown in Figure 1. Thematic mapping revealed clear spatial clustering, with persistently high prevalence observed in eastern provinces such as Papua, East Nusa Tenggara, and parts of Sulawesi, suggesting the presence of spatial dependence.

### Spatial regression

Spatial regression is one of the regression methods used to analyse spatial data, or data with spatial effects. The general model of spatial regression can be written as follows (Ferra, Tasya, Izzati, 2023, and Ferra, Tasya, Izzarti *et al.* 2023):

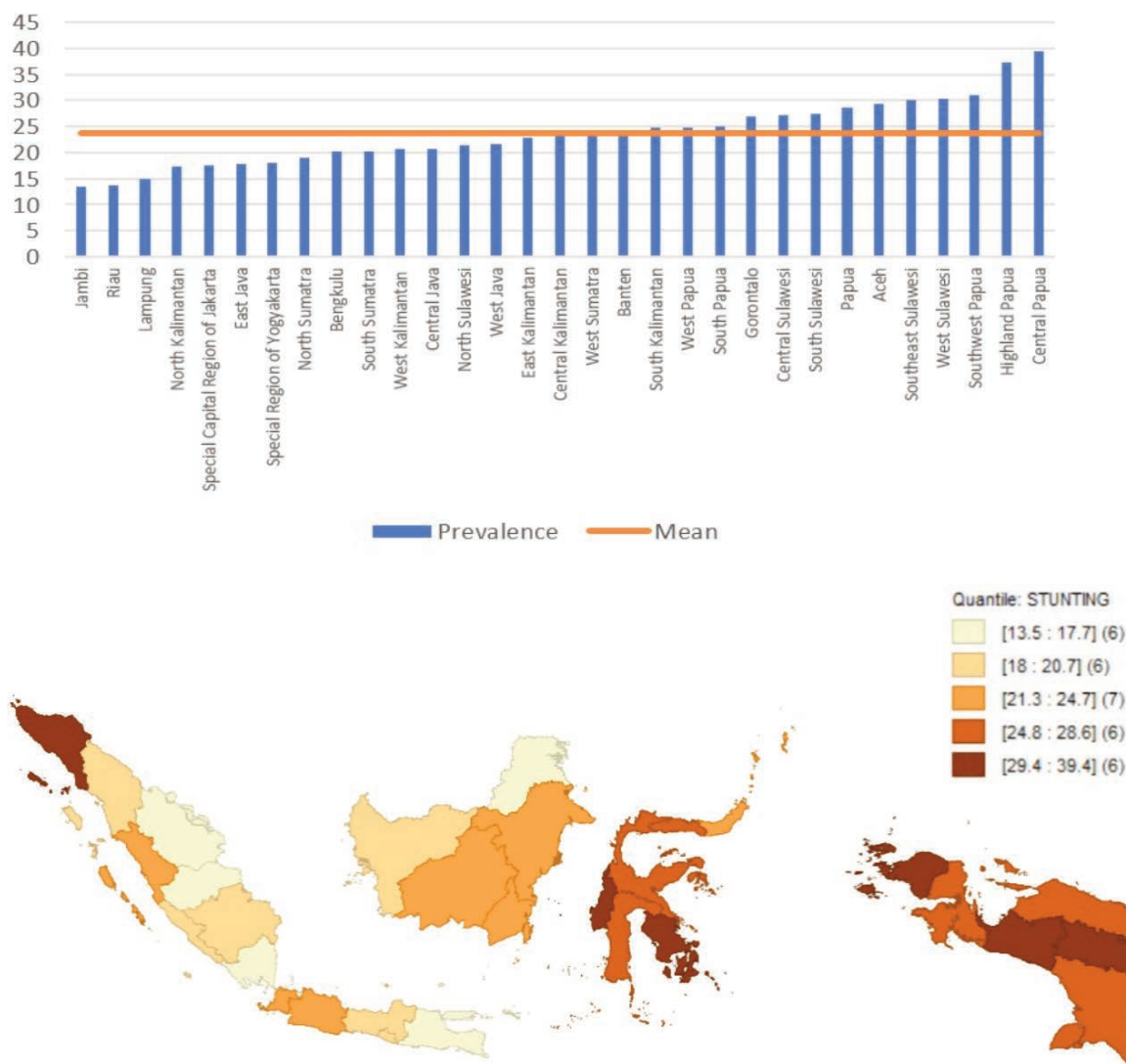


Figure 1. Stunting prevalence in Indonesia 2023.

$$y = \rho W y + X \beta + \lambda W u + \varepsilon, \varepsilon \sim N(\sigma_\varepsilon^2 I_n) \tag{Eq. 1}$$

where  $y$  is an  $n \times 1$  vector of the stunting prevalence;  $\rho$  the spatial lag parameter coefficient of the response variable;  $W$  the spatial weights matrix sized  $n \times n$ ;  $X$  an  $n \times (p+1)$  matrix of covariates;  $\beta$  is the regression parameter coefficient vector sized  $(p+1) \times 1$ ;  $\lambda$  is the residual spatial parameter coefficient;  $u$  the residual vector that has spatial effects sized  $n \times 1$ , and  $\varepsilon$  the residual vector sized  $n \times 1$ .

### Spatial weighting matrix

To capture inter-district spatial dependencies, we constructed a first-order queen contiguity matrix. This approach identifies neighbouring districts based on shared borders or vertices, capturing both direct and diagonal adjacencies. The matrix was row-standardized so that the weights of neighbouring districts summed to one for each row, ensuring comparability across regions and interpretability of spatial parameters in the estimation process (Anselin, 1988; Zhang and Xu, 2023).

The spatial influence of unit  $j$  on unit  $i$  is typically reflected in each spatial weight,  $w_{ij}$ . There are two methods for calculating the  $w_{ij}$  weight value: using contiguity information and distance information between locations. The centroid distance, also known as the Euclidean distance, between the spatial units  $i$  and  $j$  serves as the basis for the inverse distance weight matrix that is employed (Koley & Bera, 2024). The inverse of the actual distance, which is subsequently standardized, yields the value of the inverse distance location weight (Ma *et al.*, 2023). The following formula can be used to find the value of the inverse distance location weight:

$$w_{ij}^* = \frac{1}{d_{ij}} \tag{Eq. 2}$$

where  $d_{ij}$  is the distance between the  $i$ -th location and the  $j$ -th location. The value of the inverse distance weight is then standardized using the following formula:

$$w_{ij} = \begin{cases} \frac{w_{ij}^*}{\sum_{j=1}^n w_{ij}^*}, & i \neq j \\ 0, & i = j \end{cases} \tag{Eq. 3}$$

### Spatial dependency

Spatial dependency indicates the existence of assemblies between the locations of the research objects (Yasin *et al.*, 2020) and Moran's  $I$  identifies the presence of spatial dependencies (Gong *et al.*, 2020). While a positive Moran's  $I$  shows that neighbours have similar spatial effect values, a negative value indicates that neighbours have different spatial effect values (Sun *et al.* 2022). The following hypotheses were employed in this test (Yanuar *et al.*, 2023):

$H_0$  (means that there is no spatial dependency ( $I=0$ ) and  $H_1$  (that there is ( $I \neq 0$ )).

Moran's  $I$  can be formulated as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \tag{Eq. 4}$$

The test statistics used is as follows:

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}} \approx N(0,1) \tag{Eq. 5}$$

With

$$E(I) = -\frac{1}{n-1}, Var(I) = \frac{n^2 S_1 - n S_2 + 3 S_0^2}{(n^2 - 1) S_0^2} - [E(I)]^2 \text{ and } S_0 = \sum_{i=1}^n \sum_{j=1}^n$$

$$S_1 = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (w_{ij} + w_{ji})^2; \text{ and } S_2 = \sum_{i=1}^n (\sum_{j=1}^n w_{ij} + \sum_{j=1}^n w_{ji})^2,$$

where  $I$  is Moran's Index;  $n$  the number of locations;  $x_i$  the observation value at the  $i$ -th location;  $x_j$  the observation value at the  $j$ -th location;  $\bar{x}$  the average observation value;  $w_{ij}$  the standardized weight element between locations  $i$  and  $j$ ;  $E(I)$  is the expectation value of  $I$ ; and  $Var(I)$  the variance value of  $I$ . The decision basis for this test is to reject  $H_0$  at the significance level  $\alpha = 0.05$  if  $|Z(I)| > Z_{\frac{\alpha}{2}}$  or if  $< -\alpha$ , which means there is spatial dependence.

### Spatial Durbin model (SDM)

SDM is a spatial regression method that has a spatial lag with respect to the response variable and the predictor variables (Anselin, 1988). The SDM can be formally expressed as:

$$y = \rho W y + \alpha 1_n + X \beta + W X \theta + \varepsilon, \varepsilon \sim N(0, \sigma^2 I_n) \tag{Eq. 6}$$

or

$$y = \rho W y + Z \delta + \varepsilon \tag{Eq. 7}$$

where  $\begin{bmatrix} \alpha \\ \beta \\ \theta \end{bmatrix}$ ;  $Z = [1_n \ X \ WX]$ ;  $\alpha$  a constant parameter; and  $\theta$  = the spatial lag parameter vector of the predictor variables of size  $p \times 1$ .

Parameter estimation with SDM can be performed using the Maximum Likelihood Estimation (MLE) method, which aims to maximize the likelihood function. SDM also observes the outliers in the residuals, which is an observation that appears different from other observations in the data set (Yanuar *et al.*, 2024). Moran's scatterplot is a graph that shows the relationship between the observed value at a location and the average value of its neighbouring observations. Data plots in the upper left and lower right quadrants indicate the presence of negative spatial autocorrelation, which indicates that low observation areas are surrounded by high observation areas and reversed. Therefore, it can be identified that these points are categorized as spatial outliers. We also adopted a Bayesian framework for parameter estimation, offering several advantages over frequentist approaches.

### Bayesian spatial Durbin model (BSDM)

The BSDM is a sophisticated statistical approach that incorporates spatial dependence and allows for the inclusion of both direct and indirect effects of covariates on a response variable. This model is particularly useful in contexts where spatial autocorrelation is present, as it can capture the influence of neighbouring observations on the outcome of interest. Bayesian inference facilitates the incorporation of prior knowledge, provides full posterior distributions and is robust in the presence of spatial heteroskedasticity and multicollinearity (LeSage & Pace, 2009; Yanuar *et al.*, 2025). Parameter estimation was conducted using MCMC simulation. Each model was run with 12,000 iterations, with the first 2,000 discarded as burn-in. Convergence was assessed through multiple diagnostics including trace plots, effective sample sizes

and Gelman-Rubin statistics (Brooks & Gelman, 1998). Weakly informative priors were used for all parameters to avoid overfitting. Model comparison was performed using the Deviance Information Criterion (DIC), where lower values indicate better model fit. The Bayesian Spatial Autoregressive (SAR), spatial error model (SEM) and MLE models were also estimated as benchmarks to evaluate the additional explanatory power of the BSDM.

## Results

### Spatial Durbin model (SDM)

Before applying the SDM approach, the spatial dependency effect in the proposed model had to be checked first. Global spatial dependence was assessed using Moran's *I* with an inverse distance weighting matrix. The results for the response variable, predictor variables and statistic for each variable are summarized in Table 1. In this study, the critical value  $Z_{0.05}=1.645$  was used as a threshold to compare against the computed statistic for decision-making purposes.

Based on Table 1, the computed statistic for all variables exceed the critical value of  $Z_{0.05}=1.645$  leading to the rejection of the null hypothesis ( $H_0$ ). This indicates the presence of spatial dependency in both the response variable and each independent variable. Consequently, it is essential to incorporate a spatial component into the regression model. In this study, SDM is one of the appropriate spatial regression model to be used when addressing this issue. Parameter estimation in the SDM regression was based on the theoretical explanation in previous subsection, and the results were the following.

Table 2 indicates that not all explanatory variables have a statistically significant effect on the model. Therefore, the model was re-estimated by retaining only the variables with significant coefficients. The final specification based on the SDM approach as

expressed by Eq. 1 is:

$$\hat{y} = 0.2488W'y + 50.3954 - 0.1556X_2 - 0.1208X_3 - 0.2830WX_1. \quad \text{Eq. 1 applied}$$

Based on the model in Eq. 1, the first step of the SDM analysis is to examine the presence of spatial dependence in the residuals. Outlier detection in this study was carried out using Moran's scatterplot as illustrated in Figure 2.

Figure 2 shows that spatial outliers are present since 19 residual observations are found in quadrants II and IV. Such outliers could skew the estimation of the regression coefficients and intercept, which could lower the model's accuracy and dependability. The BSDM, which provides reliable parameter estimation that can

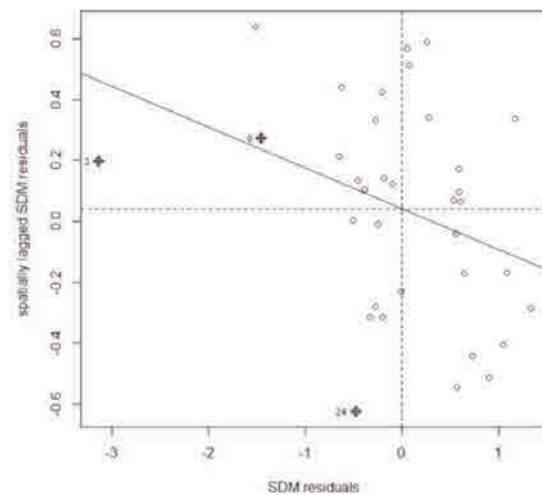


Figure 2. Moran's scatterplot of the stunting prevalence model.

Table 1. Spatial dependence test results.

Variable	Moran's <i>I</i>	Z statistics	Decision
Stunting prevalence ( <i>Y</i> )	0.5038	3.2832	Reject $H_0$
Adequate housing ( $X_1$ )	0.3652	2.4360	Reject $H_0$
Complete basic immunization ( $X_2$ )	0.4424	2.9079	Reject $H_0$
0-5 months exclusive breastfeeding ( $X_3$ )	0.4651	3.0467	Reject $H_0$

Table 2. Results of the spatial Durbin model parameter estimation.

Variable	Estimate parameter	Standard error	Z value
$\rho$	0.3029*	0.1593	1.9015
$\alpha$	47.0834*	12.7452	3.6942
$X_1$	-0.0160	0.0986	-0.1624
$X_2$	-0.1424*	0.0611	-2.3296
$X_3$	-0.1578*	0.0695	-2.2725
Lag. $X_1$	-0.2591*	0.1316	-1.9682
Lag. $X_2$	-0.0054	0.0748	-0.0722
Lag. $X_3$	0.0708	0.0886	0.7988

\*significant at  $\alpha=0.05$ ;  $\rho$ , the spatial lag parameter;  $\alpha$ , constant parameter;  $X_1$ , adequate housing;  $X_2$ , complete basic immunization;  $X_3$ , 0-5 months exclusive breastfeeding.

account for the impact of spatial outliers, was used in this study to address this problem.

### Bayesian spatial Durbin model (BSDM)

The Bayesian approach offers an effective solution for estimating SDMs, particularly when analyzing spatial data with limited samples and heteroskedasticity. Unlike classical methods relying on numerical optimization, Bayesian frameworks treat parameters as random variables with prior distributions, allowing for the incorporation of prior knowledge (LeSage & Pace, 2009). The BSDM was implemented using MCMC sampling with 12,000 iterations and 2,000 burn-in. This technique plays a pivotal role in deriving posterior distributions of complex SDM parameters, including direct and indirect spatial effects. Bayesian implementation in SDM additionally addresses spatial autocorrelation and model uncertainty through hierarchical analysis. This flexibility makes the Bayesian approach particularly superior for location-based policy analysis and modelling non-linear spatial dependencies (Lacombe *et al.*, 2014; Zhu *et al.*, 2020)

Table 3 presents the value of parameter estimation using BSDM approach. This table informs us that independent variables that have a significant effect on the prevalence of stunting among children under five in Indonesia are  $X_2$  (adequate housing),  $X_3$  (complete basic immunization) and  $\theta_1$  (the spatial lag of exclusive breastfeeding) as their 95% CIs do not include zero. These significant variables are subsequently used in the re-estimation process employing the SDM within a Bayesian framework. The results of the second stage Bayesian parameter estimation are presented in Table 4.

Every parameter has a statistically significant impact on the model, as shown in Table 4. Thus, the following formulation of the BSDM regression model for the prevalence of stunting cases in Indonesia in 2023 can be made:

$$\hat{y} = 0,2787Wy + 47,9900 - 0,1534X_2 - 0,1136X_3 - 0,2627W\theta_1. \text{ Eq. 1 applied}$$

Eq.1 here presents the posterior estimates from the BSDM. The results indicate that  $X_2$  (adequate housing) and  $X_3$  (complete basic immunization) have statistically significant direct effects on stunting prevalence. Adequate housing is associated with decreased prevalence, with complete basic immunization, exerting a protective effect. The model also reveals significant spatial spill-over effects, indicating that exclusive breastfeeding significantly influences local stunting prevalence. These findings underscore the spatial interdependence of child health determinants and highlight the importance of regional coordination in designing effective intervention strategies. Following the estimation of the BSDM model parameters, posterior convergence diagnostics were conducted for each parameter using autocorrelation plots, trace plots and the Monte Carlo Error (MC Error), which is the statistical uncertainty in a result caused by using a finite number of random samples in a simulation rather than an exhaustive calculation. These results ensure the reliability of posterior inference. The results of the convergence assessment based on MC Error are presented in Table 5.

Based on Table 4, the MC error values for all parameters are less than 1% of the Standard Deviation (SD), indicating that all parameters have achieved convergence. Subsequently, convergence diagnostics were further assessed by examining the autocorrelation plots for each parameter, as presented in Figure 3.

Autocorrelation values at lag 0 are equal to one, as shown in Figure 3, whereas values at successive lags are zero or almost zero. All five parameters exhibited the same pattern. Consequently, it can be said that all of the parameters have converged. Following that, Figure 4 displays the trace plots for every parameter. Here, the generated values exhibited patterns that converge toward specific values, indicating that all parameters achieved convergence.

**Table 3.** Results of the Bayesian spatial Durbin model parameter estimation.

Parameter	Estimated value	Lower bound	Upper bound
$\rho$	0.3103*	0.0687	0.5456
$\alpha$	47.9800*	47.1100	48.8500
$X_1$	-0.0291	-0.2314	0.1732
$X_2$	-0.1450*	-0.2786	-0.0143
$X_3$	-0.1520*	-0.3027	-0.0008
$\theta_1$	-0.2627*	-0.4811	-0.0362
$\theta_2$	-0.0068	-0.1532	0.1410
$\theta_3$	0.0778	-0.1132	0.2669

\*significant at  $\alpha=0.05$ ;  $\rho$ , the spatial lag parameter;  $\alpha$ , constant parameter;  $X_1$ , adequate housing;  $X_2$ , complete basic immunization;  $X_3$ , 0-5 months exclusive breastfeeding.

**Table 4.** Results of the Bayesian spatial Durbin model parameter estimation - stage 2.

Parameter	Estimated value	Lower bound	Upper bound
$\rho$	0.2787*	0.0686	0.4857
$\alpha$	47.9900*	47.1100	48.8700
$X_2$	-0.1534*	-0.2543	-0.0557
$X_3$	-0.1136*	-0.2214	-0.0066
$\theta_1$	-0.2627*	-0.3829	-0.1403

\*significant at  $\alpha=0.05$ ;  $\rho$ , the spatial lag parameter;  $\alpha$ , constant parameter;  $X_1$ , adequate housing;  $X_2$ , complete basic immunization;  $X_3$ , 0-5 months exclusive breastfeeding.

Subsequently, model selection was carried out to determine the best regression model. The optimal model was identified based on the values of the coefficient of determination ( $R^2$ ), mean absolute error (MAE), and root mean square error (RMSE). These values are presented for each model in Table 6.

Based on the results of the convergence diagnostics and model performance evaluation, the best regression model for representing the prevalence of stunting in Indonesia was found to be the BSDM. Compared to the SDM, The BSDM demonstrated superior performance, as indicated by the highest  $R^2$  and the lowest values both of MAE and RMSE. Table 5 reports three model comparison metrics computed from the observed  $y_i$  values and model-fitted (or predicted)  $\hat{y}_i$  values.  $R^2$  is obtained from fitted values measured the explained variance; for the BSDM,  $\hat{y}_i$  typically used the posterior predictive mean (Gelman *et al.* 2019). MAE and RMSE were obtained from residual prediction  $y_i - \hat{y}_i$ . For BSDM,  $\hat{y}_i$  was chosen as posterior predictive mean (Chai & Draxler, 2014; Salim *et al.*, 2025).

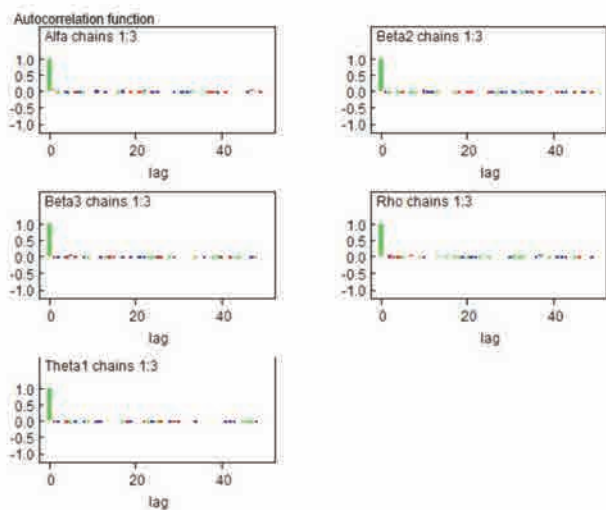


Figure 3. Autocorrelation plot.

## Discussion

Our findings strengthen the evidence that structural and behavioural determinants play a crucial role in reducing childhood stunting in Indonesia. The significant protective effect of adequate housing supports previous studies showing that improved flooring, ventilation, and sanitation reduce exposure to enteric pathogens

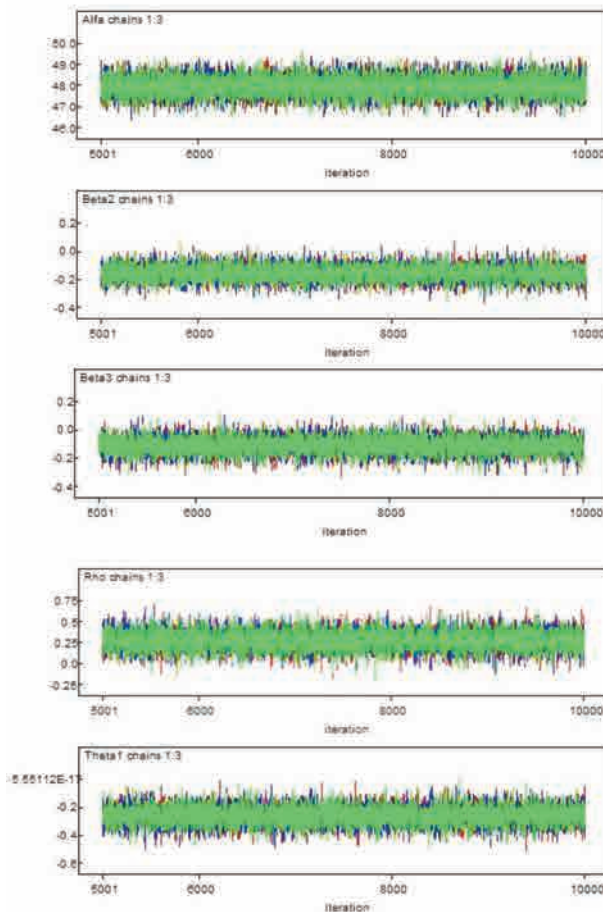


Figure 4. Trace plot.

Table 5. Convergence test using Monte Carlo error.

Parameter	SD	1% SD	MC error
$\rho$	0.1058	0.0011	0.0009
$\alpha$	0.4482	0.0045	0.0038
$\beta_2$	0.0508	0.0005	0.0004
$\beta_3$	0.0546	0.0005	0.0004
$\theta_1$	0.0614	0.0006	0.0005

SD, standard deviation;  $\rho$ , the spatial lag parameter;  $\alpha$ , constant parameter.

Table 6. Goodness of fit for the two models.

Model	$R^2$	MAE	RMSE
SDM	0.6025	3.1130	3.8719
BSDM	0.6041	3.1109	3.8645

$R^2$ , the coefficient of determination; MAE, mean absolute error; RMSE, root mean square error; SDM, spatial Durbin model; BSDM, Bayesian spatial Durbin model.

and lower the risk of growth faltering (Beal *et al.*, 2018; Mulyaningsih *et al.*, 2021). Housing interventions that meet minimum habitability standards can therefore be considered an essential component of stunting reduction strategies.

The strong association between complete basic immunization coverage and lower stunting prevalence is consistent with Dorsey *et al.* (2018), who highlighted the importance of infection prevention in maintaining healthy growth trajectories. This result underscores the need to sustain and expand immunization programs, especially in remote districts where coverage gaps remain. Although the estimated effect of exclusive breastfeeding (0–5 months) did not reach conventional statistical significance, its direction is protective, aligning with global evidence that exclusive breastfeeding improves nutrient intake and enhances infant immune function (Ames *et al.*, 2023). Strengthening breastfeeding counselling, maternity protection policies, and community support systems may amplify these benefits. Applying BSDM allowed us to account for spatial dependence and quantify inter-district spill-over effects for these three variables. The detection of spatial clustering suggests that interventions focusing only on single districts may miss cross-border influences. Coordinated planning at the provincial or regional level, targeting clusters of districts with similar vulnerabilities, could yield more substantial reductions in stunting.

These findings have clear policy implications. Housing quality improvements could be integrated into social assistance and village fund programmes. Immunization outreach should prioritize underserved areas identified as spatial hotspots, and breastfeeding promotion efforts should be embedded in maternal and child health services. Together, these strategies provide a multi-pronged, geographically informed approach to accelerate progress toward Indonesia's national stunting reduction targets.

## Conclusions

This study highlights the critical role of spatial dynamics in understanding the distribution of childhood stunting across Indonesia. Using the Bayesian BSDM, we found that local factors, particularly adequate housing and complete immunization, significantly reduce stunting prevalence, while poverty in adjacent districts exerts notable spill-over effects. These findings confirm that under-nutrition is not solely a local phenomenon but embedded within broader regional disparities.

The Bayesian framework offered robust estimation under spatial autocorrelation and heteroskedasticity, reinforcing its utility for public health modelling in decentralized systems. Our results underscore the importance of spatially informed policy approaches that extend beyond administrative boundaries. Effective stunting reduction strategies should prioritize geographically coordinated interventions, especially in high-burden clusters. Future research should integrate longitudinal data and climate-related risks to support more adaptive and equity-oriented health policies.

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