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Childhood stunting in Indonesia: assessing the performance of Bayesian spatial conditional autoregressive models

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Abstract

Stunting continues to be a significant health issue, particularly in developing nations, with Indonesia ranking third in prevalence in Southeast Asia. This research examined the risk of stunting and influencing factors in Indonesia by implementing various Bayesian spatial conditional autoregressive (CAR) models that include covariates. A total of 750 models were run, including five different Bayesian spatial CAR models (Besag-York-Mollie (BYM), CAR Leroux and three forms of localised CAR), with 30 covariate combinations and five different hyperprior combinations for each model. The Poisson distribution was employed to model the counts of stunting cases. After a comprehensive evaluation of all model selection criteria utilized, the Bayesian localised CAR model with three covariates were preferred, either allowing up to 2 clusters with a variance hyperprior of inverse-gamma (1, 0.1) or allowing 3 clusters with a variance hyperprior of inverse-gamma (1, 0.01). Poverty and recent low birth weight (LBW) births are significantly associated with an increased risk of stunting, whereas child diet diversity is inversely related to the risk of stunting. Model results indicated that Sulawesi Barat Province has the highest risk of stunting, with DKI Jakarta Province the lowest. These areas with high stunting require interventions to reduce poverty, LBW births and increase child diet diversity.

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Introduction

Stunting is a condition in children characterized by failure to grow, thus marked by a height lower than the age standard. Stunting remains a serious public health issue, especially in poor and developing countries. According to the World Health Organization (WHO), approximately 149.2 million children under five (<5 years) in the world suffered from stunting in 2020 (Gabain *et al.*, 2023), half of them in Asia (World Health Organization, 2020). Indonesia ranks third in Southeast Asia in this respect, with an average prevalence of 36.4% (Ministry of Health, 2018). In 2022, this high figure prompted the President of the Republic of Indonesia to designate stunting as a priority program, with the aim to reduce the prevalence of stunting to around 14% by 2024 (Ministry of Human Resources, 2022). Stunting has significant impacts on physical and mental health, brain development and general achievement. Despite ongoing efforts over the past 20 years, addressing the stunting problem has proven a persistent challenge (Hijrawati *et al.*, 2021).

Research exploring stunting cases and their causal factors indicate that malnutrition in children (Vatsa *et al.*, 2023) and parental education (Vaivada *et al.*, 2020) are contributing factors. Additionally, factors such as non-exclusive breastfeeding during the first 6 months, low household socio-economic status, premature birth and low maternal education level have been identified as causes of stunting in Indonesian children (Beal *et al.*, 2018). However, these studies often neglect spatial effects, even though stunting cases in one area may be influenced by values in spatially close areas. Adjacent regions often share similarities in socio-economic characteristics, environment, and access to health resources, all of which can impact the incidence of stunting.

Therefore, it is crucial to conduct analyses that account for spatial dependencies between regions.

The Bayesian spatial Conditional Autoregressive (CAR) model is a robust tool that can handle spatial dependence (Duncan *et al.*, 2019). This model produces smoothed estimates across adjacent regions (termed 'neighbours'), but variants may also allow for random variation between areas (Besag *et al.*, 1991; Leroux *et al.*, 2000). Versions of CAR models also exist which allow for discontinuities between areas (Lee & Sarran, 2015; Lee & Lawson, 2016) and for situations where adjacent regions differ greatly.

Bayesian spatial CAR models have previously been applied to examine stunting in Indonesia. These examined spatial patterns without considering covariates for either a specific province or the nation (Azis & Aswi, 2023), or they considered covariates for a specific province only (Aswi & Sukarna, 2022). Both studies demonstrated variation in stunting but had important limitations when considering national identification of important factors and areas. We therefore aimed to examine the factors influencing stunting incidence in Indonesia by implementing various Bayesian spatial CAR models that include covariate factors in the model as well as estimate the Relative Risk (RR) of stunting across Indonesia. Our primary objective was explanatory, focusing on identifying significant covariates influencing stunting incidence in Indonesia. By incorporating various covariates into Bayesian CAR models, we wished to understand these factors better and facilitate targeted interventions.

Materials and Methods

Study area and data

Indonesia is situated with a northern border adjacent to countries such as Malaysia, Vietnam, the Philippines, Singapore, Palau, Thailand and the South China Sea. Its boundaries in the south extend to Australia, Timor-Leste and the Indian Ocean, while the western frontier is marked by the Indian Ocean and the Indies. The eastern boundary is formed by the Pacific Ocean and Papua New Guinea. Indonesia comprises 34 provinces, including five major islands: Sumatra, Java, Kalimantan, Sulawesi, Papua and four groups of smaller islands, namely Riau Islands, Bangka Belitung Islands, Nusa Tenggara Islands and Maluku Islands.

Data on the number of toddlers and the number of stunted toddlers by province in 2022 were obtained from the official website of the Directorate General of Regional Development, Ministry of Home Affairs (Ministry of Home Affairs, 2022). The covariates used in this study carried out for 2022 were the following: the percentage of poverty (x_1), the percentage of babies aged less than 6 months who receive exclusive breastfeeding (x_2), the percentage of mothers giving birth to live-born children in the last two years, with the last live-born child who born with low birth weight (LBW) (x_3), percentage of children aged 12-23 months who received complete basic immunization (x_4), percentage of children aged 0-23 months who have ever been given breast milk (x_5), percentage of children aged 0-23 months who have been, and are still being given, breast milk (x_6) and the percentage of children aged 6-23 months who regularly consume at least five of the eight food and drink groups throughout the day (x_7). Poverty percentage data in 2022 were obtained from the government website Central Bureau of Statistics, 2023a). Child and maternal covariates (x_2 to x_7) were obtained from the 2022 Maternal and Child Health Profile (Sari *et al.*, 2022). Each of these seven covariates were considered *a priori* to be likely associated with stunting. For efficient writing, variable x_3 is abbreviated as Recent LBW Births and variable x_7 as Child Diet Diversity (CDD).

Correlation between covariates was assessed using Spearman's correlation coefficient, prior to running models. Given the importance of assessing the effect of variables, a Poisson model was run before any spatial CAR models to obtain estimates for each fixed effect to ensure no spatial confounding (Hodges & Reich, 2010) was influencing findings.

Statistical analysis

Five Bayesian spatial CAR models, including the Besag-York-Mollie (BYM), CAR Leroux and localised CAR with G=2, G=3 and G=5 were employed to estimate the risk of stunting and quantify the associated risk between stunting and covariates in Indonesia. The Poisson distribution was utilized to model the stunting counts, as follows.

$$y_i \sim \text{Poisson}(E_i\theta_i)$$
$$log(\theta_i) = \alpha + \boldsymbol{x}_i^T\boldsymbol{\beta} + \psi_i \qquad \text{Eq. 1}$$

Where y_i is the observed number of stunting cases for the i^{th} area. The expected value and variance of y_i is provided by the product of θ_i, which is the RR and E_i the expected number of stunting cases for the i^{th} area, which can be calculated as follows.

$$E_i = \frac{\sum_i y_i}{\sum_i n_i} n_i \qquad \text{Eq. 2}$$

Where n_i is the number of toddlers aged 0-59 months whose height was measured in 2022 in each district/city and i = 1, 2, 3, … , 34. This modelling involves an overall constant rate α and a corresponding to residual ψ_i, which incorporates the spatial structure. x_i is the vector of covariates for the i^{th} area. The vector of regression parameters is represented by $\beta = (\beta_0, \ldots, \beta_k)$. The covariate regression parameters β are given a multivariate Gaussian prior with weakly informative hyper-parameters. The spatial representation differs for each model and is detailed below. All models were computed using Markov chain Monte Carlo (MCMC) via the CAR Bayes package version 6.1.1 (Lee, 2013) within R software version 4.3.2 (R Core Team, 2019).

BYM model

One of the most widely recognized Bayesian hierarchical models utilized in disease mapping is the BYM model, the formulation of which is presented as follows:

$$\psi_i = u_i + v_i \qquad \text{Eq. 3}$$

Where $\underline{u_i}$ represents the spatially structured random effect, while v_i denotes the spatially unstructured random effect, which is typically assumed to follow a normal distribution, specifically $v_i \sim N(0,\tau_v^2)$ and for the spatially structured random effect $\underline{u_i}$, an intrinsic CAR prior distribution is employed. This prior distribution is expressed as

$$(u_i|u_j, i \neq j, \tau_u^2) \sim N\left(\frac{\sum_j u_j \omega_{ij}}{\sum_j \omega_{ij}}, \frac{\tau_u^2}{\sum_j \omega_{ij}}\right) \quad \text{Eq. 4}$$

Where ω_{ij} =1 if i and j are adjacent, otherwise =0. While various formulations have been explored, existing research indicates that opting for binary first-order adjacency weights is often a suitable and well-supported choice (Duncan & Mengersen, 2020). There are three distinct types of spatial adjacency matrix: queen contiguity, rook contiguity and bishop contiguity (Oyana & Margai, 2015). Queen contiguity was implemented in this study as it can improve the model fit (Getis & Aldstadt, 2004). The hyperpriors employed for variance terms, τ_u^2, τ_v^2 consisted of inverse-gamma (IG) distributions (Lee, 2013), specifically IG (1, 0.01) as the default hyperprior in Bayesian CAR, along with IG (1, 0.1), IG (0.5, 0.05), IG (0.1, 0.1) and IG (0.5, 0.0005).

Leroux model

While the BYM model incorporates two distinct sets of random effects, specifically a spatially structured random effect (u_i) and a spatially unstructured random effect (v_i) (, the Leroux model differs by incorporating only one single effect (u_i). This single random effect adjusts the intensity of the local neighbourhood spatial autocorrelation uniformly by a constant (ρ) representing the model as follows:

$$\psi_i = u_i$$
$$(u_i|u_j, i \neq j, \tau_u^2) \sim N\left(\frac{\rho \sum_j u_j \omega_{ij}}{\rho \sum_j \omega_{ij} + 1 - \rho}, \frac{\tau_u^2}{\rho \sum_j \omega_{ij} + 1 - \rho}\right) \quad \text{Eq. 5}$$

with hyperpriors employed for variance terms $\tau_u^2 \sim$ IG (1, 0.01) as the default hyperprior in CAR Bayes, along with IG (1, 0.1), IG (0.5, 0.05), IG (0.1, 0.1), IG (0.5, 0.0005) and $\rho \sim$ uniform (0, 1). When ρ = 1, this prior simplifies to the intrinsic CAR model, and when ρ = 0, it simplifies to the independent model (Lee, 2013).

Localised CAR model

The localised CAR model, as proposed by Lee and Saran (Lee & Sarran, 2015), enables neighbourhood random effects to vary across the geographical space, so discontinuities can occur between adjacent areas. This is realised through the partitioning of areas into a maximum of G clusters, with the incorporation of a cluster-specific mean within the model framework. The model is given by the formula:

$$\psi_i = \upsilon_i + \lambda_{Zi}$$
$$(u_i|u_j, i \neq j, \tau_u^2) \sim N\left(\frac{\sum_j u_j \omega_{ij}}{\sum_j \omega_{ij}}, \frac{\tau_u^2}{\sum_j \omega_{ij}}\right) \quad \text{Eq. 6}$$

where ω_{ij} = 1 if i *and* j are adjacent, otherwise = 0, with the hyperprior given by $\tau_u^2 \sim$ IG (1, 0.01) as the default hyperprior in CAR Bayes, along with IG (1, 0.1), IG (0.5, 0.05), IG (0.1, 0.1) and IG (0.5, 0.0005). The areas are divided into a maximum of G clusters, each with its own intercept structure arranged as $\lambda_1 < \lambda_2 < \ldots < \lambda_G$. The prior distribution for λ_j is specified as uniform (λ_{j-1}, λ_{j+1}) for j = 1, 2, …, G where $\lambda_0 = -\infty$ and $\lambda_{G+1} = +\infty$. Each area's allocation to a group is determined by a variable Z_1 represented by the formula:

$$f(Z_i) = \frac{\exp(-\delta(Z_i - G^*)^2)}{\sum_{r=1}^{G} \exp(-\delta(r - G^*)^2)} \quad \text{Eq. 7}$$

where the penalty parameter is defined as $\delta \sim$ uniform (1, 10) and $G^* = (G+1)/2$ when G is odd and $G^* = G/2$ when G is even. It is recommended that G be a small and odd number (Lee & Sarran, 2015). In accordance with this recommendation, we employed various Bayesian localised CAR models, each featuring a different maximum number of clusters: two clusters (G=2), three clusters (G=3) and five clusters (G=5) for each hyperprior.

Comparing models

The five distinct model formulations, each subjected to five varied prior specifications, and evaluated across 30 diverse combinations of covariates, culminated in the execution of a total of 750 models. The models were compared using goodness-of-fit measures, namely the deviance information criterion (DIC) (Spiegelhalter *et al.*, 2002), the Watanabe-Akaike information criterion (WAIC) (Watanabe, 2010) and the modified Moran's index (MMI) for residuals (Carrijo & Da Silva, 2017). Models with the lowest DIC and WAIC values and those with MMI residuals approaching zero indicate a better fit. DIC evaluates Bayesian model fit by balancing goodness of fit and model complexity, while WAIC provides a fully Bayesian alternative that considers the entire posterior distribution. A MMI value near zero indicates minimal spatial correlation in residuals, suggesting a well-fitted spatial model. If MMI deviates significantly from zero, it may imply unaccounted spatial dependence. Comparisons between model formulations and combinations of covariates were also conducted by evaluating the 95% posterior Credible Interval (CI), deemed significant when it excludes zero. Additionally, convergence checking is required for the accurate representation of the posterior distribution after the use of MCMC and this was examined using trace plots.

Results

In 2022, Indonesia reported a total of 1,321,295 cases of stunting, with a mean of 38,862, a median of 17,888, and a standard deviation of 54,718. The provinces with the lowest stunting cases were North Sulawesi (3,080), Bangka Belitung Islands (4,077), and North Kalimantan (4,767). Conversely, the highest incidence of stunting was observed in West Java (221,065), East Java (190,128), and Central Java (184,364). The toddler population in Indonesia for the same year was 15,798,238, with a mean of 464,654, a median of 217,775, and a standard deviation of 668,104. Figure 1 illustrates the distribution of stunting cases across Indonesia.

The statistical values of Moran's I, expectation and standard deviation (SD) for the observational data were 0.361, -0.030 and 0.157, respectively, with p-value = 0.013. With the Moran's I value for the observed data of 0.361 and p-value = 0.013, the null hypothesis of no spatial autocorrelation was rejected indicating that there is a positive spatial autocorrelation in the stunting case data. The MMI value was 0.579. The Spearman correlations between stunting cases and covariates are detailed in Table 1. A substantial correlation (r_s= 0.849) between variable x_5 and x_6 was found, with a high correlation between variable x_2 and x_6 (r_s= 0.607) and x_2 and x_5 (r_s= 0.566). Given these considerable correlations, variables x_2 and x_6 were omitted from further analysis. As a result, only five covariates were included in the spatial models.

Out of the 750 model combinations based on the five distinct Bayesian spatial CAR models, only 127 converged. Surprisingly, none of the BYM or Leroux models converged. From the 150 combinations used for each of the localised CAR models, 29 models converged for G=2, 44 for G=3 and 54 for G=5. From the 127 convergent models, the preferred model was selected based on the smallest DIC and WAIC outcomes and a residual MMI value close to zero. An overview of the results for the best performing models is given in Table 2.

Two models were chosen for estimating the RR of toddler stunting in Indonesia: the localised CAR model with G=2 and a hyperprior IG (1, 0.1) (M387), which had the residual MMI value closest to zero, and the localised CAR model with a hyperprior IG (1, 0.01) (M535) when G=3, which had the lowest DIC and WAIC values, as well as a residual MMI value closest to zero. The summary results for parameters of the preferred localised CAR models are presented in Table 3.

The key covariates found were consistently the percentage of poverty (x_1), Recent LBWs (x_3) and Child Diet Diversity (CDD) (x_7). As poverty and LBWs increased, so did stunting risk (significant positive association). As CDD increased, stunting risk diminished (significant negative association). Values were similar between the two preferred models, with an increase in stunting by 5% (i.e. exp (0.049) gives 1.05) as poverty increased by one unit, 4% as LBW proportions increased, and a decrease by 3% (factor of 0.97) in stunting as CDD increased (Table 3). These associations

Table 1. Correlation between stunting and covariates.

	Stunting	x_1	x_2	x_3	x_4	x_5	x_6	x_7
x_1	0.022 (0.902)							
x_2	0.392 (0.022)	0.121 (0.497)						
x_3	-0.073 (0.682)	0.179 (0.310)	-0.033 (0.852)					
x_4	0.107 (0.546)	-0.117 (0.509)	0.155 (0.382)	-0.208 (0.239)				
x_5	0.226 (0.199)	-0.134 (0.452)	0.566 (0.000)	-0.095 (0.594)	0.054 (0.763)			
x_6	0.394 (0.021)	-0.037 (0.834)	0.607 (0.000)	-0.231 (0.188)	-0.103 (0.562)	0.849 (0.000)		
x_7	0.326 (0.060)	-0.231 (0.189)	0.402 (0.018)	-0.545 (0.001)	0.164 (0.355)	0.306 (0.078)	0.483 (0.004)	

Cell contents: Spearman rho (p-value).

Table 2. Overview of results obtained by the Bayesian spatial conditional autoregressive (CAR) models.

Hyper-prior	Model	Cova-riate	DIC	WAIC	MMI residual	Covariate coefficient percentile		Number of areas per cluster				
						2.5%	97.5%	G1	G2	G3	G4	G5
G = 2												
IG (1, 0.01)	M386	x_1 + x_3 + x_7	492.4	510.9	-0.44	0.0484 0.0416 -0.0259	0.0489 0.0431 -0.0258	19	15	-	-	-
IG (1, 0.1)	M387	x_1 + x_3 + x_7	496.1	525.9	-0.05	0.0489 0.0416 -0.0259	0.0491 0.0428 -0.0257	19	15	-	-	-
G = 3												
IG (1, 0.01)	M535	x_1 + x_3 + x_7	512.1	593.7	-0.13	0.0489 0.0416 -0.0259	0.0491 0.0419 -0.0257	9	16	9	-	-
G = 5												
IG (0.5, 0.05)	M689	x_1 + x_3 + x_7	549.2	849.6	-0.23	0.0489 0.0411 -0.0259	0.0492 0.0416 -0.0259	4	11	10	6	3
IG (0.5, 0.0005)	M690	x_1 + x_3 + x_7	547.7	842.2	-0.60	0.0487 0.0410 -0.0260	0.0491 0.0419 -0.0259	4	11	10	6	3

DIC, deviance information criterion; WAIC, Watanabe-Akaike information criterion; MMI, modified Moran's index; IG, inverse-gamma were consistent with findings from the non-spatial Poisson model, confirming that spatial confounding was not impacting results.

The clustering of regions, referred to as the Localised structure (LS), and RR values were presented in Table 4 and Figure 2. Even when areas were placed in different clusters, the RR values obtained using the localised CAR model with G=2 and G=3 were almost identical (Table 4). Mapping the RR of the stunting cases using the localised CAR model (under G = 2) with hyperprior IG (1, 0.1) and the localised CAR model (under G = 3) with hyperprior IG (1, 0.01) is given in Figure 3.

The highest RR values based on the localised CAR model with G=2 and G=3 were found in Sulawesi Barat Province (RR=2.77), followed by Nusa Tenggara Timur Province (RR=2.67) and Nusa Tenggara Barat Province (RR=2.22). Conversely, the lowest RR values based on the localised CAR model with G=2 and G=3 are observed in DKI Jakarta Province (RR=0.15), followed by North Sulawesi Province (RR=0.28) and South Sumatra Province (RR=0.37).

Discussion

This paper presents an application of the Bayesian spatial CAR model to assess its effectiveness in modelling stunting cases and the impact of various covariates associated with stunting cases in Indonesia. The creation of 750 models was designed to thoroughly

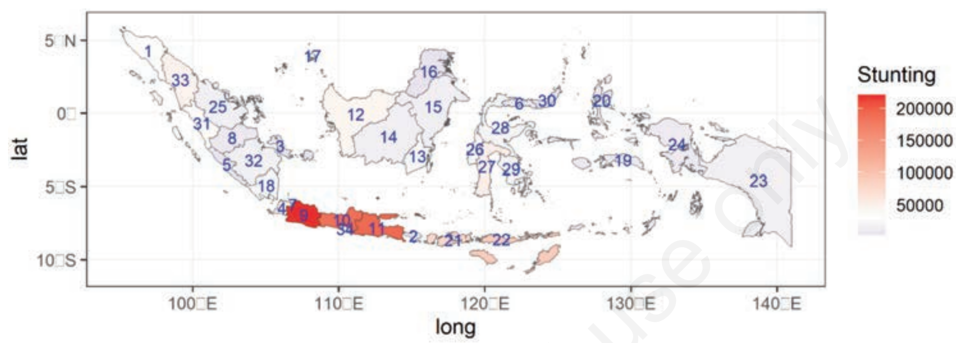

Figure 1. Thematic map of the distribution of stunting cases in Indonesia in 2022.

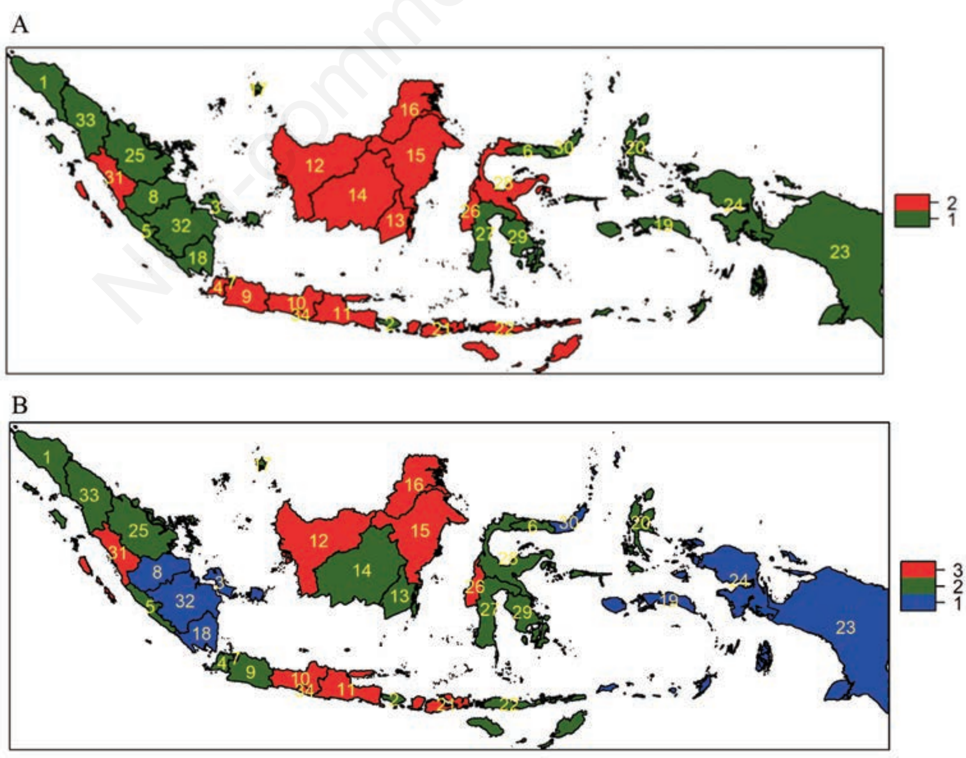

Figure 2. Thematic map of provincial Stunting case groupings in Indonesia. A) the localised G = 2 model with hyperprior IG (1, 0.1); B) the localised G = 3 model with hyperprior IG (1, 0.01).

explore the spatial patterns and ensure robustness in identifying significant risk factors and spatial patterns. The range of models allowed greater understanding of potential spatial dependencies, data variability and the complex and multifaceted nature of stunting. Convergence checking is however essential for ensuring the validity of Bayesian spatial model analyses using MCMC techniques as it ensures that the Markov chains have reached the stationary distribution, indicating that the generated samples accurately represent the posterior distribution. Without convergence, the inferences drawn from the model may be biased or inaccurate.

The selection of specific spatial CAR priors was guided by the need to comprehensively address different dimensions of spatial dependence and variability in stunting rates across Indonesia. Each model offers unique strengths that contribute to a more nuanced understanding of the spatial patterns. The BYM model provides a robust baseline by accounting for both structured and unstructured spatial effects, the Leroux model offers flexibility in adjusting the intensity of spatial autocorrelation, while the localised CAR model captures localised variations and discontinuities, which are crucial for identifying clusters with distinct stunting rates.

While BYM and Leroux models are commonly used in spatial analyses, localised forms allowing for discontinuities are less common, partly due to their greater complexity. Yet as demonstrated here, there are instances when they will perform better. The findings of this study align partially with previous research, which suggests that localised CAR models are preferable when count data and the variation in counts between areas are high (Aswi *et al.*, 2020).

Table 3. Summary results for parameters of the preferred localised Bayesian spatial conditional autoregressive (CAR) models.

Spatial localised CAR model with G=2 and hyperprior IG (1, 0.1)	Mean	95% CI
	0.0491	0.0489; 0.0491
LBW	0.0424	0.0416; 0.0428
CDD	-0.0258	-0.0259; -0.0257
lambda1	-0.5119	-0.5185; -0.5054
lambda2	0.4867	0.4823; 0.4912
tau2	0.1465	0.0913; 0.2333
delta	1.1325	1.0036; 1.4467
Spatial localised CAR model with G=3 and hyperprior IG (1, 0.01)		
Poverty	0.0490	0.0489; 0.0491
LBW	0.0417	0.0416; 0.0419
CDD	-0.0258	-0.0259; -0.0257
Lambda 1	-0.8394	-0.8506; -0.8282
Lambda 2	-0.079	-0.0844; -0.0733
Lambda 3	0.7106	0.7049; 0.7160
Tau 2	0.1239	0.0772; 0.1979
Delta	1.1662	1.0047; 1.5353

LBW, low birthweight; CDD, child diet diversity; lambda: the intercept for the appropriate cluster, where Lamba 1<Lambda 2 <Lambda 3; Tau 2, the variance parameter associated with the spatial random effects ui; Delta, the penalty parameter.

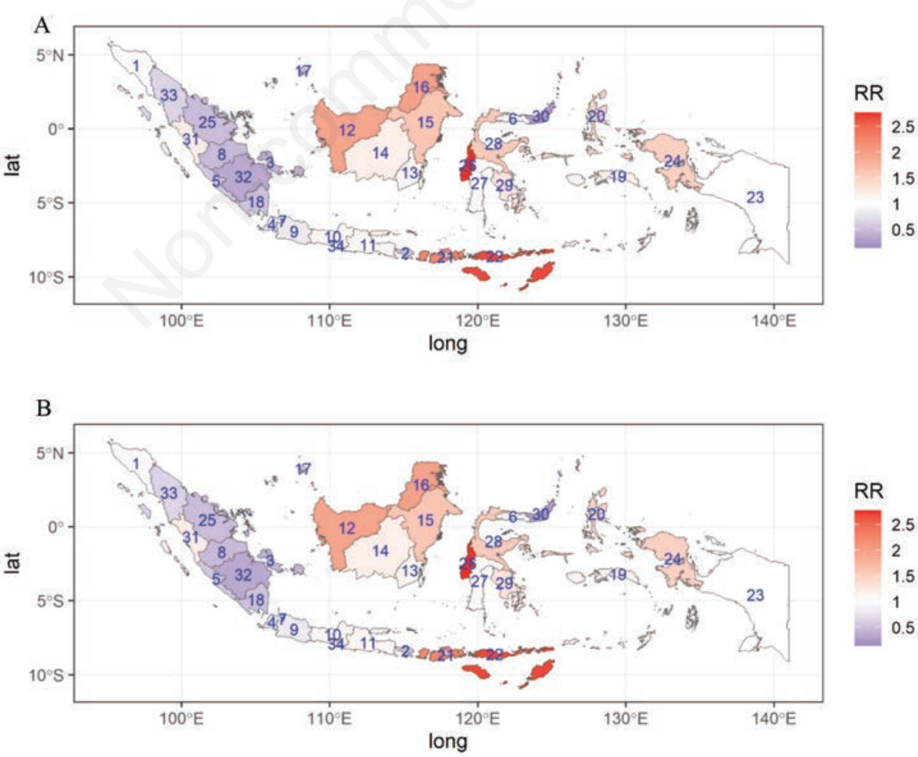

Figure 3. Mapping the RR of stunting cases in Indonesia in 2022. **A**) the localised G = 2 model with hyperprior IG (1, 0.1), **B**) the localised G = 3 model with hyperprior IG (1, 0.01).

The covariates we consistently identified as associated with stunting in Indonesia are in agreement with those reported elsewhere. For example, previous research in Ghana suggests that high rates of childhood stunting in various districts are predominantly linked to socioeconomic disparities, particularly poverty and the limited availability and use of healthcare services (Jonah *et al.*, 2018; Aheto, 2020; Yaya *et al.*, 2020; Johnson, 2022). While our data considered the regional proportion of LBWs, previous research has found associations between stunting and children's birth weights along with other factors, such as maternal education and the body mass index (BMI) that can also influence the child's birth weight (Uwiringiyimana *et al.*, 2022). Our findings also demonstrate a negative association between the percentage of children aged 6-23 months, who regularly consume at least five of the eight different food groups and the incidence of childhood stunting. These results are in line with previous studies suggesting that access to diverse foods is a significant predictor of malnutrition (Kinyoki *et al.*, 2015; Akseer *et al.*, 2018) and that maternal education and household food security offer protection against stunting of different degrees (Hagos *et al.*, 2017).

The province of Sulawesi Barat had the highest relative risk for stunting (RR=2.77, 95% CI 2.73, 2.81). This area exhibits a high level of poverty and elevated rates of early and child marriage. In March 2022, 11.75% of residents lived in poverty, representing 165,720 people Central Bureau of Statistics, 2023b). Most of the population (50.24% of those aged 15+ years during 2022) in this

Table 4. Outcomes by province based on the preferred models.

ID	Province	M387 (G=2) LS	RR	95% CI	M535 (G=3) LS	RR	CI
1	Aceh	1	0.96	(0.94;0.97)	2	0.96	(0.94;0.98)
2	Bali	1	0.53	(0.52;0.54)	2	0.53	(0.52;0.54)
3	Bangka Belitung	1	0.47	(0.45;0.48)	1	0.47	(0.45;0.48)
4	Banten	2	0.82	(0.81;0.82)	2	0.82	(0.81;0.83)
5	Bengkulu	1	0.58	(0.56;0.59)	2	0.58	(0.56;0.59)
6	Gorontalo	1	0.90	(0.87;0.92)	2	0.89	(0.87;0.92)
7	DKI Jakarta	1	0.15	(0.14;0.15)	1	0.15	(0.14;0.15)
8	Jambi	1	0.49	(0.48;0.50)	1	0.49	(0.47;0.50)
9	Jawa Barat	2	0.82	(0.82;0.83)	2	0.82	(0.81;0.83)
10	Jawa Tengah	2	1.12	(1.11;1.13)	3	1.12	(1.11;1.13)
11	Jawa Timur	2	1.13	(1.12;1.14)	3	1.13	(1.12;1.14)
12	Kalimantan Barat	2	1.94	(1.92;1.96)	3	1.94	(1.92;1.97)
13	Kalimantan Selatan	2	1.12	(1.10;1.13)	2	1.12	(1.10;1.13)
14	Kalimantan Tengah	2	1.21	(1.19;1.23)	2	1.21	(1.19;1.23)
15	Kalimantan Timur	2	1.62	(1.59;1.64)	3	1.62	(1.59;1.64)
16	Kalimantan Utara	2	1.96	(1.91;2.02)	3	1.96	(1.91;2.01)
17	Kepulauan Riau	2	0.59	(0.57;0.60)	2	0.59	(0.57;0.60)
18	Lampung	1	0.54	(0.53;0.55)	1	0.54	(0.53;0.55)
19	Maluku	1	1.18	(1.16;1.21)	1	1.18	(1.15;1.21)
20	Maluku Utara	1	1.47	(1.43;1.50)	2	1.47	(1.43;1.50)
21	Nusa Tenggara Barat	2	2.22	(2.20;2.24)	3	2.22	(2.19;2.24)
22	Nusa Tenggara Timur	2	2.67	(2.65;2.70)	2	2.67	(2.64;2.71)
23	Papua	1	1.01	(0.99;1.03)	1	1.01	(0.99;1.03)
24	Papua Barat	1	1.52	(1.48;1.55)	1	1.51	(1.48;1.55)
25	Riau	1	0.50	(0.49;0.51)	2	0.50	(0.49;0.51)
26	Sulawesi Barat	2	2.77	(2.73;2.81)	3	2.77	(2.73;2.81)
27	Sulawesi Selatan	1	1.08	(1.07;1.10)	2	1.08	(1.07;1.09)
28	Sulawesi Tengah	1	1.57	(1.55;1.59)	2	1.57	(1.55;1.59)
29	Sulawesi Tenggara	1	1.32	(1.30;1.34)	2	1.32	(1.30;1.34)
30	Sulawesi Utara	1	0.28	(0.27;0.29)	1	0.28	(0.27;0.29)
31	Sumatera Barat	2	1.23	(1.22;1.25)	3	1.23	(1.22;1.25)
32	Sumatera Selatan	1	0.37	(0.37;0.38)	1	0.37	(0.36;0.38)
33	Sumatera Utara	1	0.66	(0.65;0.67)	2	0.66	(0.65;0.67)
34	DI Yogyakarta	2	1.10	(1.08;1.11)	3	1.10	(1.08;1.11)

LS, localised structure; RR, relative risk; CI, credible interval.

province work in the agriculture, forestry and fisheries sectors (Central Bureau of Statistics, 2023b). The incidence of marriage among girls under the age of 18 is particularly prevalent in Sulawesi Barat Province, where the rate of child marriage (57.09% of females and 54.11% of males aged 10+ years were married) is higher than the national average and slightly higher among girls from the poorest households (Central Bureau of Statistics, 2023b). In 2022 the province of Sulawesi Barat had 99,033 toddlers, 22,903 of which were affected by stunting, resulting in a stunting rate of 23.13%, the highest in Indonesia (data from the official website of the Directorate General of Regional Development, Ministry of Home Affairs (Ministry of Home Affairs, 2022).

Limitations of this study included ecological rather than individual-level data (the most recent data being just for 2022) since the new stunting data announced in 2022 were not provided at a higher resolution than the province level. Therefore, we could only explore spatial patterns without being able to consider how things were changing across years. Another limitation of the current study is its focus on a single time period. Stunting is a dynamic phenomenon influenced by various factors that change over time. Incorporating a temporal dimension into the spatial analysis would provide a more comprehensive understanding of stunting trends and the effectiveness of intervention programs. Future research should explore spatiotemporal models to capture the dynamic nature of stunting and enable robust spatiotemporal analyses. In addition, variables for modelling can be selected in many ways. Popular approaches include stepwise selection, which has several disadvantages (Smith, 2018), so the least absolute shrinkage and selection operator (LASSO) is increasingly used. No approach is guaranteed to produce a model with the most important variables (Heinze *et al.*, 2018). Computational/time constraints may necessitate conducting variable selection in a simple, non-spatial model initially, but our models ran quickly (<20 seconds per model on a standard computer) enabling our best subset approach.

The strengths of this study include examining variation across the entire nation via spatial models, the comprehensive comparison of models and using models that allow for discontinuities between areas. Another strength lies in its use of a Bayesian approach, chosen for its ability to handle spatial dependencies and incorporate prior information, which are crucial for accurately modelling the incidence of stunting in Indonesia. Traditional methods, such as Poisson regression, fail to address spatial autocorrelation, which leads to biased estimates and underestimated standard errors (Waller & Gotway, 2004; Hodges & Reich, 2010). Stunting cases in one region are likely influenced by neighbouring regions due to shared socio-economic and environmental factors. Bayesian CAR models explicitly account for these spatial dependencies, providing more accurate and reliable estimates. These models offer a flexible framework to incorporate various sources of uncertainty and to model complex hierarchical structures, essential for understanding the multifaceted nature of stunting. This approach not only addresses inherent spatial dependencies but includes also prior information and controls for potential confounding factors.

Conclusions

There is great variation in childhood stunting between Indonesian provinces, as demonstrated using Bayesian spatial models. Higher percentages of poverty and/or recent LBWs and reduced child diet diversity all increase the risk of stunting. The area with the highest risk was found to be Sulawesi Barat Province, while DKI Jakarta Province had the lowest risk. It is hoped these findings will help to inform interventions to reduce stunting and poverty.

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