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Spatially Varying Regression Coefficient Model For Predicting Stunting Hotspots In Indonesia

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Abstract: Stunting is a significant issue, particularly in the context of Indonesia. Identifying crucial risk factors is crucial for mitigating and developing effective strategies to control stunting. A Bayesian approach was employed to develop a regression model that incorporates spatial variation, allowing risk factors to vary across different districts and cities. The aim was to obtain the most optimal regression model. The analysis revealed that the impact of immunization varies across districts and cities in Indonesia when it comes to explaining the differences in stunting prevalence. The hotspot prediction results indicate that most urban districts in Indonesia remain hotspot areas, with a stunting risk exceeding 20%. The government must ensure the effective implementation of the immunization program in order to mitigate the prevalence of stunting in Indonesia. The novelty of this research lies in the use of Bayesian approaches to spatial analysis in identifying and understanding stunting risk factors as well as the prediction of stunting hotspots in Indonesia. This approach provides in-depth insight into local variations in the prevalence of stunting and the effectiveness of health interventions, which supports more effective and targeted policy development.

Keywords: Bayesian-INLA; Hotspot; Spatially varying coefficient; Stunting

Introduction

Stunting remains a prevalent issue in global public health. Based on data from the World Health Organization (WHO), it is estimated that there are approximately 149 million children under the age of five worldwide who are experiencing stunted growth by the year 2020. The majority of children affected by stunting, over 90%, reside in developing nations, primarily in Asia and Africa. According to WHO data on stunting prevalence, Indonesia ranks third in Southeast Asia with an average of 36.4% of short news prevalence between 2005 and 2017. According to the World Health Organization (WHO) in 2015, stunting refers to a growth and developmental issue in children that arises from persistent malnutrition and frequent infections. It is characterized by a below-average length or height compared to the standard. According to WHO (2020), stunting is a condition where a child's height or length is below -2 standard deviations (SD) on the WHO growth curve for a specific age. This condition is caused by inadequate nutrition and/or repeated or chronic infections during the first 1000 days of life. The value is 1000 HPK. According to (La Ode Alifariki, 2020), stunting has negative effects on children's physical and cognitive growth, as well as their motor development and language skills (WHO, 2013)

Stunting is influenced by various factors, but the primary cause is insufficient food consumption and the presence of infection (Umeta M et al., 2003). Other factors that influence stunting include lack of immunization status, exclusive breastfeeding, adequate zinc and iron nutrients, family income, food availability within the family, food diversity, genetic factors (Setiyabudi, 2019), low parental education level, maternal height < 150 cm, high-risk maternal age at delivery, low birth weight, and short birth length (Putri & Nuzuliana, 2020)

Based on the research conducted by Nadhiroh & Ni'mah, (2010), birth length, history of exclusive

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breastfeeding, family income, maternal education, and maternal nutritional knowledge are factors associated with the occurrence of stunting in toddlers. Maternal education is important because a lack of maternal knowledge about health and nutrition before and during pregnancy, as well as after childbirth, can impact stunting. Based on research conducted by Sutarto & Indriyani, (2018), approximately 60% of children aged 0-6 months do not receive exclusive breastfeeding, and 2 out of 3 children aged 0-24 months do not receive complementary foods to breastfeeding. (MP- ASI). MP-ASI is given/started to be introduced when the toddler is over 6 months old. In addition to introducing new types of food to infants, complementary feeding (MPASI) can also meet the nutritional needs of the baby's body that can no longer be supported by breast milk, as well as build the child's immune system and the development of the immunological system against food and beverages. Additionally, a study conducted in Nepal by Paudel et al., (2012) revealed that socio-economic factors are related to the incidence of stunting, which is caused by mothers who are unemployed and lack food.

Hence, in order to mitigate and diminish stunting in Indonesia, it is imperative to possess a comprehensive comprehension of the factors that exert influence on it. The advantages of stunting control encompass the provision of sufficient nutrition to expectant mothers and children, the supplementation of children who are at risk of stunting, enhanced sanitation and environmental hygiene, education and socialization regarding the significance of nutrition and health in pregnant women and children, and the consistent monitoring and evaluation of child growth. According to (qar Bhutta et al., 2008), long-term efforts to reduce stunting should include improvements in addressing factors such as poverty, low education, disease burden, and lack of women's empowerment, which are known to affect nutrient intake.

Various factors, such as inadequate nutrition, unsanitary conditions, and unhealthy surroundings, can exert varying influences on stunts in cities and districts. These influences may differ due to disparities in population and environmental attributes between these locations. As a result of these disparities, the factors that influence stunting can differ between cities and districts, and the strategies to reduce the risk of stunting can also vary between these two locations. Aridiyah et al., (2015) argues that the factors influencing the chronic nutritional status of young individuals differ between urban and rural areas, necessitating adjustments in settlement strategies. The study focuses on the district/city as the unit of observation, therefore it is crucial to consider the potential spatial effects of the districts/cities in Indonesia. The initial phases reveal the spatial impacts, which are observable from the spatial representation of the stunting variables depicted in Figure 1.

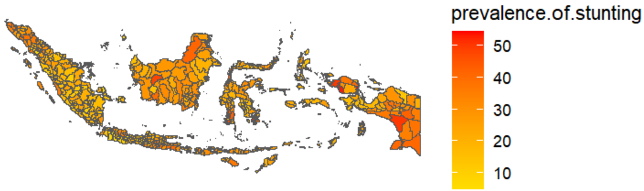


Figure 1. Spatial distribution of stunting in Indonesia, 2022

Figure 1 shows that the prevalence of stunting in every district and city in Indonesia is consistently above 10%. This figure is still significantly below the government's target of 8%. The prevalence of stunting is believed to vary across districts and cities, with districts generally exhibiting higher average rates of stunting compared to cities. The conditions described above indicate the presence of spatial heterogeneity among districts and cities. To identify factors influencing the prevalence of stunting, it is crucial to consider this spatial variation. Therefore, modeling that involves spatially varying coefficient regression is necessary, especially for accurately identifying hotspots. Accurate hotspot identification is a vital step for the government, as it allows for the early detection of areas requiring the most urgent attention. This prioritization ensures that resources can be allocated effectively to hotspot locations.

The purpose of this study is to develop a Bayesian spatial multigroup model to analyze the prevalence of stunting in Indonesia. The objectives are to identify the stunting risk factors in each district and city and to achieve accurate hotspot prediction. Additionally, the study aims to explain the significant impact of these risk factors in different regions. The remainder of this manuscript is organized as follows: Section 2, Data and Methodology, provides a comprehensive explanation of the varying coefficient regression model using a Bayesian approach. Section 3, Application and Prediction, illustrates the application of the model to predict stunting in Indonesia. Finally, Section 4 presents the conclusions drawn from the study.

Method

Data

Indonesia is comprised of 34 provinces, 416 districts, and 98 cities, encompassing territories that exhibit extensive cultural, social, and economic variations. Every province, district, and city possess distinct attributes that can impact the nutritional status and well-being of children. The data utilized in this study comprises stunting data extracted from the Indonesian Nutritional Status Survey (SSGI) pocketbook, which was published by the Ministry of Health of the Republic of Indonesia in 2022. In addition, predictor variables such as poverty, asylum allowance of less than 6 months, and immunization were acquired from the Central Statistics Authority in 2022.

Method

This study utilized a Bayesian methodology. The Bayesian method is a data analysis approach that utilizes Bayes' theorem to update the available knowledge about the parameters in a statistical model with information from the observed data (Van de Schoot et al., 2021). In the Bayesian framework, parameters are considered to be random variables that follow a prior distribution (Wagenmakers et al., 2008).The posterior distribution can be obtained by combining the prior and likelihood, and from this posterior distribution, a Bayesian estimator can be derived. For further details, a flowchart is shown in this study.

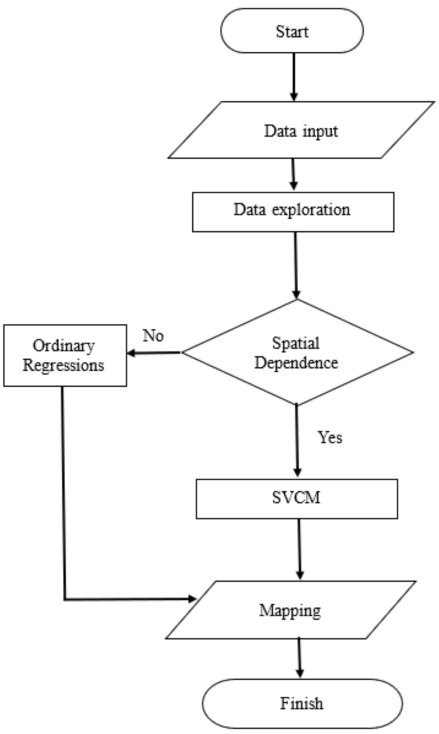


Figure 1. Research Flow

Bayesian Spatially Varying Coefficient Model (SVCM)

The conventional regression model is inadequate for analyzing spatial data. Thus, it is imperative to create models that can consider spatial effects, such as spatial dependencies and spatial heterogeneity. A spatially variable coefficient model (SVCM) is a mathematical model that is employed to compute regression coefficients that vary across space and account for the existence of spatial dependencies and heterogeneity in them (Cressie, 1993). (Congdon, 2014) developed the SVCM approach to account for the impact of spatial dependency on the regression parameters in equation (1). The expression for a model with spatially varying coefficients for m groups is as follows:

$$E[y_i] = \beta_0 + f(\beta_{1j}X_{1i}) + f(\beta_{2j}X_{2i}) + \cdots + f(\beta_{Kj}X_{Ki}); j = 1, \dots, m \tag{1}$$

with m expressing many groups on data with $m \leq N$. The model (1) can be expanded by including random components of spatial dependence and heterogeneity.

$$\eta_i = \beta_0 + \omega_i + v_i + f(\beta_{1j}X_{1i}) + f(\beta_{2j}X_{2i}) + \cdots + f(\beta_{Kj}X_{Ki}) \tag{2}$$

To estimate the spatial model in equation (2) using the Bayesian method, we employ a Laplace approximation known as Integrated Nested Laplace Approximation (INLA).

Suppose the data observed in the area to i, is derived from the probability distribution $p(\boldsymbol{y}_i|\boldsymbol{\Omega}, \boldsymbol{\Sigma})$ with unknown parameters $\boldsymbol{\Omega} = (\beta_0, \beta_{1i}, \beta_2, \beta_{3i}, \boldsymbol{\omega}', \boldsymbol{v}')'$. Unknown parameter $\boldsymbol{\Omega}$ is taken as a random variable with the priors $p(\boldsymbol{\Omega}|\boldsymbol{\Sigma})$ and the hyperparameter unknowns $\boldsymbol{\Sigma} = Diag(\sigma_\varepsilon^2, \sigma_\omega^2, \sigma_v^2, \sigma_{\beta_1}^2, \sigma_{\beta_2}^2, \sigma_{\beta_3}^2)'$ and with the hyperprior $p(\boldsymbol{\Sigma})$. The combined posterior density of $\boldsymbol{\Omega}$ and $\boldsymbol{\Sigma}$ conditional $\boldsymbol{y}$ is defined (Jaya & Folmer, 2019b):

$$p(\boldsymbol{\Omega}, \boldsymbol{\Sigma}|\boldsymbol{y}) = \frac{p(\boldsymbol{y}|\boldsymbol{\Omega}, \boldsymbol{\Sigma})p(\boldsymbol{\Omega}|\boldsymbol{\Sigma})p(\boldsymbol{\Sigma})}{p(\boldsymbol{y}|\boldsymbol{\Sigma})} \tag{3}$$

with $p(\boldsymbol{y}|\boldsymbol{\Omega}, \boldsymbol{\Sigma})$ is a function of the likelihood of the prevalence of stunting **y** and $p(\boldsymbol{y}|\boldsymbol{\Sigma})$ are marginal likelihoods of the conditional data of the hyperparameter $\boldsymbol{\Sigma}$ which is a normalization constant because it does not depend on $\boldsymbol{\Omega}$ so can be ignored in estimates. Therefore, the combined posterior density is defined as follows (Jaya &Andriyana, 2020):

$$p(\boldsymbol{\Omega}, \boldsymbol{\Sigma}|\boldsymbol{y}) \propto p(\boldsymbol{y}|\boldsymbol{\Omega})p(\boldsymbol{\Omega}|\boldsymbol{\Sigma})p(\boldsymbol{\Sigma}) \tag{4}$$

with a sign equal to (=) replaced by a sign proportional to ($\propto$).

Inference Using INLA

The first phase consists of the likelihood function of the observed y variable, $p(\boldsymbol{y}|\boldsymbol{\Omega}, \boldsymbol{\Sigma})$, which can be rewritten as follows (Jaya & Folmer, 2019):

$$p(\boldsymbol{y}|\boldsymbol{\Omega}, \boldsymbol{\Sigma}) = \prod_{i=1}^{n} p(\boldsymbol{y}_i|\boldsymbol{\Omega}_i, \boldsymbol{\Sigma}) = \prod_{i=1}^{n}\prod_{t=1}^{T} p(\boldsymbol{y}_{it}|\boldsymbol{\Omega}_{it}, \boldsymbol{\Sigma}) \tag{5}$$

with $\boldsymbol{y}$ is a vector that contains the observation value, the vector $\boldsymbol{\Omega}$ is an unknown parameter and $\boldsymbol{\Sigma}$ is a hyperparameter of $\boldsymbol{\Omega}$.

The second phase consists of the latent Gaussian field $\boldsymbol{\Omega}$ conditional vector hyperparameter $\boldsymbol{\Sigma}$, $p(\boldsymbol{\Omega}|\boldsymbol{\Sigma})$, which follows the Gaussians multivariate distribution. The prior density function of $\boldsymbol{\Omega}$ is observed as follows:

$$p(\boldsymbol{\Omega}|\boldsymbol{\Sigma}) = (2\pi)^{nT}|\mathbf{Q}(\boldsymbol{\Sigma})|^{\frac{1}{2}} \exp\left(-\frac{1}{2}\boldsymbol{\Omega}'\mathbf{Q}(\boldsymbol{\Sigma})\boldsymbol{\Omega}\right) \quad (6)$$

with $|\cdot|$ specifies determinants and $\mathbf{Q}(\boldsymbol{\Sigma})$ specifies sparse/rare precision matrices.

The third stage involves $p(\boldsymbol{\Sigma})$ which is the hyperprior distributions $\boldsymbol{\Sigma}$. $p(\boldsymbol{\Sigma})$ does not need Gaussian distributions and the correct distribution for the precision parameter is the Inverse Gamma. Of the three stages described above then the distribution of the posterior combination written in the equation (4) can be rewritten as follows:

$$p(\boldsymbol{\Omega},\boldsymbol{\Sigma}|\boldsymbol{y}) = \frac{p(\boldsymbol{\Sigma})p(\boldsymbol{\Omega}|\boldsymbol{\Sigma})p(\boldsymbol{y}|\boldsymbol{\Omega},\boldsymbol{\Sigma})}{p(\boldsymbol{y}|\boldsymbol{\Sigma})}$$

$$\propto p(\boldsymbol{\Sigma})|\mathbf{Q}(\boldsymbol{\Sigma})|^{\frac{1}{2}} \exp\left(-\frac{1}{2}\boldsymbol{\Omega}'\mathbf{Q}(\boldsymbol{\Sigma})\boldsymbol{\Omega} + \sum_{i=1}^{n} log(\boldsymbol{y_i}|\boldsymbol{\Omega_i},\boldsymbol{\Sigma})\right) \quad (7)$$

The INLA procedure does not consider the full posterior distribution of $\boldsymbol{\Omega}$ and $\boldsymbol{\Sigma}$ but is based on a marginal lateral distribution approach i.e. $p(\boldsymbol{\Omega_i}|\boldsymbol{y})$ and $p(\boldsymbol{\Sigma_k}|\boldsymbol{y})$. The posterior marginal distribution for $\boldsymbol{\Omega_i}$ is defined as follows:

$$p(\boldsymbol{\Omega_i}|\boldsymbol{y}) = \int p(\boldsymbol{\Omega_i}, \boldsymbol{\Sigma}|\boldsymbol{y})\, d\boldsymbol{\Sigma} = \int p(\boldsymbol{\Omega_i}|\boldsymbol{\Sigma},\boldsymbol{y})\, p(\boldsymbol{\Sigma}|\boldsymbol{y})\, d\boldsymbol{\Sigma}, \quad i = 1, \dots, n \quad (8)$$

with n is the number of spatial units. And the marginal posterior distribution of $\boldsymbol{\Sigma_k}$ is defined as follows:

$$p(\boldsymbol{\Sigma_k}|\boldsymbol{y}) = \int p(\boldsymbol{\Sigma}|\boldsymbol{y})\, d\boldsymbol{\Sigma_{-k}}, \quad k = 1, \dots, 6 \quad (9)$$

with $\boldsymbol{\Sigma_{-k}}$ shows all elements in $\boldsymbol{\Sigma}$ except for element $-k$.

Result and Discussion

Analysis Descriptive

The data used in this study are stunting data in Indonesia in 2022, below is a summary of the research variables in Table 2.

Table 2. Result of Analysis Descriptive

Variable	Mean	SD	Min	Max
Stunting (Y)	24.28	8.57	4.80	54.50
Immunization (X_1)	53.76	18.43	5.68	85.77
Exclusive ass gift < 6 months (X_2)	25.77	7.56	0.30	54.83
Poverty (X_3)	11.682	7.27	2.28	42.03

From the table above it can be seen that stunting cases with the minimum exclusive breastfeeding factor of 0.30% and the maximum immunization of 85.77%. This indicates that exclusive milk delivery for children is still very low, while the immunization coverage for children has been quite high. According to Figure 1, the spatial distribution of stunting in Indonesia can be described as follows. The dark red areas indicate regions with a very high percentage of stunting (close to or exceeding 50%). In contrast, orange to yellow areas represent regions with a lower percentage of stunting (ranging from around 10% to close to 50%). The dark red regions are predominantly located in the eastern part of Indonesia, such as Papua and East Nusa Tenggara, which exhibit very high levels of stunting. This figure clearly illustrates that the prevalence of stunting in Indonesia varies significantly between districts and cities. Additionally, the color groupings between districts and cities suggest a spatial effect on stunting data in Indonesia. Districts and cities with high stunting rates tend to be clustered around other high stunting areas. Two spatial effects are evident: spatial dependency and spatial heterogeneity. The figure shows that the number of stunting cases has spatial dependencies, indicating a connection between neighboring regions. This implies the presence of similar influencing factors, such as access to healthcare, sanitation, and other determinants. Furthermore, there is a spatial heterogeneity effect, where the number of stunting cases differs between cities and districts. It can be observed that districts generally have higher stunting rates compared to city areas.

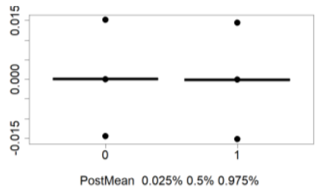
Spatially varying coefficient model

The initial step in Bayesian modeling using inla involves selecting the optimal model. At this stage, we choose the optimal model by identifying risk factors that exhibit time-varying regression coefficients. We employed multiple model selection criteria, namely Deviance Information Criteria (DIC), Watanabe Akaike Information Criteria (WAIC), and log-Marginal likelihood (LML). The results of the model comparison are displayed in Table 3.

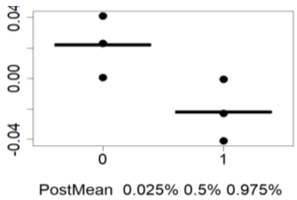
Table 3. Model comparison

Spatially varying variable	WAIC	DIC	LML
Immunization	3599.18	3598.07	-1847.10
Exclusive breastfeeding gift < 6 months	3605.78	3604.40	-1847.74
Poverty	3607.17	3605.81	-1849.28

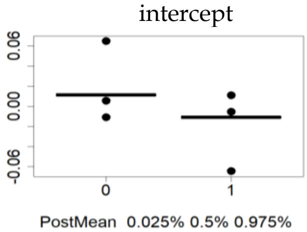
According to Table 3, we chose a regression model that takes into account the varying effects of immunization in different districts and cities. This model has the lowest Deviance Information Criterion (DIC) and within-cluster sum of squares (WIC), and the highest Log Marginal Likelihood (LML). To support that models with spatially varying immunization are best, we show the effects of spatially varying for all variables, including intercepts on the picture.



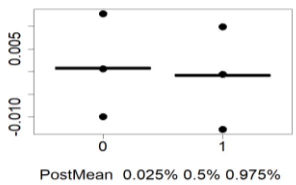
(a) Spatialy varying intercept



(b) Spatially variying immunitation



(c) Spatially varying Exclusive breastfeeding gift < 6 months



(d) Spatially varying poverty

Figure 2. Spatially varying effects

Figure 2a shows that the data distribution for the spatially varying intercept is similar in groups 0 (districts) and 1 (cities), with an average of 0 in both groups. The quantile range suggests that the majority of the data is in close proximity to the mean, exhibiting minimal variability. This boxplot offers a lucid depiction of the distribution of data in both groups, revealing no noteworthy disparities in terms of distribution and mean.

Figure 2b displays the data distribution for the immunization variable, indicating that the values of the immunization parameter in districts (group 0) span from approximately -0.02 to 0.04. The values exhibit a slight positive inclination, with an average or median of approximately 0.02, indicating a slightly elevated immunization impact in districts. The immunization parameter values for cities in group 1 range from approximately -0.04 to 0.02, with a slightly negative trend and an average or median value of around -0.02. This implies that the impact of immunization in urban areas may be marginally less significant compared to rural areas. Therefore, it is imperative for the government to prioritize immunization initiatives in urban areas.

According to Figure 2c, the data distribution for the variable "exclusive breastfeeding of less than 6 months" in districts (group 0) exhibits parameter values that span from approximately -0.03 to 0.06. The distribution shows a slightly positive trend, with an average or median value around 0.03. Within urban areas (group 1), the parameter values span from approximately -0.06 to 0.03, exhibiting higher levels of variation and an average or median value close to 0. The disparities between the two categories suggest that districts generally exhibit slightly higher parameter values for exclusive breastfeeding compared to cities, although there is variation within both groups.

Figure 2d illustrates that the data distribution for the poverty variable is highly similar and concentrated around 0 in both districts (group 0) and cities (group 1). There is no notable distinction between the two categories. In summary, these findings indicate that the poverty variable does not have a substantial impact on the adjustment, as the posterior averages and confidence intervals for both categories are nearly indistinguishable. Put simply, there are no notable disparities in the poverty variable between districts and cities.

Table 4. Summary statistics for the fixed effects

Variable	Mean	SD	Quantile (0.025)	Quantile (0.975)
Intercept	23.242	1.698	19.910	26.572
Immunization	-0.079	0.019	-0.117	-0.041
Exclusive ass gift < 6 months	-0.056	0.044	-0.142	0.029
Poverty	0.489	0.048	0.395	0.583

Table 4 shows that the coefficient of immunization and exclusive assigning for less than 6 months has a negative value, while the poverty variable has a positive value. The 95% credible interval for the immunization variable is [-0.117; -0.041]. For the exclusive ass granting variable <6 months, the interval is [0.142; 0.029]. Lastly, for the poverty variable, the interval is [0.395; 0.583]. A 95% credible interval indicating a non-zero value for the immunization and poverty variables suggests that these variables have a statistically significant impact. Conversely, a zero value in the credible interval for the exclusive assigning variable <6 months indicates that it does not have a significant impact. Hence, the variables of immunization and poverty exert a positive and substantial impact on the percentage of stunting in Indonesia.

According to the Table 5, the Gaussian observation variability has an average of 7.97 and a standard deviation of approximately 0.26. This indicates that the stunting observation data has a significant level of variability. The variable variability of immunization has an average of 0.019 and a standard deviation of 0.014. This suggests that the random effects of immunization against stunts contribute relatively little to the overall variability of observations. The of immunization on stunting shows significantly less variation compared to the overall variability in observations of stunting. This suggests that regular immunization has a more uniform impact on reducing stunting, although there may be some variations in certain instances. The percentage range indicates that, for the most part, the variability of immunization effects is minimal. However, there are certain scenarios where the effects can exhibit greater variation.

Table 5. Summary statistics for the random effects

	Mean	SD	Quantile (0.025)	Quantile (0.975)
SD for the Gaussian observations	7.9653	0.2607	7.4562	8.4795
SD for Immunization	0.0194	0.0143	0.0046	0.0579

The significant variability in Gaussian observations indicates that stunting is influenced by numerous other factors that exhibit substantial variability. It demonstrates the necessity of considering factors beyond immunization when assessing and addressing stunting problems. In general, immunization appears to be a consistent factor in decreasing stunting. However, due to the significant variation in overall stunting rates, a more comprehensive approach that considers other factors is necessary to effectively address stunting issues.

Mapping Prediction of Stunting Prevalence

After selecting the optimal model, which is the model that displays the spatially varying impact of immunization, a predictive analysis was conducted to identify areas with very high levels of stunting prevalence. This analysis aims to find regions with stunting risk exceeding the limits set by WHO standards.

Predictions were made using the optimal model that considers spatial variation in the impact of immunization. In other words, this model takes into account that the effect of immunization on reducing stunting may vary across different regions. According to WHO standards, areas with stunting prevalence rates exceeding 20% are classified as high-risk zones. This means that areas falling into this category require special attention and more intensive interventions to reduce stunting rates. The results of the predictive analysis are illustrated in Figure 2. This figure provides a visualization of areas with very high stunting prevalence rates, based on the selected model. By looking at this map, policymakers and relevant parties can identify which areas most urgently need intervention.

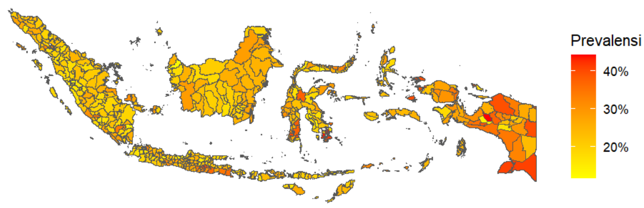


Figure 2. Spatial Distribution of Predicted Stunting Prevalence

The colors in Figure 2 indicate the percentage of stunting prevalence, with a color gradient from yellow to red. Yellow indicates areas with relatively lower stunting prevalence, around 20%. Orange indicates areas with moderate stunting prevalence, around 30%. Meanwhile, red indicates areas with high stunting prevalence, over 40%.

From the map, it can be seen that the regions in the eastern part of Indonesia, such as Papua and some parts of Nusa Tenggara, have a higher prevalence of stunting (marked in red and orange). Meanwhile, the regions in the western and central parts of Indonesia, such as Sumatra and Java, have a lower prevalence. (ditandai dengan warna kuning).

To clarify further, this study also presents the spatial distribution of exceedance probability in figure 3. Exceedance probability is used to calculate the probability that the prevalence of stunting will exceed the WHO threshold that has been set at 20%.

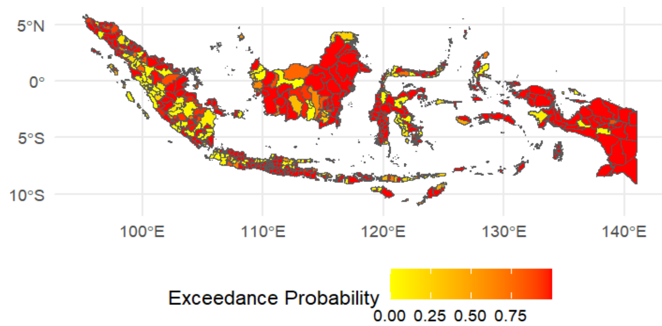


Figure 3. Spatial distribution of exceedance probability

The image above displays a region of Indonesia exhibiting a probability exceedance for a relative risk exceeding 20%. Yellow areas indicate a relatively low probability, ranging from 0% to 25% of encountering a risk higher than 20%. Orange areas represent a moderate probability, ranging from 25% to 50%. Red areas indicate a high probability, ranging from 50% to 75%, while dark red areas indicate a very high probability exceeding 75%. The map highlights several regions in Indonesia with high and very high likelihoods of relative risks surpassing 20%, signifying significant potential risks. Areas shaded in red and dark red represent major hotspots with relatively high-risk levels, potentially including parts of Sumatra, Kalimantan, Sulawesi, and Papua. These high probability regions warrant special attention in policy planning and intervention strategies to mitigate the risk of stunting.

Conclusion

The Spatially Varying Coefficient Model was created to detect risk factors that have different effects depending on the spatial locations, which in this study are districts or cities. The study employed Bayesian Integrated Nested Laplace Approximation (INLA) to model regression coefficients that vary spatially. Analysis of 2022 data on stunting and risk factors, including immunization, exclusive breastfeeding for less than 6 months, and poverty, revealed that the impact of immunization varies among different districts and cities. There is a correlation between the increase in immunization rates in urban areas and a more rapid decrease in stunting rates, as compared to rural areas. The hotspot analysis results, according to the criteria set by the World Health Organization (WHO), indicate that numerous districts and cities in Indonesia can be classified as hotspot areas due to the prevalence of stunting exceeding 20%.

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Author Contributions
Investigation. U.N.S.I. I.G.N.M.J and R.A; formal analysis. U.N.S.I. I.G.N.M.J and R.A ; investigation. U.N.S.I. I.G.N.M.J and R.A; resources. U.N.S.I. I.G.N.M.J and R.A; data curation. U.N.S.I. I.G.N.M.J and R.A: writing—original draft preparation. U.N.S.I. I.G.N.M.J and R.A; writing—review and editing. U.N.S.I. I.G.N.M.J and R.A: visualization. U.N.S.I. I.G.N.M.J and R.A ; supervision. U.N.S.I. I.G.N.M.J and R.A; project administration. U.N.S.I. I.G.N.M.J and R.A; funding acquisition. U.N.S.I. I.G.N.M.J and R.A. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest
We certify that there is no conflict of interest with any financial. Personal and other relationships with other peoples or organisation related to the material discussed in the manuscript.

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