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MODELING PREVALENCE OF STUNTING IN RELATION TO HUMAN DEVELOPMENT INDEX IN INDONESIA

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Abstract: The prevalence of stunting is a crucial indicator of the human development index. Human development in Indonesia can be improved by effectively allocating resources to implement health policies that directly impact the prevalence of stunting in children under five. Using Bayesian spatial regression, we examine the effects of the prevalence of stunting and other unobserved factors on the spatial variation of stunting in Indonesia's 34 provinces. We discovered that stunting's prevalence has a statistically significant effect on human development. There is also a strong spatial effect here, which accounts for unobservable factors such as socioeconomic level. Continuous efforts to reduce stunting in all of Indonesia's provinces will benefit the human development index.

Keywords: stunting; human development index; Bayesian; spatial.

2010 AMS Subject Classification: 93A30.

1. INTRODUCTION

Stunting refers to children who experience stunted growth and development as a result of insufficient nutrition, frequent infection, and lack psychological stimulation [1]. Stunting has a

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deleterious influence on a child's functional development early in life, notably during the first 1000 days from conception to the age of two. Several of these consequences include worse cognitive and academic performance, lower adult income, less productivity, and, when combined with excessive weight gain later in childhood, an increased risk of acquiring chronic diseases associated with nutrition in adulthood [1]. According to the WHO [2], 127 million children under the age of five would be stunted by 2025. As a result, additional funding and action are required to meet the WHO 2025 aim of decreasing that number to 100 million.

Indonesia, a developing Asian country, has a disproportionately high rate of stunting among under-five children. Indonesia ranks second in Asia in terms of stunting, behind Cambodia [3]. Stunting prevalence reaches 12.1 % in 2021, according to the Ministry of Internal Affairs [4].

Stunting is strongly related to human development index [5] [6] [7]. It is a reliable predictor of income inequalities in human development [8] [9]. According to [9], examining a child's health and nutritional status can help identify disparities in human development within a population.

Several studies have been undertaken to determine the association between stunting and the human development index. They do, however, use stunting as the response variable rather than critical factors affecting the human development index (HDI) [3] [10].

In this study, we take a unique perspective. In 2021, we examine the prevalence of stunting as measured by the human development index across 34 provinces in Indonesia. We develop a Bayesian spatial regression model that accounts for both stunting prevalence and spatial unobserved factors simultaneously. According to [11], spatially structured effects can be used to account the effect of unobserved factors. Additionally, we identify provinces that have a statistically low or a statistically high human development index using exceedance probability method.

The remainder of the paper is structured in the following manner. The next section discusses the materials and methods used. Following that is the Application part, which demonstrates the effects of prevalence of stunting on human development index across 34 provinces in Indonesia, in 2021. The last part discusses, summarizes, and makes recommendations for further work.

2. MATERIAL AND METHOD

2.1 Material

We use stunting data from Ministry of Internal Affairs [4] that can be accessed from (https://aksi.bangda.kemendagri.go.id/emonev/DashPrev/index/1). The human development index data was obtained from Central Bureau of Statistics [12] that can be accessed from (https://www.bps.go.id/indicator/26/494/1/-metode-baru-indeks-pembangunan-manusia-menurut-provinsi.html). The data were recorded in Table 1.

Table 1. Research variables

id	Province	Number of Children under five	HDI (%)	Prevalence of Stunting (%)
1	Kepulauan Bangka Belitung	58,252	71.69	5.90
2	Gorontalo	52,781	69.00	8.50
3	Riau	394,324	72.94	6.00
4	DKI Jakarta	371,515	81.11	3.20
5	Kepulauan Riau	81,823	75.79	7.60
6	Sulawesi Selatan	478,000	72.24	10.40
7	Sumatera Selatan	385,055	70.24	4.40
8	Kalimantan Barat	158,415	67.90	21.00
9	Aceh	273,612	72.18	12.10
10	Bengkulu	52,920	71.64	6.30
11	Lampung	484,108	69.90	6.10
12	Jawa Tengah	2,046,602	72.16	9.00
13	Nusa Tenggara Barat	368,865	68.65	21.70
14	Sumatera Utara	749,867	72.00	6.70
15	Jambi	151,086	71.63	3.00
16	Banten	859,736	72.72	6.70
17	Jawa Timur	2,025,819	72.14	10.70
18	DI Yogyakarta	168,436	80.22	10.60
19	Kalimantan Selatan	246,865	71.28	10.40
20	Sulawesi Utara	34,033	73.30	3.00
21	Kalimantan Utara	27,191	71.19	18.50
22	Sulawesi Barat	88,660	66.36	19.30
23	Maluku Utara	34,073	68.76	13.00
24	Kalimantan Tengah	105,359	71.25	12.70
25	Nusa Tenggara Timur	385,605	65.28	22.60
26	Papua Barat	55,669	65.26	13.00
27	Jawa Barat	3,149,244	72.45	8.30
28	Sulawesi Tenggara	50,781	71.66	18.50
29	Sumatera Barat	243,596	72.65	15.10
30	Papua	137,657	60.62	10.10
31	Kalimantan Timur	100,733	76.88	11.80
32	Maluku	167,203	69.71	6.80
33	Bali	96,944	75.69	5.00
34	Sulawesi Tengah	76,969	69.79	13.20

2.2 Method

Bayesian spatial regression models have been used often to model prevalence of stunting on human development index. Bayesian regression models have been successfully to model spatial and or spatiotemporal data ([11] [13] [14] [15] [16] [17] [18]). Let y_i and x_i denotes the HDI and prevalence of stunting at i-th province in Indonesia. We assume the HDI given prevalence rate follows Gaussian distribution:

$$y_i|x_i \sim Gaussian(\beta_0 + \beta_1 x_i, \sigma^2) \tag{1}$$

where β_0 denotes the intercept, β_1 regression slop, and σ^2 variance error. To account the prevalence rate and spatially structured effects we develop Gaussian linear model as follows:

$$E[y_i|x_i] = \eta_i = \beta_0 + \beta_1 x_i + \omega_i \tag{2}$$

where ω_i denotes the spatially structured effects.

A vague Gaussian prior distribution is assigned to the parameters β_0 and β_1, that is, $\{\beta_0, \beta_1\} \sim Gaussian(0,10^6)$ [11]. For the spatially structured effect the Leroux Conditional Autoregressive prior is imposed [19]. The LCAR prior reads (Leroux et al. 2000):

$$\omega_i|\boldsymbol{\omega}_{-i}, \sigma_\omega^2, \mathbf{W} \sim Gaussian\left(\frac{\rho\sum_{j=1}^{n} w_{ij}\omega_j}{\rho\sum_{j=1}^{n} w_{ij} + 1 - \rho}, \frac{\sigma_\omega^2}{\left(\rho\sum_{j=1}^{n} w_{ij} + 1 - \rho\right)}\right) \tag{3}$$

where ρ denotes the spatial autoregressive parameter with w_{ij} is an element of the spatial weights matrix **W** defined as:

$$w_{ij} = \begin{cases} 1 \text{ if } i \text{ and } j \text{ are adjacent neighbors} \\ 0 \text{ otherwise} \end{cases}$$

and σ_ω^2 is the variance parameter of σ_ω^2.

We proposed the value 25 as the scale parameter for the hyper-priority HC. It is possible that not all of the model's components (2) must be included. To evaluate our model, we will use the deviance information criterion (DIC), the Watanabe Akaike information criterion (WAIC), and the marginal predictive likelihood (MPL) (MPL). Choropleth maps are used to visualize the geographical distribution of HDI and stunting prevalence.

3. MAIN RESULTS

Table 2 shows the Descriptive statistics of research variables. In 2021, almost 14 million child was born across Indonesia's 34 provinces. North Kalimantan has the lowest birth rate. This is due to the province's fairly modest population. Additionally, West Java, the province with the highest birth rate in 2021, has a population of more than 3 million.

The provinces of Jami and North Sulawesi have the lowest stunting prevalence, at 3%. Meanwhile, the province of East Nusa Tenggara has the highest stunting rate at 22.6 %. Following that, the findings of the descriptive analysis of the human development index data indicate that the DKI Jakarta province owns the highest HDI value of 80.8 %. Jogjakarta is in second position with an HDI of 80.0. Notably, Papua Province has the lowest HDI, at 60.8 % in 2021. Spatial distribution of number of children, prevalence of stunting and HDI are presented in Figures, 1(a-c).

Table 2. Descriptive statistics of research variables

Variable	Minimum	Maximum	Mean	Median
Number of children	27,191	3,149,244	416,523.471	162,809
Prevalence of Stunting (%)	3.00	22.60	10.62	10.25
HDI (%)	60.62	81.11	71.65	71.36

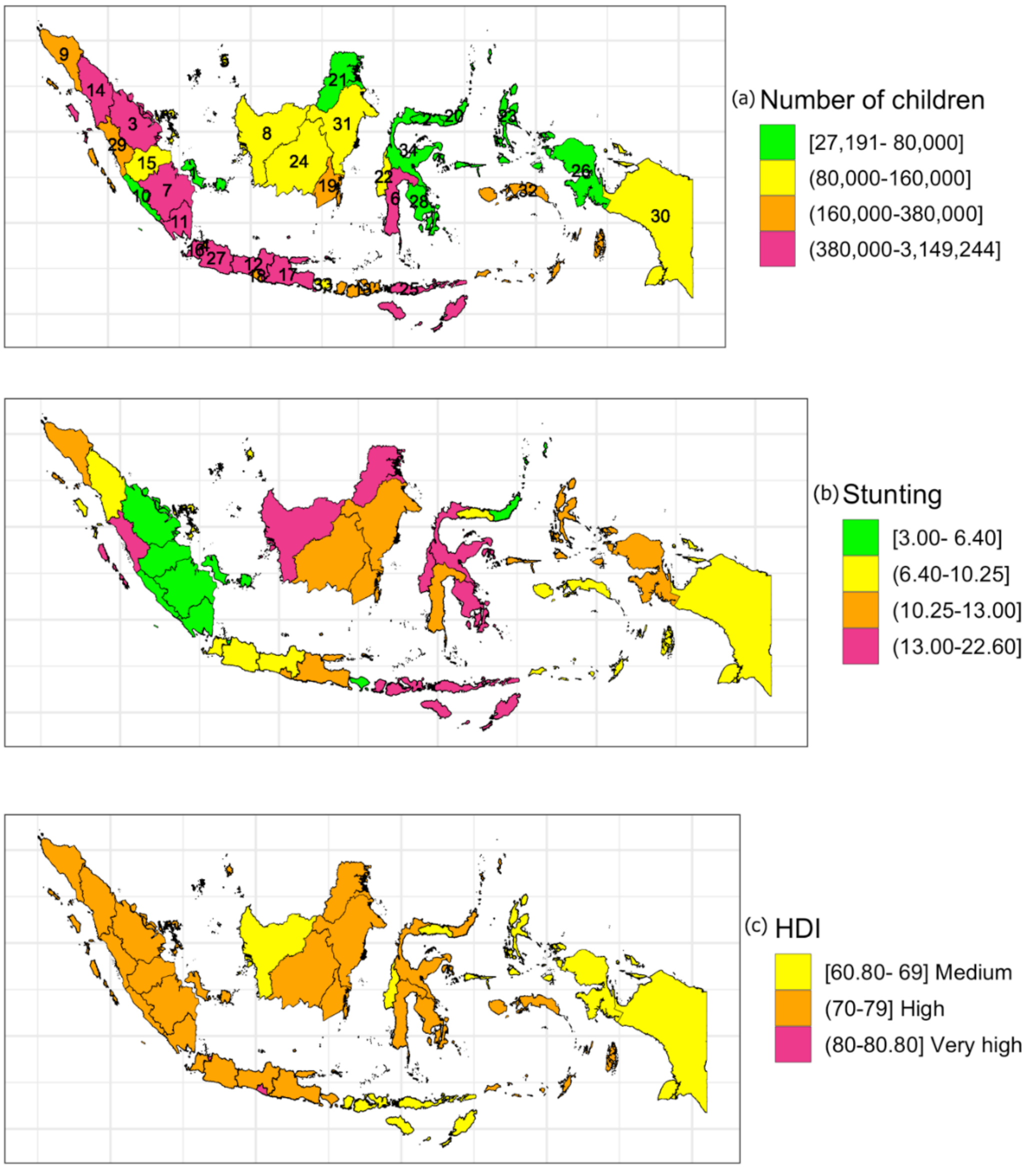

Figure 1. (a) Number of children, (b) prevalence of stunting and (c) human development index (HDI) in 2021 (Note: id province can be seen in Appendix 1)

The number of children, the prevalence of stunting, and the HDI appear to cluster by province in Figure 1(a-c). The provinces with a high number of children, a high prevalence of stunting, and a low HDI are grouped together with other provinces with a high number of children, while the provinces with a low number of children are grouped together with other provinces with a low number of children. It appears to be the case for the prevalence of stunting and HDI as well. As a result, we employ spatial regression analysis was conducted the association between stunting prevalence and HDI across Indonesian provinces. To determine whether our model is significantly superior to standard regression models, we compare them using deviance information criteria (DIC), Watanabe Akaike information criteria (WAIC), and marginal predictive likelihood (MPL) (MPL). The best model is the one with the lowest DIC and WAIC values and the highest MPL value. The results of the model comparison are shown in Table 3.

Table 3. Model comparison

	DIC	WAIC	MPL
Ordinary model	185.37	184.97	-114.60
Spatial model	-169.94	-180.38	-112.41

The DIC and WAIC of the spatial model are significantly lower than those of the regular regression model, as shown in Table 3. The MPL of an ordinary regression model is significantly less than that of a spatial model. According to DIC, WAIC, and MPL criteria, the spatial model is significantly more effective in modeling the prevalence of stunting on HDI in Indonesia.

Table 4. Posterior mean of fixed effects

Parameter	Mean	SD	q(0.025)	q(0.50)	q(0.975)
Intercept	74.079	1.376	71.377	74.079	76.779
Prevalence of stunting	-0.290	0.110	-0.506	-0.290	-0.073

Table 4 displays the posterior mean of fixed effects based on the spatial regression model. The intercept of 74.079 indicates the overall mean of the HDI, while the slope regression -0.286 indicates that if the prevalence rate increases by 1%, the HID index will drop by 0.286 %. The impacts of stunting prevalence are statistically significant, as evidenced by the 95 % credible interval [-0.503; -0.070] not including a zero value.

Table 5. Posterior mean of hyperparameters

Hyperparameter	Mean	SD	q(0.025)	q(0.50)	q(0.975)	Fraction of variance (%)
SD Gaussian error	0.012	0.003	0.008	0.012	0.021	0.002
SD Leroux Spatial Dependence	3.068	0.589	1.895	3.095	4.564	99.998
Autoregressive coefficients	0.865	0.260	0.999	0.999	0.999	

The posterior mean of hyperparameters is shown in Table 5. The standard deviation of the Leroux spatial model is substantially higher than the standard deviation of the Gaussian error, indicating that the geographical effect has a significant impact on HDI variance. The spatial autoregressive coefficient of 0.865 indicates that the geographical effect of the unobserved variable has a significant influence on the HDI variation. The spatial random effect accounts for unobserved factors that have a large geographical dependency between provinces and influence the variation in HDI between provinces in Indonesia. Unobserved influences could include the socioeconomic situation of each province, as we know that stunting is also influenced by socioeconomic status.

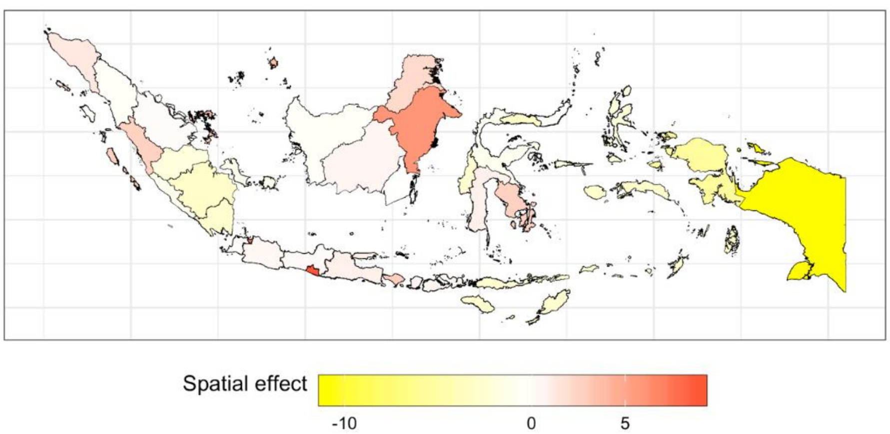

Figure 2. Spatial effect

Figure 2 depicts the spatial influence in Indonesia's 34 provinces. The spatial effects appear to be substantially grouped. The spatial effects of Papua and Papua Barat are extremely negative. In contrast, the spatial impacts were quite substantial in DKI Jakarta and DI Yogyakarta. It suggests that, in addition to the prevalence of stunting, there are important unobserved factors that have a significant impact on HDI. The answer could be that the socioeconomic conditions in DKI Jakarta and DI Yogyakarta are relatively high, while they are rather low in Papua and Papua Barat. Furthermore, we know that socioeconomic conditions vary greatly between neighboring provinces.

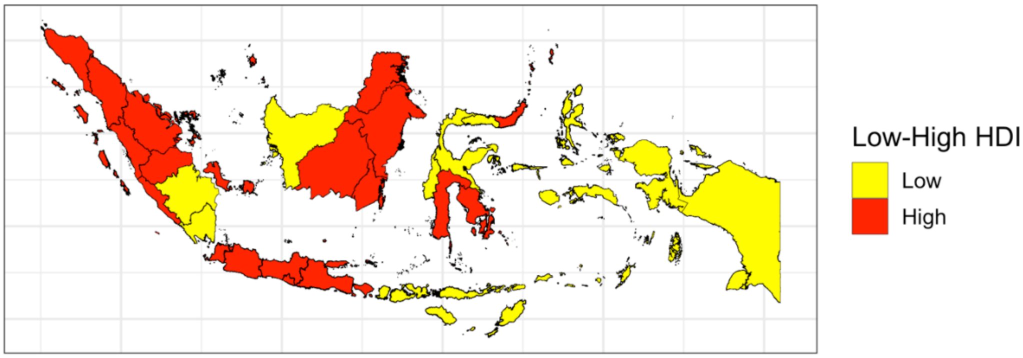

Figure 3. Significant Low-High Human Development Index (2021)

Figure 3 depicts the low-high HDI that are statistically significant with a cut off of 70%. The red region denotes provinces where the HDI score is statistically significant at or above 70%. The yellow one, on the other hand, is classified as low because the HDI score is not much larger than 70 %. The detail classification of low-high provinces is presented in Table 4.

Table 6. The classification of provinces based on prediction HDI

id	Province	Classification	id	Province	Classification
2	Gorontalo	Low	1	Kepulauan Bangka Belitung	High
8	Kalimantan Barat	Low	3	Riau	High
11	Lampung	Low	4	DKI Jakarta	High
13	Nusa Tenggara Barat	Low	5	Kepulauan Riau	High
22	Sulawesi Barat	Low	6	Sulawesi Selatan	High
23	Maluku Utara	Low	9	Aceh	High
25	Nusa Tenggara Timur	Low	10	Bengkulu	High
26	Papua Barat	Low	12	Jawa Tengah	High
30	Papua	Low	14	Sumatera Utara	High
32	Maluku	Low	15	Jambi	High
34	Sulawesi Tengah	Low	16	Banten	High
7	Sumatera Selatan	Low	17	Jawa Timur	High
			18	DI Yogyakarta	High
			19	Kalimantan Selatan	High
			20	Sulawesi Utara	High
			21	Kalimantan Utara	High
			24	Kalimantan Tengah	High
			27	Jawa Barat	High
			28	Sulawesi Tenggara	High
			29	Sumatera Barat	High
			31	Kalimantan Timur	High
			33	Bali	High

According to Table 6, 12 provinces have a low HDI and 22 have a high HDI. The provinces of Java island have a high HDI, indicating that they have a low rate of stunting and may have a high socioeconomic condition, such as income per capita.

4. CONCLUSION

Stunting is a reliable indicator of inequities in human development across Indonesia's provinces. It is consistent with some stunting research. [8] [9]. According to [9], children's health and nutritional condition can be to examine the disparities in human development that exist within a population. We discovered that stunting has a detrimental influence on human development across provinces in this study utilizing Bayesian spatial regression analysis. Increasing the prevalence of stunting by one % results in a drop of around 0.286 % in the human development index. Additionally, we discovered that unobserved components have large spatially dependent effects via spatial effects. We discovered that Papua and Papua Barat had highly negative spatial effects, indicating that other factors, such as low socioeconomic status, contribute to the human development index and may also play a role in stunting. By considering the spatial effects our model can explains 100% variation of human development index.

According to the findings of this study, the Indonesian government should pay closer attention to toddler stunting. Reduced stunting prevalence is a critical aspect in boosting the human development index. Economic interdependence between provinces is another factor to examine, as it impacts not only the human development index, but also the stunting rate in Indonesia.

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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Appendix 1: Id Label

id	Province Label	id	Province Label
1	Kepulauan Bangka Belitung	18	DI Yogyakarta
2	Gorontalo	19	Kalimantan Selatan
3	Riau	20	Sulawesi Utara
4	DKI Jakarta	21	Kalimantan Utara
5	Kepulauan Riau	22	Sulawesi Barat
6	Sulawesi Selatan	23	Maluku Utara
7	Sumatera Selatan	24	Kalimantan Tengah
8	Kalimantan Barat	25	Nusa Tenggara Timur
9	Aceh	26	Papua Barat
10	Bengkulu	27	Jawa Barat
11	Lampung	28	Sulawesi Tenggara
12	Jawa Tengah	29	Sumatera Barat
13	Nusa Tenggara Barat	30	Papua
14	Sumatera Utara	31	Kalimantan Timur
15	Jambi	32	Maluku
16	Banten	33	Bali
17	Jawa Timur	34	Sulawesi Tengah