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Zakiyah Mar'ah, Isma Muthahharah, and Sitti Masyitah Meliyana R

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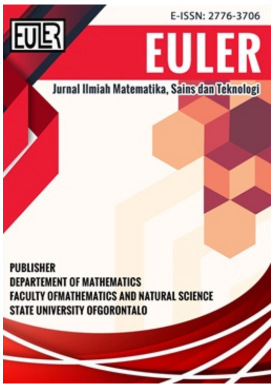

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Research Article

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SAR-FEM Spatial Panel Regression for Spatio-Temporal Modeling of Stunting Cases in Indonesia

Zakiyah Mar'ah[1,*], **Isma Muthahharah**[1], **Sitti Masyitah Meliyana R**[1]

[1]*Department of Statistics, Universitas Negeri Makassar, Jalan Daeng Tata 90224, Indonesia*

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ABSTRACT. *Stunting remains a crucial issue in Indonesia, with a prevalence of 21.5% in 2023. This study aims to model the number of stunting cases in toddlers in 34 provinces in Indonesia (2020–2022) using Spatial Panel Regression to address the weaknesses of traditional regression that ignore the effects of spatial and temporal dependencies. Predictor variables analyzed include the percentage of malnutrition, underweight, poor population, access to basic health facilities, and access to drinking water services. The selection of the best model specification was carried out using the Chow test, Hausman, and the Bayesian log-marginal posterior probabilities approach. The results of the diagnostic test confirmed the existence of spatial and temporal autocorrelation in stunting cases. Based on the Bayesian analysis, the Spatial Autoregressive (SAR) Fixed Effect (FEM) model was selected as the most optimal model with a log-marginal value of -21.360, a posterior probability of 0.630, and a coefficient of determination (R^2) of 0.880. Impact analysis shows that the percentage of underweight children and access to health facilities have a significant direct effect on stunting in a region. However, no significant indirect spillover effect from neighboring provinces was found. Therefore, policymakers are advised to formulate stunting management strategies that focus on precisely addressing local determinants in each region.*

1. Introduction

Stunting remains a crucial public health issue in Indonesia. According to the 2023 Indonesian Health Survey (SKI), the national stunting prevalence reached 21.5%, exceeding the 20% maximum standard set by the World Health Organization (WHO) [1]. This situation is quite alarming, placing Indonesia in the second-highest position in Southeast Asia after Cambodia, and making it one of the five countries with the highest burden of stunting among children in the world, along with India, Nigeria, and Pakistan [2]. The high number of stunting cases and wide disparities between provinces indicate the strong role of regional factors. Various previous studies have attempted to model this phenomenon, for example through the Spatial Error Model [3], Bayesian CAR Leroux [4], and Geographically Weighted Lasso [5]. Empirically, these studies confirm the existence of significant positive spatial autocorrelation in stunting cases across regions in Indonesia.

Although the determinants of stunting have been extensively researched, the majority of approaches still rely on ordinary linear regression (OLS) [6, 7] or traditional panel regression [8]. These methods have a fundamental weakness because they assume independence between regions, thus failing to account for the effects of spatial dependence. Meanwhile, studies that have shifted to utilizing spatial econometrics [3, 9–11] or point approach spatial model [5, 12–15] tend to be limited to the use of cross-sectional data, thus failing to

*Corresponding Author.

Email : *zakiyahm@unm.ac.id* (Z. Mar'ah)
Homepage : http://ejurnal.ung.ac.id/index.php/euler/index / E-ISSN : 2776-3706

capture temporal dynamics simultaneously. These basic spatial models also often fail to capture spatial spillover effects from neighboring regions and generally focus on micro-scale or household-level approaches.

Given these methodological limitations, more comprehensive modeling specifications are needed. This research addresses this research gap by applying a macro-scale Spatial Panel Regression Model. The novelty of this research lies in the model's ability to simultaneously accommodate heterogeneity and dependency in data across both spatial and temporal dimensions. Furthermore, the model specification selection is robust using a Bayesian log-marginal posterior probabilities approach. This approach allows for efficient and unbiased estimation of direct and indirect impacts between regions, thereby providing a more comprehensive understanding of spatial structure as a basis for formulating precise stunting management policies.

Therefore, the primary objective of this research is to model the macro-level determinants of stunting in Indonesia using a Spatial Panel Regression approach. Specifically, this study aims to (1) determine the most robust spatial panel model specification using the Bayesian log-marginal posterior probabilities approach, (2) estimate the direct and indirect (spatial spillover) effects of regional factors on stunting cases and (3) analyze the spatio-temporal dynamics to provide evidence-based policy recommendations for targeted stunting interventions.

2. Methods

2.1. Data

The data used in this study is secondary data obtained from the Ministry of Health of the Republic of Indonesia. The data used is a panel data set, which measures the the number of stunting cases in 34 provinces in Indonesia from 2020 to 2022. The variables used in this study are the number of stunting cases as the dependent variable (Y). The dependent variable was transformed using the natural logarithm to reduce heterogeneity and improve model stability. Because all provinces reported positive stunting cases counts during the observation period, no zero-value adjustment was required. Meanwhile, five independent variables (X):

- X_1: Percentage of malnutrition
  Percentage of toddlers aged 0–59 months classified as severely malnourished (BB/TB or BB/PB < -3 SD) relative to the total number of measured toddlers aged 0–59 months [1].
- X_2: Percentage of underweight children
  Percentage of toddlers aged 0–59 months with underweight nutritional status based on the weight-for-age index (BB/U < -2 SD) relative to the total number of toddlers aged 0–59 months measured [1].
- X_3: Percentage of poor people
  Percentage of population living below the poverty line relative to the total population in each province [1].
- X_4: Percentage of access to basic health facilities
  Percentage of population having access to basic health service facilities relative to the total population in each province [1].
- X_5: Percentage of access to drinking water services
  Percentage of households with access to proper drinking water services relative to the total number of households in each province [1].

2.2. Research Procedures

The research was conducted in several analytical stages:

1. Data exploration, which provides a general overview of the characteristics of the stunting cases used.
2. Selection of a panel regression model using the Chow and Hausman tests.
3. Testing the classical assumptions of the residuals from the obtained panel regression model is conducted to ensure the validity and reliability of the estimates.
4. Selection of a panel spatial regression model using Bayesian log-marginal posterior probabilities.
5. Testing the parameter estimates of the selected panel spatial regression model.
6. Interpretation and discussion of the modeling results.

2.3. Chow Test

The Chow test is used to determine the best model between the FEM (Fixed Effect Model) and CEM (Common Effect Model) for estimating panel data [16]. The hypothesis and F statistic of the Chow test are as follows:

$H_0 : \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_N = 0$ (CEM),
H_1 : there is at least one $\mu_i \neq 0$ (FEM),

Test statistics:

$$F_0 = \frac{(RRSS - URSS)/(N-1)}{URSS/(NT-p)}, \tag{1}$$

where RRSS is the restricted residual sum of squares for CEM. URSS is the unrestricted residual sum of squares for FEM. N is the number of observations. T is the number of time periods. p is the number of explanatory variables.

2.4. Hausman Test

The Hausman test is a statistical test used to determine the best model between FEM (Fixed Effect Model) and REM (Random Effect Model) to estimate panel data [16]. The following are the hypotheses and test statistics of the Hausman test:

$H_0 : corr(x_{it}, \varepsilon_i) = 0$ (REM),
$H_1 : corr(x_{it}, \varepsilon_i) \neq 0$ (FEM),

Test statistics:

$$W = (\hat{\beta}_{\text{FEM}} - \hat{\beta}_{\text{REM}})^T [var(\hat{\beta}_{\text{FEM}}) - var(\hat{\beta}_{\text{REM}})]^{-1} (\hat{\beta}_{\text{FEM}} - \hat{\beta}_{\text{REM}}), \tag{2}$$

where $\hat{\beta}_{\text{FEM}}$ is vector of FEM parameter estimates. $\hat{\beta}_{\text{REM}}$ is vector of REM parameter estimates.

2.5. The Classical Assumptions

Testing the classical assumptions of the residuals from the obtained panel regression model is conducted through the following diagnostic checks:

2.5.1. Normality Test

Assessed visually using a Quantile-Quantile (Q-Q) plot to evaluate the distribution of the residuals.

2.5.2. Multicollinearity Test

Evaluated using the Variance Inflation Factor (VIF) to ensure no severe correlation exists among the independent variables. There is multicollinearity if VIF > 10 [17].

$$VIF = \frac{1}{(1 - R_K^2)}, \tag{3}$$

where R_K^2 is the Coefficient of Determination obtained by regressing the K-th independent variable against all other independent variables in the model.

2.5.3. Heteroskedasticity Test

Examined utilizing the Breusch-Pagan test to check for constant variance in the residuals [18].

$H_0 : \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2$,
H_1 : there is at least one $\sigma_i \neq \sigma^2$,

Test statistics:

$$BP = \frac{1}{2} f^T Z(Z^T Z)^{-1} Z^T f, \tag{4}$$

where $f = (f_1, \ldots, f_n)^T$ with $f = \left(\frac{\varepsilon_i^2}{\sigma^2} - 1\right)$, $\varepsilon_i = y_i - \hat{y}_i$ is the least squares residual for the i-th observation. Z is a matrix of size $n \times (p+1)$ containing standardized normalized vectors for each observation.

2.5.4. Autocorrelation Tests

Evaluated across two dimensions to capture the complexity of the data:

- Temporal Autocorrelation: Detected using the Breusch-Godfrey test [16].

  $H_0 : \rho_1 = \rho_2 = \cdots = \rho_p = 0$,
  H_1 : there is at least one $\rho_i \neq 0$,

  $$BG = (n - p)R^2, \tag{5}$$

  where n is total initial observations/sample. p is number of residual lags included in the auxiliary regression. R^2 is the coefficient of determination of the auxiliary regression.
- Spatial Autocorrelation: Identified using LM test by Baltagi, Song and Koh [19].

  $$LM_\lambda = \frac{D_\lambda^2}{\mathrm{T} \cdot \mathrm{tr}(W'W + W^2)}, \tag{6}$$

  $$D_\lambda^2 = \frac{\hat{u}'(I_T \otimes W)\hat{u}}{\hat{\sigma}_u^2}, \tag{7}$$

  where $\hat{u}$ is the residual vector from the Pooled OLS estimation. T is the number of time periods. W is the spatial weight matrix. tr is the trace (number of main diagonal elements) of the product matrix W. I_T is the identity matrix of size T x T.

2.6. Bayesian Log-Marginal Posterior Probabilities

The selection of a panel spatial regression model using the Bayesian approach is carried out through several systematic stages, starting from determining the set of candidate models (such as SAR, SEM, or SDM) to determining the prior distribution for the parameters and prior probabilities of each model which are generally assumed to be uniform, namely:

$$p(M_k) = \frac{1}{K}. \tag{8}$$

The core of the process is to calculate the marginal likelihood by integrating the likelihood function over the prior parameters through the equation:

$$p(y \mid M_k) = \int p(y \mid \theta_k, M_k) p(\theta_k \mid M_k)\, d\theta_k, \tag{9}$$

because these integral values can be very small and cause computational underflow in computer systems, the calculations are transformed into natural logarithmic forms (log-marginal likelihood or LM_k). The final step is to compare the posterior probabilities between the candidate models to select the model specification and spatial weighting matrix that is best supported by the empirical data. To extract the final posterior probabilities from these log-marginal values, we apply Bayes' rule with additional computational stability tricks to prevent the calculation from producing exponentiation errors (such as infinity or NaN).

$$p(M_k \mid y) = \frac{\exp(LM_k - LM_{\text{max}})}{\sum_{j=1}^{K} \exp(LM_j - LM_{\text{max}})} \tag{10}$$

where LM_{max} is the largest (closest to zero) log-marginal value of all the models evaluated [20–22].

2.7. Spatial Autoregressive Fixed Effect Model

The SAR-FEM model refers to the development of a spatial autoregressive model that integrates fixed effects to control for unobserved heterogeneity between units. In general, this model follows the specifications of [23] and [20], where the dependent variable is influenced by its spatial lag through a spatial weight matrix, as well as by the independent variables and individual and time fixed effects.

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + X_{it}\beta + c_i + \varepsilon_{it} \tag{11}$$

Where W is the spatial weight matrix and ci is the individual fixed effects. The spatial weight matrix used in this study was constructed using queen contiguity, where provinces sharing either a boundary or a vertex were considered neighbors. The matrix was subsequently row-standardized, therefore each row summed to one before estimation.

3. Results and Discussion

3.1. Data Exploration

To provide an initial overview of the distribution of stunting cases in Indonesia, spatial data exploration was conducted at the provincial level for the period 2020–2022. The following thematic map visualizations were used to identify differences in case intensity between regions and changes in distribution from year to year.

The thematic maps of stunting cases in Indonesia from 2020 to 2022 in Figure 1 to 3 show a relatively consistent spatial pattern, with the highest concentration of cases on the island of Java, particularly in the provinces of West Java, Central Java, and East Java.

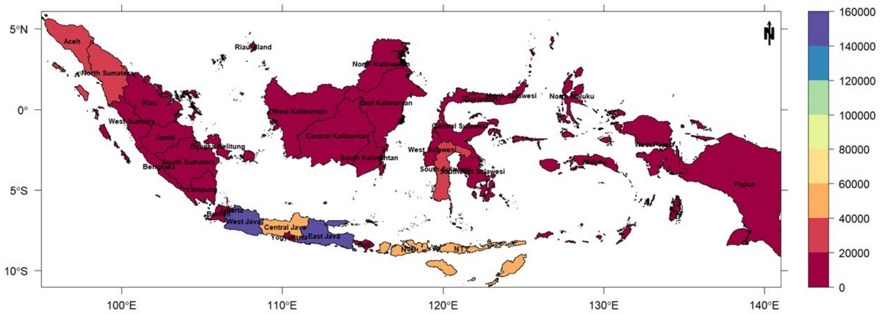

Figure 1. Distribution of stunting cases in Indonesia in 2020.

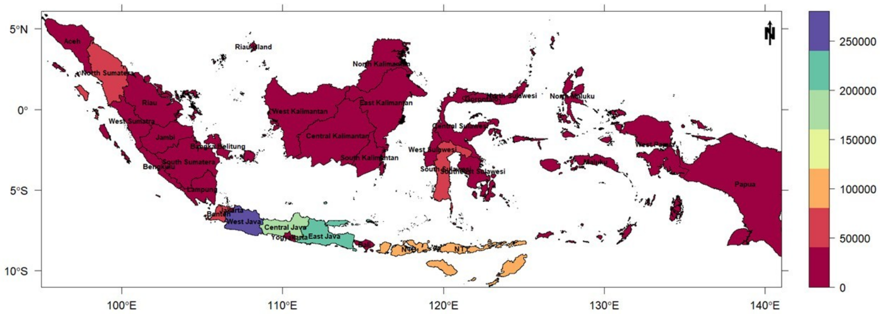

Figure 2. Distribution of stunting cases in Indonesia in 2021.

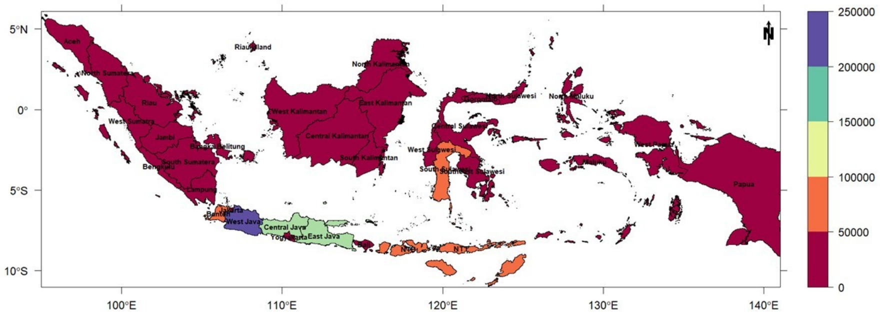

Figure 3. Distribution of stunting cases in Indonesia in 2022.

The high number of cases in these regions correlates with their large population, making their absolute contribution to the national total dominant. Outside of Java, several provinces in Eastern Indonesia, such as East Nusa Tenggara and South Sulawesi, also show relatively high numbers of cases compared to other regions, although they remain below those in Java.

Temporally, there is a dynamic change in the number of stunting cases between years, as evidenced by variations in color intensity on the map. From 2020 to 2021, several provinces in Java experienced an increase in the number of cases, while in 2022 a shift was observed, with a significant increase in South Sulawesi and changes in several other provinces in Sulawesi. Conversely, some provinces in Sumatra and Kalimantan tended to show a more stable pattern with less significant changes over the three years of observation.

Based on visual observations of changes between years, several provinces exhibited relatively high fluctuations in the number of cases, including South Sulawesi, East Nusa Tenggara, Central Java, East Java, West Java, Banten, Jakarta, Central Sulawesi, Southeast Sulawesi, and Bali (shown in Figure 4). This fluctuation indicates the dynamics of factors influencing stunting incidence, including policy interventions, socioeconomic conditions, and access to health services.

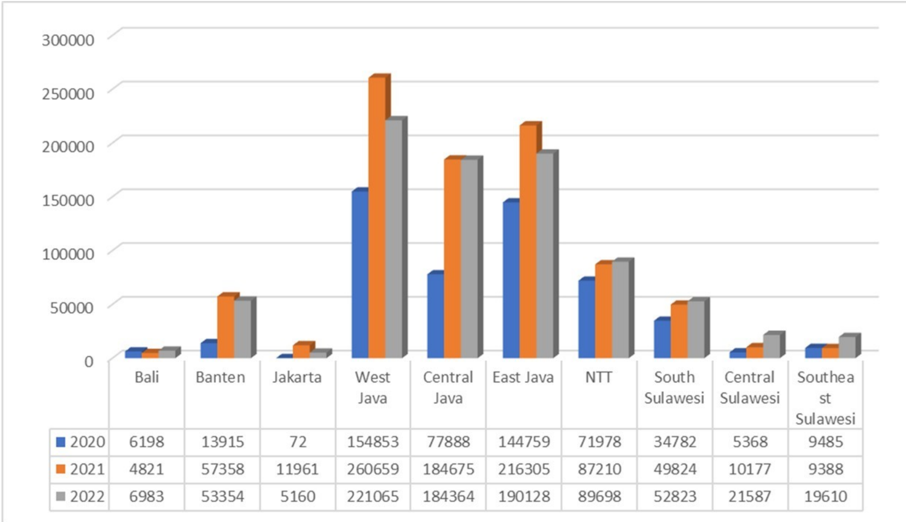

Figure 4. Fluctuating Trends in Stunting Cases in 10 Selected Provinces, 2020–2022.

The graph shows that the 10 provinces with the most fluctuating stunting cases during the 2020–2022 period experienced significant changes, with a general pattern of a sharp increase in 2021 followed by a decline or stabilization in 2022. Provinces such as West Java and East Java recorded the largest spikes in 2021 before declining in 2022, although still higher than 2020. Central Java remained relatively stable after a large increase in 2021, while East Nusa Tenggara (NTT) and South Sulawesi showed a gradual upward trend each year. On the other hand, provinces such as Banten and DKI Jakarta experienced extreme fluctuations, with a drastic increase in 2021 followed by a sharp decline in 2022. Meanwhile, several provinces with smaller numbers, such as Bali and Southeast Sulawesi, continued to show variation, albeit on a smaller scale. Overall, these fluctuations indicate strong dynamics in the handling or reporting of stunting cases between years in various regions.

3.2. Regression Panel Model

The panel regression model appropriate to the stunting cases was selected in two stages. First, the Chow test was used to determine whether the Fixed Effects Model (FEM) or the Common Effects Model (CEM) was appropriate. Based on Table 1, the FEM model was selected at the 10% significance level. A significance level of 10% was adopted because the study used macro-level provincial panel data with relatively limited observations, where a slightly more flexible threshold is commonly considered acceptable in exploratory spatial econometric studies.

Table 1. Chow test.

F	df_1	df_2	p-value	conclusion
9.378	33	63	3.298×10^{-14}	FEM

Next, a Hausman test was performed to determine whether the Fixed Effects Model (FEM) or Random Effects Model (REM) fit the data. The FEM model was selected at a 10% significance level.

From the two panel model tests, it is indicated that the data on the number of stunting cases is suitable for modeling with the FEM panel regression model. The selection of FEM for this stunting cases indicates that there are significant differences in characteristics between

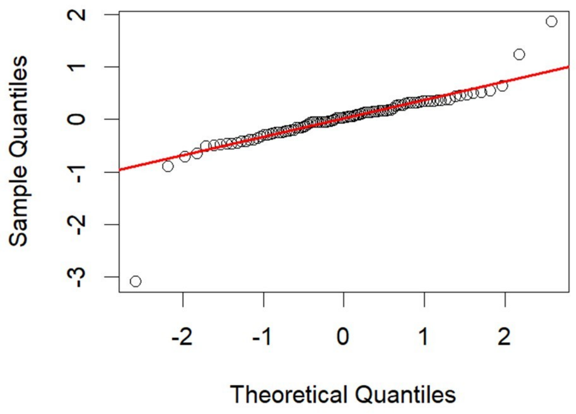

Figure 5. Normal Q-Q plot.

provinces that influence the number of stunting cases, and these differences are time-invariant throughout the observation period. This means that each province has unique factors, such as socioeconomic conditions, culture, quality of health services, and local policies, that are not directly observed but influence stunting cases, and therefore need to be controlled for in the model. By using FEM, the influence of these fixed factors can be accommodated through different intercepts for each province, resulting in a more accurate estimate of the relationship between the independent variables and stunting cases. Thus, the variations analyzed in the model primarily originate from changes within a province over time, rather than differences between provinces, making the model results more accurate in explaining the temporal dynamics of stunting.

Table 2. Hausman test.

χ^2	df	p-value	conclusion
18.665	5	0.0022	FEM

3.3. Model Assumption Test

After selecting the Fixed Effect Model (FEM), classical assumption testing is performed to ensure that the model produces unbiased, efficient, and consistent estimators, thus ensuring reliable statistical inference results. This testing is important because violations of assumptions such as heteroscedasticity, autocorrelation, or residual non-normality can lead to inaccurate standard errors. Testing is performed on the residuals from the FEM model, rather than classical linear regression, because these residuals reflect the panel data structure by considering fixed effects on each observation unit, thus providing a more accurate evaluation of the model's suitability.

Evaluation of residual normality through a visual approach Normal Q-Q Plot (Figure 5) shows that most of the data follows the theoretical normal distribution, characterized by the majority of observation points being close to the diagonal line. Although there are minor deviations in the form of outliers in the tail of the distribution, this visual diagnosis is considered more relevant for large datasets than formal statistical tests that tend to be too sensitive to rejecting the null hypothesis due to small deviations. Moreover, the strict fulfillment of the normality assumption can be relaxed thanks to the asymptotic justification of the Central Limit Theorem, which guarantees that at large sample sizes, the sampling distribution of the estimator will automatically converge to normal regardless of the original shape of the error distribution [16]. Therefore, the consistency and unbiasedness of the model parameters will not be distorted by such minor anomalies, a basis strengthened by methodological studies [24, 25], therefore this regression model remains practically valid for the purposes of further statistical inference.

The heteroscedasticity test was conducted using the Breusch-Pagan test and obtained a BP value of 5.985 with a p-value of $0.307 > \alpha = 0.1$, hence the residual data is indicated to be homogeneous at a real level of 10%.

Multicollinearity testing was performed using the VIF test, and VIF values < 10 were obtained for each independent variable. This indicates that all independent variables do not have multicollinearity.

Table 3. VIF test.

Variable	X1	X2	X3	X4	X5
VIF value	1.858	1.475	1.074	3.039	1.482

Temporal autocorrelation testing was performed using the Breusch-Godfrey test, a statistical test used to detect the presence of autocorrelation in the residuals of a panel model. The Chi-square value was 24.696 with a p-value of $1.787 \times 10^{-5} < \alpha = 0.1$, indicating that the residuals have autocorrelation at a 10% significance level. This indicates a dependency between observation times.

The spatial autocorrelation test was carried out using Spatial LM test and obtained LM value of 7.029 with p-value of $2.084 \times 10^{-12} < \alpha = 0.1$. Hence, it is indicated that there is a relationship between the locations of stunting cases at a real level of 10%.

The Breusch-Godfrey test results indicate temporal autocorrelation, while the Spatial LM test indicates spatial autocorrelation. The presence of both types of dependency (temporal and spatial) provides a strong basis for the use of Spatial Panel Regression, which can simultaneously accommodate these complex error structures.

3.4. *Panel Spatial Regression Model Selection*

Next, a panel spatial regression model is selected. The selection is made using Bayesian log-marginal posterior probabilities [22].

Table 4. Panel spatial regression model selection.

Model	SAR	SDM	SEM	SDEM
Log marginals	-21.360	-26.500	-21.913	-26.526
Model probability	0.630	0.003	0.3622	0.003

Table 4 presents the results of the panel spatial regression model selection test using the Bayesian log-marginal posterior probabilities approach. In this test, four spatial model specifications were compared: the Spatial Autoregressive (SAR), the Spatial Durbin Model (SDM), the Spatial Error Model (SEM), and the Spatial Durbin Error Model (SDEM). The best model was evaluated using two main indicators: log marginals (the higher the value or the closer to zero, the better the model fits the data) and model probability (the higher the probability, the greater the likelihood that the model is the most appropriate).

Based on the estimation results using the Bayesian Model Comparison approach, the Spatial Autoregressive (SAR) model was identified as the most optimal specification for explaining the distribution of stunting cases, with a model probability value of 0.6302. This model's superiority is supported by a log marginal likelihood value of -21.3604, which is statistically higher than the Spatial Error Model (SEM), Spatial Durbin Model (SDM), and Spatial Durbin Error Model (SDEM). The probability dominance of the SAR model indicates that the dynamics of stunting cases in the observed panel data have a stronger fit with the spatial dependence mechanism of the dependent variable, where the concentration of stunting cases in a region is structurally linked to surrounding regions.

Substantively, the selection of the SAR model implies a significant spatial lag effect on stunting cases between provinces. This indicates that the high or low number of stunting cases in a province is not only influenced by internal factors (variables X_1 to X_5) but is also directly influenced by the number of stunting cases in neighboring provinces through spatial spillover effects.

3.5. Spatial Autoregressive with Fixed Effect Model (SAR-FEM)

Based on the analysis results, the best SAR-FEM model for stunting cases in Indonesia was obtained. The parameter estimation results of the SAR panel model with individual fixed effects are shown in Table 5.

Table 5. Parameter estimation results.

	Estimate	Std. Error	t-value	p-value
X_1	0.128	0.152	0.840	0.401
X_2	0.036	0.018	2.001	0.045
X_3	0.020	0.030	0.657	0.511
X_4	0.088	0.048	1.827	0.068
X_5	0.032	0.038	0.823	0.410
rho	0.060	0.096	0.624	0.532

Based on the estimation results, the spatial autoregressive coefficient (rho) was recorded at 0.0599, but this value was not statistically significant (p-value = 0.532). This indicates that although previous model comparisons tended to favor the SAR specification, this data does not provide strong enough evidence to suggest a direct spatial dependence or significant "contagion" effect on the number of stunting cases between provinces. In other words, the distribution of stunting cases in this study is more local and more influenced by the internal characteristics of each region than by interactions between neighboring regions.

Of the predictor variables, only variable X_2 (the percentage of underweight children) showed a significant effect at the 95% confidence level. Considering the model uses a log(Y) transformation and independent variables in percentage form, the coefficient of 0.036 indicates that every 1 percent increase in variable X_2 is associated with an increase in the number of stunting cases of approximately 3.60%. In addition, variable X_4 (the percentage of access to basic health facilities) shows a weak influence (significant at the 10% level), while variables X_1 (the percentage of malnutrition), X_3 (the percentage of poor people), and X_5 (percentage of access to drinking water services) are not proven to have a significant influence. These results emphasize that stunting reduction policies must be more specifically focused on the factors represented by variables X_2 and X_4 in each province.

Based on the estimation results in Table 5, the SAR-FEM model equation formed is:

$$y_{it} = 0.060 \sum_{j=1}^{N} w_{ij} y_{jt} + 0.128 X_{1,it} + 0.036 X_{2,it} + 0.020 X_{3,it} + 0.088 X_{4,it} + 0.032 X_{5,it} + c_i + \varepsilon_{it},$$

where c_i is the regional fixed effect.

The goodness-of-fit of the Spatial Autoregressive Fixed Effects Model (SAR-FEM) estimation indicated that the model was able to explain a substantial proportion of the variation in stunting cases. The coefficient of determination ($R^2 = 0.880$) suggests that approximately 88% of the temporal and regional variation in stunting cases can be associated with the combined contribution of the predictor variables, spatial dependence effects, and province-specific fixed effects. However, this relatively high R^2 value should be interpreted cautiously because, in fixed-effects models, part of the explained variation may arise from unobserved heterogeneity captured through province-specific intercepts rather than solely from the explanatory variables. In addition, the relatively small error variance value (0.229) indicates that the residual variation not explained by the model is comparatively low, suggesting that the model provides a reasonably good representation of the spatio-temporal dynamics of stunting in the observed regions.

In the panel spatial regression model, interpretation should not only be based on the standard regression coefficients, but should also be based on the Impact values which are divided into three categories [26].

Table 6. Direct impact estimates for spatial model.

	Estimate	Std. Error	t-value	p-value
X_1	0.142	0.149	0.955	0.340
X_2	0.035	0.017	2.012	0.044
X_3	0.022	0.031	0.728	0.467
X_4	0.086	0.049	1.744	0.081
X_5	0.036	0.037	0.973	0.330

The direct effect measures the impact of changes in the independent variable in a province on the number of stunting cases in that province (including any feedback effects back to the province of origin). Table 6 shows only variable X_2 shows a statistically significant direct effect at the 95% confidence level (p-value = 0.044). Assuming a logarithmic transformation of variable Y, the direct coefficient of 0.035 indicates that every 1 percent increase in variable X_2 in a province will increase the number of stunting cases in that province by 3.50% on average, assuming other variables remain constant. Variable X_4 shows a significant effect (alpha = 10%), while X_1, X_3, and X_5 have no significant direct impact.

Table 7. Indirect impact estimates for spatial model.

	Estimate	Std. Error	t-value	p-value
X_1	0.009	0.022	0.411	0.681
X_2	0.002	0.003	0.517	0.605
X_3	0.001	0.004	0.306	0.759
X_4	0.005	0.010	0.515	0.607
X_5	0.002	0.005	0.424	0.671

The indirect effect measures the impact of changes in independent variables in a province on the number of stunting cases in neighboring provinces (spillover/contagion effects). Table 7 shows that none of the independent variables have a significant indirect effect (all p-values > 0.1). This finding is very consistent with the insignificance of the rho coefficient (spatial lag) in Table 5. Empirically, this means that changes in percentage conditions X_1 to X_5 in one region will not "spillover" or affect stunting cases in adjacent administrative regions. Although the SAR specification was selected as the preferred model based on Bayesian comparison, the estimated spatial lag coefficient (rho) and indirect effects were statistically insignificant. Therefore, the evidence for substantive spatial spillover effects between provinces remains limited in this dataset.

Table 8. Total impact estimates for spatial model.

	Estimate	Std. Error	t-value	p-value
X_1	0.151	0.158	0.955	0.339
X_2	0.037	0.018	2.030	0.042
X_3	0.023	0.032	0.723	0.469
X_4	0.091	0.052	1.737	0.082
X_5	0.038	0.039	0.964	0.335

Table 8 shows the total effect which is the sum of the direct and indirect effects. Because the indirect effect is very small and not statistically significant, the magnitude of the total effect in the model is almost entirely driven by the magnitude of the direct effect. Variable X_2 and X_4 are significant predictor of the total effect (p-value < 0.1), confirming that the solution to the stunting problem associated with variable X_2 and X_4 are highly localized.

This spatio-temporal modeling suggests that policy interventions to reduce stunting cases should consider regional characteristics and localized conditions. Because no statistically significant spatial spillover effects were identified in this study, improvements in the independent variables (particularly X_2 and X_4) in one province were not observed to produce significant positive externalities in neighboring provinces within the context of the fitted model and dataset. Therefore, the effectiveness of intervention policies may be more strongly reflected within the province where the improvements occur.

3.6. Discussion

Estimation results using the Spatial Autoregressive Fixed Effects Model (SAR-FEM) indicate that the dynamics of stunting cases at the provincial level in Indonesia during the 2020–2022 period are highly localized. This finding is confirmed by the insignificant spatial lag coefficient (rho) and the zero indirect impact, which empirically indicates the absence of spatial spillover effects between provinces. The selection of the SAR model through Bayesian model comparison indicates that the SAR specification provides the best relative fit among the candidate spatial panel models evaluated. However, the insignificance of the spatial lag coefficient suggests that the magnitude of spatial dependence is weak. Therefore, the superiority of the SAR model should be interpreted as a relative statistical preference rather than strong evidence of substantive spatial spillover. The variable of the percentage of underweight toddlers (X_2) proved to be the most statistically significant primary determinant, where every 1% increase in this variable directly contributed to a 3.50% increase in stunting cases, which was also marginally supported by the factor of access to basic health facilities (X_4). This empirical finding is substantially in line with previous fundamental literature reviews [27] which confirms that proximal nutritional status (underweight) and health infrastructure gaps are the main deterministic predictors of stunting in Indonesia. The positive association between access to health facilities (X_4) and stunting cases may reflect several underlying mechanisms. Provinces with better health facility access may also have larger populations, more intensive screening systems, and more comprehensive reporting mechanisms, resulting in higher recorded numbers of stunting cases. In addition, reverse causality may occur because regions with higher stunting burdens often receive greater health infrastructure interventions from the government.

The high coefficient of determination ($R^2 = 88\%$) with low error variance in this model confirms that spatio-temporal variation in stunting is largely driven by heterogeneity in internal regional characteristics. Therefore, policy intervention design cannot rely on positive externalities from neighboring provinces but must be decentralized at each administrative location.

This model's characteristics have comprehensive relevance to recent spatial econometric studies, such as previous research [28] which confirms the accuracy of spatial panel regression in evaluating macro-scale determinants of toddler stunting. However, from a regional perspective, this finding regarding the absence of empirical spatial dependency provides a novelty that critically complements previous literature [29]. Most previous studies focusing on micro-scale units of analysis (such as districts/cities or villages) generally found strong spatial clustering due to environmental homogeneity and proximity to social interactions. In contrast, findings at the macro-scale (provincial) demonstrate that regional autonomy, local policy divergence, and administrative jurisdictional boundaries act as insulators; the success or failure of nutrition intervention programs is isolated within the province itself. This reconciles the academic view that national stunting mitigation strategies should be implemented through a spatial targeting approach based on the fiscal capacity and specific health service capabilities of each region, rather than solely on geographic proximity.

This study focuses on the spatial distribution of the absolute burden of stunting cases, which is directly relevant to policy planning and allocation of intervention resources. However, because provinces with larger populations tend to contribute more cases, the results should not be interpreted as prevalence-based risk estimates. Future studies are encouraged to incorporate prevalence-based indicators or population exposure adjustments to obtain a more proportionate representation of stunting risk across provinces.

4. Conclusion

This study establishes the Spatial Autoregressive Fixed Effects Model (SAR-FEM) as the most robust spatial panel model specification, which empirically reveals that the dynamics of stunting cases at the provincial level in Indonesia are highly localized. The estimation results show that the percentage of underweight children (X_2) and access to basic health facilities (X_4) have a significant direct effect on the increase in stunting cases, while the absence of spatial spillover effects proves that changes in determinants in one province do not affect neighboring provinces. Given the high variation in cases that are purely driven by the internal capacity of each administrative region, the resulting policy recommendations emphasize the importance of a decentralized spatial targeting approach; where resource allocation for nutrition improvement programs and primary health infrastructure must be focused independently and specifically in each province.

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