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Factors Influencing Stunting Incidence in Toddlers in Kendari City, Indonesia: A Spatial Regression Analysis in 2024

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ABSTRACT

Stunting is a serious global health issue, including in Indonesia. This study aimed to analyze factors influencing stunting incidence among toddlers in Kendari City, Indonesia, using a spatial regression approach. This study employed a descriptive ecological design using secondary data from the Kendari City Health Office in 2024 across 11 sub-districts. Spatial analysis was conducted using a Queen contiguity weighting matrix. The results showed that Moran's I value was not statistically significant ($p>0.05$), indicating weak global spatial autocorrelation. However, Lagrange Multiplier tests revealed that the LM-Lag and Robust LM-Lag were significant ($p<0.05$), suggesting the presence of spatial dependence. Therefore, the Spatial Autoregressive (SAR) model was selected. The SAR model demonstrated better performance compared to the OLS model (AIC=83.20; R^2=97.91%). Significant factors influencing stunting incidence included the number of toddlers, low birth weight (LBW), unmonitored child growth, lack of complementary feeding (MP-ASI), incomplete basic immunization, and lack of additional nutritional intake. These findings highlight the importance of spatial-based interventions in addressing stunting at the sub-district level.

INTRODUCTION

Stunting is a nutritional disorder that affects young children, particularly those under five years old, and occurs when chronic malnutrition hampers their growth, resulting in a body length or height that falls below the established standard (Probohastuti & Rengga, 2019). The primary factors directly contributing to nutritional issues, such as stunting, are inadequate nutrient intake and poor health conditions (Ministry of National Development Planning / National Development Planning, 2018).

Stunting is a widespread issue affecting toddlers globally. The nutritional status of toddlers experiencing stunting is identified by a height-for-age measurement that falls below -2 standard deviations compared to the benchmarks established by the World Health Organization. As a result, addressing stunting is a crucial aspect of nutrition for toddlers, as it reflects ongoing chronic nutritional challenges they face (World Health Organization, 2025).

Worldwide, stunting affected around 149.2 million children under the age of five, or approximately 21.9% of that age group, in 2020 (Wulandari & Laksono, 2023). In 2018, more than half of the stunted toddlers worldwide Wulandari were from Asia, totaling 81.7 million cases (UNICEF/WHO/World Bank Group, 2021). Indonesia has reported a significant rate of stunting in toddlers, with about one in every toddler facing the condition. Furthermore, Indonesia is ranked as the fourth highest globally for stunting rates and third highest in the Southeast Asia Region, averaging a prevalence of 36.4% from 2005 to 2017 (Abdulla et al., 2023). Data from Riskesdas conducted in 2007, 2013, and 2018 indicated that the national prevalence of stunting among toddlers was 36.8%, 37.2%, and 30.8%, respectively. While these numbers show some fluctuation and a general downward trend, they still exceed 30% (UNICEF, 2020). The global target aims to reduce stunting prevalence to 17.5% by 2030 to lessen its long-term effects. In line with this, Indonesia has made reducing stunting a national priority, setting a goal to bring the rate down to 14% by 2024 as part of its National Medium-Term Development Plan (Laksono et al., 2022).

According to the 2018 Basic Health Research (Riskesdas), the rate of stunting was at 30.80 percent (Statistics Indonesia, 2022); however, the 2022 Indonesian Nutritional Status Study (SSGI) indicated that the stunting prevalence among toddlers in Indonesia had decreased to 21.6 percent. Despite this reduction in stunting rates nationwide, data from the 2022 SSGI revealed that certain provinces, including Southeast Sulawesi, have not achieved the national target of 27.7%, maintaining one of the highest stunting prevalence rates in the country. Kendari City is an area that has a prevalence rate below the standard, standing at 19.5% (Ministry of Health Republic Indonesia, 2023). In this context, the advancement in stunting reduction is inconsistent across different regions and sub-regions, particularly with significant disparities in stunting rates among provinces (Ministry of Health Republic Indonesia, 2022). Furthermore, Kendari City, one of the cities situated in Southeast Sulawesi Province, has seen a rise in stunting cases over the past three years, with increases of 0.95% in 2021, 1.40% in 2022, and 1.69% in 2023 (Pertiwi et al., 2024)

The Kendari City Government has taken various strategic steps in an effort to prevent stunting, one of which is by mapping stunting locations (loci) to provide specific interventions. In 2023, several sub-districts in Kendari City were designated as stunting loci, including Kendari District. The scope of specific program interventions varies in each sub-district, depending on the prevalence of stunting, which continues to increase every year, although the number of loci has decreased compared to the previous year. Even so, the government continues to intervene throughout the region, not limited to stunting locus areas. This aims to ensure that the stunting reduction acceleration program can continue to run optimally. To that end, the Kendari City Government is establishing cross-sector cooperation in accelerating the reduction of stunting rates in 2023 (Pertiwi et al., 2024).

To meet the stunting target for 2024, the government has enacted a Presidential Regulation, which focuses on the rapid reduction of stunting. This regulation outlines that the efforts to reduce stunting in Indonesia are conducted in a comprehensive, integrated manner with a focus on quality, through collaboration among various sectors (President of Republic Indonesia, 2020). In addition, prevention and handling of stunting cases can be attempted, one of which is by analyzing the risk factors suspected of influencing stunting. Stunting is caused by several factors, namely direct and indirect factors. Direct factors that can influence the occurrence of stunting include inadequate nutritional intake and nutritional status, such as LBW (Aditia et al., 2023).

Previous research stated that family income, parenting patterns of exclusive breastfeeding and complementary feeding, psychosocial stimulation, and parenting habits are risk factors for the incidence of stunting in toddlers aged 24-59 months at the Kendari City Stunting Focus Location in 2023 (Wardana et al., 2023). In addition, spatial mapping of stunting in Kendari City has been carried out previously, especially to analyze the relationship between the achievement of specific program interventions and the reduction of stunting in the region. The mapping is part of the research I conducted in 2023, which focused on analyzing spatial correlation patterns between two dependent variables (stunting cases) with one independent variable, namely the achievement of specific nutritional interventions in Kendari City. However, until now, spatial modeling that examines the risk of stunting cases more comprehensively, especially based on the sub-district level in Kendari City, has not been carried out. In addition, the data taken is also different, namely, data from 2024.

This is a form of further research where the findings that have been obtained provide significant evidence that several specific nutritional intervention achievements are related to stunting incidents in several areas that are spread in clusters. This provides a recommendation for further in-depth research into which risk factors cause stunting incidents in the Kendari city area, using GeoDa for spatial regression modeling. In addition, this study aims to assist the government in intervening quickly in dealing with cases based on risk factors for stunting incidents in the Kendari city area. The novelty of this study lies in the integration of spatial regression modeling at the sub-district level using recent 2024 data, providing a more localized and updated analysis compared to previous studies that primarily focused on correlation or non-spatial approaches.

METHOD

This study employed a descriptive ecological observational design conducted in Kendari City, Indonesia (3°54′30″–4°3′11″ South Latitude and 122°23′–122°39′ East Longitude). The unit of analysis consisted of 11 sub-districts, using aggregate secondary data obtained from the Kendari City Health Office. The study focused on the number of stunting cases among toddlers recorded from January 1 to December 31, 2024. Researchers took data in February 2025 from the routine database managed by the Kendari City Health Office. In addition, data related to stunting risk factors include the dependent variable, namely the number of stunting cases in toddlers (y), and the independent variables include the number of toddlers (x1), the LBW cases (x2), the toddler growth that is not monitored (x3), the babies under 6 months old who do not receive exclusive breastfeeding (x4), the toddlers aged 6-23 months who do not receive complementary foods (MP-ASI) (x5), the babies who do not receive complete basic immunization (x6) and the malnourished toddlers who do not receive additional nutritional intake (x7). Data was taken based on each sub-district in Kendari City in 2024, and we used aggregate data sourced from the Kendari City Health Office report in 2024, and all variables were measured at the sub-district level.

Given the relatively small number of observations (n = 11 sub-districts) and the inclusion of multiple predictors, this study acknowledges the potential risk of overfitting and multicollinearity. Multicollinearity was assessed using the Condition Index (CI), where values above 30 indicate potential collinearity. However, no variables were removed because all predictors are theoretically established determinants of stunting and have been empirically identified as significant in previous spatial analysis. In particular, prior research by Tria Saras Pertiwi (2024), using Local Indicators of Spatial Association (LISA), demonstrated significant local spatial autocorrelation of these variables across several sub-districts in Kendari City (Pertiwi et al., 2024). This indicates that each variable contributes to localized spatial clustering patterns and should be retained to avoid model misspecification and loss of spatial information. Therefore, instead of eliminating variables, model robustness was assessed by comparing Ordinary Least Squares (OLS) and spatial regression results.

The first step in Spatial Modelling Analysis (Spatial regression) is to decide on spatial weighting to determine neighbors (Eryando et al., 2022). Spatial analysis was conducted using a spatial weighting matrix (W) based on the Queen contiguity approach, where neighboring areas are defined by shared borders or vertices. The spatial weights matrix was row-standardized to ensure comparability across regions. To incorporate spatial influence within a model, weighting factors must be integrated into the analysis (Yasin et al., 2021). So Queen's spatial weighting matrix is considered suitable for this situation. The spatial weighting matrix used is Queen's spatial weighting matrix using the GeoDa application.

The analytical procedure consisted of three stages. First, Ordinary Least Squares (OLS) regression was performed as a baseline model, including diagnostic tests for normality, heteroskedasticity, and multicollinearity (Penghui et al., 2011). Second, spatial autocorrelation was assessed using Moran's I to identify global spatial patterns. Third, spatial dependence was further evaluated using Lagrange Multiplier (LM) test diagnostics, including LM-Lag, LM-Error, and their robust forms, which are recommended for selecting the appropriate spatial regression mode (Robinson & Rossi, 2014; Sugiarti, 2013). Spatial processing and analysis related to stunting incidents are conducted using open-source software for visualizing spatial models, specifically the GeoDa application (Anselin, 2020). Then, the AIC and SIC methods are methods that can be used to select the best regression model discovered by Akaike and Schwarz. After conducting spatial regression testing, the best regression model was selected using the AIC and SIC methods (Fathurahman, 2009). Although Moran's I provides a global measure of spatial autocorrelation, it may not detect localized spatial clustering due to spatial heterogeneity. Therefore, the use of Local Indicators of Spatial Association (LISA) in prior studies strengthens the justification for incorporating spatial modeling in this study (Pertiwi et al., 2024). The results of this selection utilize the GeoDa application to display the results for each model.

RESULTS

Spatial Weighting Matrix

Using the acquired data, a spatial regression modeling analysis was performed to investigate the spatial risk factors linked to stunting cases according to each variable. This analysis was carried out using standardized weighting with a queen contiguity matrix, where the number of neighboring occurrences is assessed based on the alignment of adjacent sides and angles, assigning equal weight to each closest neighbor while designating zero weight to all other neighbors (Wardana et al., 2023). The weighting results using the queen contiguity matrix revealed that of the 11 observed sub-districts, the maximum number of inter-district proximity areas was 5. Furthermore, the minimum inter-district proximity was 1 sub-district, allowing these weighting results to be used for further spatial autocorrelation analysis. Therefore, the greater the number of neighbors, the greater the potential for interaction between a sub-district and other sub-districts. The following table shows the neighborhood relationships for each sub-district (Table 1).

Table 1. Spatial weighting with queen contiguity test result from GeoDa

Component	Value
Type	Queen contiguity
Observation	11
Min. neighbors	1
Max. neighbors	5
Mean neighbors	3.09
Median neighbors	4.00

Figure 1 illustrates the spatial distribution of stunting cases across subdistricts in Kendari City in 2024. The highest number of cases is observed in Kendari Subdistrict (≥111 cases), indicating a priority area for stunting intervention, followed by Kendari Barat and Puuwatu with relatively high case numbers (80–111 cases). Most other subdistricts fall into lower categories, reflecting fewer reported stunting cases. This spatial variation indicates unequal distribution of stunting across Kendari City and highlights the importance of area-based intervention strategies.

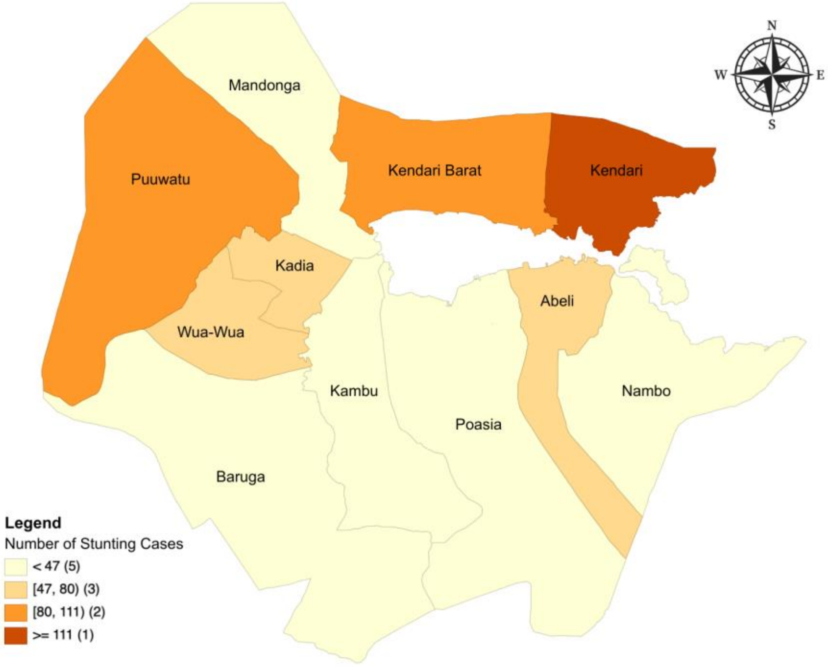

Figure 1. Spatial distribution map of stunting cases in Kendari City by subdistrict, 2024

Spatial regression analysis result

The Lagrange Multiplier (LM) test serves as a foundation for choosing a suitable spatial regression model. The initial step in this test involves developing a straightforward regression model through Ordinary Least Squares (OLS) (LeSage & Pace, 2009). The variables analyzed in this test include the dependent variable and the independent variables. This secondary data comes from Kendari City in 2024 through the Kendari City Health Office. Based on the results of the regression analysis through OLS carried out using the GeoDa application (Table 2).

Table 2. Ordinary Least Squares (OLS) test results

	Coef.	Std. Error	P-*value*
Const.	82.0839	16.18	0.01
χ_1	0.0038	0.01	0.04
χ_2	-3.0605	0.97	0.05
χ_3	-0.1057	0.02	0.02
χ_4	0.0040	0.075	0.96
χ_5	0.9198	0.152	0.009
χ_6	-0.4428	0.167	0.07
χ_7	-8.0101	2.377	0.04
Prob (F-Statistic)	0.04344		

The results show that the Prob (F-Statistic) value is 0.04344, which means the p-value <0.05 at a significance level of α=0.05; in other words, all regression models are significant in explaining the variation of the dependent variable. The OLS equation obtained is as follows:

$$\gamma = 82.0839 + 0.0038\chi_1 - 3.0605\,\chi_2 - 0.1057\chi_3 + 0.0040\chi_4 + 0.9198\chi_5 - 0.4428\chi_6 - 8.0101\chi_7$$

Partially, the variables that have a significant contribution to this model include the variable number of toddlers (χ_1) p-value=0.047, variable number of LBW cases (χ_2) p-value=0.051, variable Number of toddler growths that are not monitored (χ_3) p-value=0.021, Variable: Number of toddlers aged 6-23 months who do not receive complementary foods or MP-ASI (χ_5) p-value=0.009, and the variable Number of malnourished toddlers who do not receive additional nutritional intake (χ_7) p-value=0.043.

Normality test

The Lagrange Multiplier (LM) test serves as a foundation for choosing a suitable spatial regression model. The initial step in this test involves developing a straightforward regression model through Ordinary Least Squares (OLS) (Sugiarti, 2013). The formula is as follows.

$$JB = \frac{N}{6}(S^2 + \frac{(K-3)^2}{4}$$

In this study, the Jarque-Bera normality test was performed using the GeoDa application. The test results showed a probability value of 0.88400, which is greater than α=0.05, thus concluding that the model residuals are normally distributed.

Multicollinearity test

The multicollinearity test checks whether there is multicollinearity between independent variables or not by calculating the CI condition using the following formula (Anselin, 2020).

$$CI = \sqrt{\frac{\rho maks}{\rho min}}$$

Then the results of the calculations carried out using the GeoDa application obtained a CI value of 35.84, which means that this value is greater than 30, so there is an indication of high multicollinearity, which means that several variables may be highly correlated with each other or it is assumed that there is a relationship between independent variables so that the non-multicollinearity assumption is not met (Sugiarti, 2013). Although the multicollinearity Condition Index (CI = 35.84) indicates potential high correlation among independent variables, no corrective measures (e.g., variable elimination or PCA) were applied due to strong theoretical and empirical justification for retaining all predictors as established determinants of stunting. Multicollinearity is known to inflate the variance of coefficient estimates without introducing bias to the model itself, and thus does not invalidate model significance or predictive capability, as discussed by Belsley et al. (2005) and supported in applied regression studies such as Midi et al. (2010), which highlight that multicollinearity is common in health data and can be tolerated when variables are theoretically important (Belsley et al., 2005; Midi et al., 2010). Similar approaches have been adopted in spatial epidemiological studies (Anselin, 2020), where theoretically relevant variables are retained despite collinearity concerns.

Homoscedasticity test

In checking whether the error has a homogeneous variance, the Breusch Pagan statistical test is carried out using the following formula (Anselin, 2020).

$$F = \frac{R^2_{\varepsilon^2/k}}{1 - R^2_{\varepsilon^2/(n-k-1)}} \sim F_{\alpha,(k,n-k-1)}$$

Then, the results of this test using the GeoDa application obtained a Breusch Pagan value of 5.1496, or through the p-value obtained of 0.64171>0.05 (α), then the error has a homogeneous variance, so the assumption of homoscedasticity is fulfilled, or it can be concluded that in this case there is no indication of heteroscedasticity (the error variance is identical). From these results, it can be stated that the OLS regression model fulfills homoscedasticity or fulfills the classical regression assumptions for the analysis of stunting case data in toddlers in Kendari City, so that this model can be used as an analysis tool or the OLS regression assumptions are still said to be efficient.

Results of spatial regression tests with several methods

The presence of a spatial model is determined through a Lagrange Multiplier (LM) test(Robinson & Rossi, 2014). If the LM_{error} test yields a significant result, then the appropriate model is the SEM. If the LM-lag test is significant, the suitable model is the SAR. In cases where both tests are significant, the relevant model is the Spatial Autoregressive Moving Average (SARMA). Additionally, when both tests are significant, a Robust Lagrange Multiplier test is conducted. This test includes the Robust LM_{error} and Robust LM_{lag} (Penghui et al., 2011). The Lagrange Multiplier test is composed of LM-lag and LM-error, where LM_{lag} is utilized for identifying the SAR model (Robinson & Rossi, 2014). If the LM_{error} test is significant, then the appropriate model is SEM. If the LM_{lag} test is significant, then the appropriate model is SAR. If both are significant, then the appropriate model is Spatial Autoregressive Moving Average (SARMA). A robust Lagrange Multiplier test is also performed when both are significant. This test consists of Robust LM_{error} and Robust LM_{lag} (Penghui et al., 2011). Lagrange Multiplier: the test consists of LM_{lag} and LM_{error}. Dimana LMlag used for SAR model identification (Robinson & Rossi, 2014).

The results of Moran's I statistical test using the GeoDa application were obtained, namely -0.2692 with Z_{value} -1.0758 and $Z_{\alpha/2}$ 0.28202 or p-value less than α=0.05, so it can be concluded that there is no spatial autocorrelation. However, Moran's I statistic has a weakness, namely, it is less sensitive in detecting the presence of spatial autocorrelation because it requires a high error rate, so as to ensure the existence of spatial autocorrelation (Sugiarti, 2013). Therefore, researchers present the results of several other methods, namely LM_{Lag} (SAR), Robust LM_{Lag}, LM_{error} (SEM), and Robust LM_{error}. The results of the statistical tests obtained using the GeoDa application, using several other methods, are shown in Table 3. To further investigate spatial dependence, Lagrange Multiplier (LM) test diagnostics were performed. The results show that LM_{lag} (value = 6.15; p = 0.01) and Robust LM_{lag} (value = 5.53; p = 0.01) are statistically significant, while LM_{error} and Robust LM_{error} are not significant ($p > 0.05$). These findings indicate that spatial dependence is present in the lag form rather than in the error term (Table 3). This pattern is consistent with evidence from prior analysis using Local Indicators of Spatial Association (LISA), which identified significant local spatial clustering in several districts (Pertiwi et al., 2024). Therefore, despite the non-significant global Moran's I, the diagnostic tests support the presence of spatial interaction effects, and the Spatial Autoregressive Model (SAR) is selected as the most appropriate model for further analysis.

Table 3. Results of spatial autocorrelation regression model using several methods in GeoDa

Test Model	MI/ DF	M value	*p-value*
Moran's Index (Error)	-0.26	1.07	0.28
LM-Lag (SAR)	1	6.15	0.01
Robust LM (Lag)	1	5.53	0.01
LM-error (SEM)	1	0.98	0.32
Robust LM (error)	1	0.36	0.54

The test results show that the LM_{lag} (SAR) test statistic has a spatial lag autocorrelation with a p-value of 0.01311 (p-value<0.05), indicating spatial autocorrelation. Similarly, the Robust LM_{Lag} test results show spatial autocorrelation with a p-value of 0.01859 (p-value < 0.05). However, the LM_{error} (SEM) results differ, with a p-value of 0.32198 (p-value>0.05), indicating no spatial autocorrelation. This is also consistent with the Robust LM_{error} value, which is 0.54462 (p-value>0.05), indicating no spatial autocorrelation. Thus, the above results indicate that SAR modeling is more suitable for spatial regression of stunting cases among toddlers in Kendari City.

Spatial lag regression test (SAR)

In the test results of the two models, namely Lagrange Multiplier-Lag (SAR) and Robust $LM_{Lag,\ it}$ can be concluded that several of these methods for stunting cases in toddlers in Kendari City indicate spatial autocorrelation. Although the α values differ due to the Moran test's inability to detect autocorrelation, or the Moran test method being less sensitive in detecting autocorrelation, researchers used different confidence intervals. However, researchers still present the Lagrange Multiplier (Lag) as a comparative material in drawing better conclusions. The spatial lag regression model used is a model that involves the dependent spatial lag variable. This model was obtained based on the test results in **Table 4**.

Table 4. LM-Lag (SAR) test using GeoDa

	Coef.	Std. Error	p-value
$W\gamma$	-0.4126	0.1212	0.00067
Const.	120.45	12.617	0.00000
χ_1	0.0438	0.0045	0.00000
χ_2	-4.3871	0.4956	0.00000
χ_3	-0.1371	0.0125	0.00000
χ_4	0.0388	0.0296	0.19092
χ_5	1.0273	0.0668	0.00000
χ_6	-9.0557	0.9205	0.00000
χ_7	-0.4823	0.0063	0.00000

The LM_{lag} (SAR) equation obtained is as follows.

$$\gamma = 120.45 - 0.4126\gamma + 0.0438\chi_1 - 4.3871\chi_2 - 0.1371\chi_3 + 0.0388\chi_4 + 1.0273\chi_5 - 9.0557\chi_6 - 0.4823\chi_7$$

Partially, the average variable that has a significant contribution to this model includes the variable number of toddlers (χ_1), number of LBW cases (χ_2), Number of toddler growths that are not monitored (χ_3), The number of toddlers aged 6-23 months who do not receive complementary foods or MP-ASI (χ_5), Number of babies who do not receive complete basic immunization (χ_6) and the number of malnourished toddlers who do not receive additional nutritional intake (χ_7) with p-*value* < 0.05, while the variable Number of babies aged less than 6 months who do not receive exclusive breastfeeding (χ_4) not significant because the p-*value* > 0.05, so it can be concluded that the number of toddlers, the case of LBW, the growth of toddlers that are not monitored, the factor of toddlers aged 6-23 months not receiving complementary foods or MP-ASI, the factor of babies who do not receive complete basic immunizations and the factor of malnourished toddlers who do not receive additional nutritional intake have a significant influence on the number of cases of stunting toddlers in Kendari City in 2024. Meanwhile, the spatial lag test suggests that spatial influences or location factors influence the observation of stunting cases in toddlers in each region. Regions with spatial factors that are close to each other (both astronomically and geographically) will influence the observation of stunting cases in toddlers in Kendari City.

Best model selection

Various techniques can be utilized to identify the most effective regression model, including Akaike's Information Criterion (AIC) and the Schwarz Information Criterion (SIC). The primary benefits of AIC and SIC lie in their ability to choose the optimal regression model for forecasting, specifically by assessing how well the model fits the current data (in-sample forecasting) and predicting future values (out-of-sample forecasting) (Fathurahman, 2009). The selection of the best model in the results of the previous model test using the GeoDa application is shown in Table 5.

Table 5. Best spatial model selection test in GeoDa

Value	OLS	SAR
R-squared	0.958288	0.979193
AIC	88.1396	83.2087
SIC	91.3228	86.7898

The modeling results show that the value of the R-*squared* OLS model is smaller than the SAR model (95.82% < 97.91%), which means that the SAR model is more capable of explaining 97.91% of the variation in Stunting Cases in the Kendari City area in 2024. In addition, the SAR model yields smaller AIC and SIC values compared to the OLS model (AIC: 83.20 < 88.13; SIC: 86.78 < 91.32), indicating a better model fit. Thus, it can be said that the smaller the AIC and SIC values, the better the model is compared to other models, namely the OLS model. Overall, the lower AIC and SIC values confirm that the SAR model performs better than the OLS model in explaining the spatial pattern of stunting cases.

DISCUSSION

The findings show that the global Moran's I was not statistically significant, indicating no overall spatial autocorrelation pattern. However, this result should be interpreted with caution. Global spatial statistics are known to have limitations in detecting localized spatial dependence due to spatial heterogeneity and masking effects, where opposing spatial patterns across regions cancel each other out. This limitation has been highlighted by Anselin (2020), who proposed Local Indicators of Spatial Association (LISA) to capture local spatial clustering. Empirical evidence supporting this phenomenon is observed in previous research conducted by Pertiwi (2024), which identified significant local spatial autocorrelation in several districts, particularly in Kambu District. This suggests that spatial dependence exists at the local level even when it is not detected globally (Pertiwi et al., 2024).

Furthermore, the significant LM-Lag and Robust LM-Lag results indicate that spatial dependence occurs through spatial interaction effects rather than through spatial error processes. This supports the selection of the Spatial Autoregressive Model (SAR), which captures the influence of neighboring regions. This approach aligns with spatial econometric theory (Anselin, 2020; LeSage & Pace, 2009). Regarding multicollinearity, although the Condition Index indicates potential collinearity, this does not invalidate the model. Multicollinearity primarily affects the variance of coefficients rather than introducing bias, and it is commonly encountered in public health data where explanatory variables are inherently related. Similar findings have been reported in applied studies such as Midi et al. (2010). In this study, the consistency of coefficient signs and significance between OLS and SAR models indicates that the results remain robust despite the presence of multicollinearity (Midi et al., 2010).

The results of the SAR test show that the variable that significantly influences cases of stunting in toddlers in Kendari City is the number of toddlers (x_1) and unmonitored toddler growth (x_3), which shows the significance of its contribution to the increase in stunting incidents in Kendari City. Significant contribution to the number of toddlers (x_1) and unmonitored toddler growth (x_3) shows the important role of monitoring toddler growth in preventing stunting. This aligns with the Window of Opportunity theory, commonly known as the golden period, referring to the crucial first 1000 days of life that play a vital role in a child's growth and development. This concept is grounded in the understanding that from the fetal stage up to the age of two, a remarkably swift growth and development process takes place, unlike what occurs in other age groups (Anugrahini et al., 2024). Furthermore, quantitatively, the indicator of toddlers weighed reflects monitoring coverage, while qualitatively, it indicates early detection coverage. The higher the percentage of toddlers weighed, the greater the proportion of toddlers whose growth is monitored, and the greater the likelihood that nutritional problems can be identified early (Wigati & Ekasari, 2020). This is in line with Wigati's research (2020) that toddlers whose growth is not monitored enough or whose frequency of visits to the integrated health post (posyandu) is low have a 3.1 times more dominant influence on the incidence of stunting in toddlers aged 3-5 years when compared with children who regularly attend the integrated health post and whose growth and development are monitored.

The Spatial Autoregressive (SAR) analysis results indicated that the variable most significantly associated with stunting among toddlers in Kendari City was the incidence of low birth weight (LBW) (x_2). The significant cases of LBW explain that low birth weight conditions contribute to the risk of stunting. According to World Health Organization (2020), LBW represents a key risk factor for stunting, as nutritional deficiencies often begin during fetal development (World Health Organization, 2020) This highlights the critical importance of ensuring healthy pregnancies and normal birth weights, since infants born smaller or shorter are more likely to face inhibited growth, delayed development, and a higher risk of non-communicable diseases later in life (Trihono et al., 2015). This research is also in line with Noor et al. (2022), Syam et al. (2019) and Haile et al. (2016) that LBW has a significant influence on the incidence of stunting. Sartika's research (2021) also showed that LBW is a predictor of stunting and the likelihood of stunting increases significantly among children whose birth weight is <2,500 g. In addition, the results of Aryastami's et al. (2017) research show that babies born with low birth weight are 1.74 times more likely to experience stunting than babies born with normal weight.

Furthermore, the results of the SAR test showed that the variable that significantly influenced cases of stunting in toddlers in Kendari City was that toddlers aged 6-23 months did not receive complementary foods or MP-ASI (x_5), and malnourished toddlers who did not receive additional nutritional intake (x_7). Providing complementary foods that are not timely or do not meet nutritional quality has an impact on the child's linear growth, and inadequate complementary foods can cause growth failure at the age of over 6 months (World Health Organization, 2020). According to Trihono et al. (2015), improving the behavior of providing breast milk and complementary feeding can overcome the problem of stunting in Indonesia (Trihono et al., 2015). In addition, poor quality MP-ASI also has a higher risk of stunting in toddlers (Aditia et al., 2023).

Then, the variable that significantly influences cases of stunting in toddlers in Kendari City is babies who do not receive complete basic immunization (x_6). In contrast, infants under six months of age who were not exclusively breastfed showed no significant association with stunting incidence. These findings are consistent with the study by Prabowo & Peristiowati (2023), which reported that exclusive breastfeeding does not have a significant correlation with stunting, whereas immunization status is related to the occurrence of stunting among toddlers in the working area of the Buntu Batu Health Center, Enrekang Regency (Prabowo & Peristiowati, 2023). Another study by Syam (2019) found a link between immunization history and stunting. If a toddler lacks immunity to a disease, they will lose energy more quickly due to infectious diseases. The first reaction to infection is a decreased appetite, leading to the child refusing food from their mother. Refusing food means a reduction in nutrient intake (Syam et al., 2019). According to Sartika (2021), the possibility of stunting increases significantly among children who do not receive complete basic immunization when they are 9–11 months old. (Sartika et al., 2021) SAR modeling studied by Eryando et al. (2022) revealed the following variables that have a significant impact on the prevalence of stunting in various regions of the country, such as immunization and supplementary food for children under 5 years old.

LIMITATION

This study has several limitations that should be considered when interpreting the results. First, the use of an ecological design based on aggregated sub-district data may lead to ecological fallacy, where relationships observed at the group level may not necessarily represent individual-level associations. Second, the relatively small sample size (n = 11 sub-districts) increases the risk of overfitting and may limit the generalizability of the findings. Third, although multicollinearity was detected (CI > 30), all variables were retained due to strong theoretical and empirical justification, particularly based on prior spatial analysis using LISA. However, this condition may affect the stability of coefficient estimates, and therefore, the interpretation of the results should be made with caution.

CONCLUSION

The number of toddlers, low birth weight (LBW) cases, unmonitored toddler growth, toddlers aged 6-23 months who do not receive complementary foods or MP-ASI, infants who do not receive complete basic immunizations, and malnourished toddlers who do not receive additional nutritional intake has a significant impact on the number of stunting cases in Kendari City in 2024. Meanwhile, the spatial lag test suggests that the spatial influence or location factor influences the observation of stunting cases in toddlers in each region. Regions that have spatial factors in proximity (both astronomically and geographically) will influence the observation of stunting cases in toddlers in Kendari City. Then, based on the AIC value in the SAR model, it is smaller than the AIC value in the OLS model (83.20 < 88.13). This is also shown from the results of the SIC value of the SAR model, which is smaller than the AIC value in the OLS model (86.78 < 91.32). Thus, it can be said that the smaller the AIC and SIC values, the better the model is compared to other models, namely the OLS Model. These findings underscore the importance of spatially integrated public health interventions. Efforts to reduce stunting should not be implemented in isolation but must consider inter-regional linkages, particularly by strengthening early detection through routine growth monitoring and improving maternal and child health services, including LBW prevention and nutrition programs. However, this study has several limitations that should be acknowledged. The use of an ecological design based on aggregated data may lead to ecological fallacy, limiting individual-level interpretation. In addition, the relatively small sample size (n = 11) increases the risk of overfitting, and the presence of multicollinearity may affect the stability of coefficient estimates. Therefore, the results should be interpreted with caution. Future research is recommended to use larger datasets, incorporate individual-level data, and explore more advanced spatial modeling approaches to enhance the robustness of findings.

AUTHOR'S DECLARATION

Authors' contributions and responsibilities

TSP: Writing original draft (lead), visualization, funding acquisition, conceptualization, data analysis (lead); **MN**: Writing original draft (supporting), data cleaning & processing; **WZQ**: Writing original draft (supporting), supervision (lead), validation (equal), review and editing (equal); **KDJ**: Writing original draft (supporting), validation (equal), review and editing (equal); **AS**: Data collection (lead), supervision, editing, and finalization of the manuscript.

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Availability of data and materials

All data are available from the authors.

Competing interests

The authors declare no competing interests.

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