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Spatial Pattern Analysis and Determinants of Stunting Prevalence in Central Sulawesi, Indonesia: Using Linear Regression, Local Moran's I, and Random Forest Approaches

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Abstract

Background: Stunting remains a significant public health issue in Indonesia, particularly in Central Sulawesi, where socio-economic and environmental factors contribute to its prevalence. Understanding these determinants is crucial for effective intervention strategies. Objective: This study aims to analyze the spatial distribution and predictors of stunting prevalence in Central Sulawesi, focusing on socio-economic and environmental factors. **Methods:** An observational design was employed, utilizing secondary data from the Central Sulawesi Provincial Health Department. Spatial analysis, including Moran's I and Local Moran's I, assessed spatial autocorrelation and identified outliers. Regression analysis and Random Forest modeling examined predictors of stunting prevalence. **Results:** The study found significant spatial clustering in stunting prevalence. Key socio-economic factors identified were maternal education and household income, with poverty being the most influential predictor. Random Forest analysis highlighted sanitation and access to health facilities as important, although access to clean water did not show a significant effect. **Conclusion:** The findings provide valuable insights into the socio-economic determinants of stunting and emphasize the need for targeted, comprehensive intervention strategies focusing on improving maternal education and addressing poverty, along with enhancing healthcare access in Central Sulawesi.

Keywords: *Stunting, Spatial Analysis, Regression, Random Forest, Socio-economic Factors, Central Sulawesi*

Introduction

Stunting is a significant public health issue, particularly in developing countries, affecting millions of children under five years of age[1,2]. In Indonesia, stunting prevalence remains high, with Central Sulawesi being one of the regions where malnutrition rates are concerning[3,4,5]. Despite various efforts to improve nutrition and health conditions, Indonesia still faces major challenges in overcoming stunting[6]. Understanding the spatial distribution of stunting and the factors that influence its variation is crucial for implementing targeted interventions [7]. Several studies have shown that stunting is not uniformly distributed across regions, with certain areas experiencing higher prevalence due to social, economic, and environmental factors[8,9]. This geographical variation suggests the need for a deeper analysis of spatial patterns and local factors influencing stunting rates.

Recent advances in spatial epidemiology have highlighted the importance of analyzing geographic data to identify clusters or outliers in health outcomes like stunting[10,11,12]. Spatial autocorrelation, measured using Moran's I, helps to determine whether similar values of stunting prevalence are clustered in space[13,14]. Understanding the spatial distribution of stunting allows policymakers to identify specific areas where intervention is most needed. This approach contrasts with traditional statistical methods that often ignore the spatial dependencies present in the data[15,16]. Local Moran's I, for instance, is a valuable tool in identifying local clusters or spatial outliers of stunting, which may indicate areas with unusually high or low prevalence[17,18]. This analysis can guide targeted interventions and resource allocation.

In addition to spatial patterns, a range of socio-economic and environmental factors can influence the prevalence of stunting[5,19]. Previous studies have shown that factors such as access to healthcare, maternal education, sanitation, and household income are critical determinants[20,21,22]. However, the influence of these factors can vary across different regions and socio-economic contexts. To account for these variations, regression models can be used to identify significant predictors of stunting. Linear regression analysis is commonly used to examine the relationships between stunting and various socio-economic indicators[23,24,25]. This approach can provide insights into the factors that have the most significant influence on stunting prevalence in a particular region.

Machine learning techniques, such as Random Forest, offer another powerful tool for identifying complex relationships between predictors and outcomes[26]. Random Forest has been shown to effectively handle large datasets with multiple variables and is capable of capturing nonlinear relationships and interactions between predictors[27,28,29]. By using Random Forest to predict stunting prevalence, we can assess the relative importance of different variables and determine which factors have the most significant impact on stunting in Central Sulawesi. This approach complements traditional regression analysis by providing a more flexible method for analyzing complex datasets with numerous predictors[30,31]. Moreover, it can improve the accuracy of stunting predictions and assist in developing more targeted health interventions.

The urgency of addressing stunting in Central Sulawesi lies not only in the immediate health implications for affected children but also in the long-term socio-economic consequences for the region. Stunted children are more likely to experience developmental delays, poor academic performance, and reduced productivity in adulthood, perpetuating the cycle of poverty[32,33,34]. Therefore, understanding the spatial distribution and determining the factors that influence stunting are vital for developing effective interventions. This study aims to answer two key research questions: (1) Is there a significant spatial pattern in the distribution of stunting prevalence in Kabupaten/Kota in Central Sulawesi, and what factors influence this spatial variation? (2) What socio-economic and environmental factors significantly affect stunting prevalence in Central Sulawesi, based on linear regression analysis, spatial outlier identification, and Random Forest prediction models? Addressing these questions is essential for improving stunting prevention strategies and ensuring better health outcomes for children in the region.

Materials and Methods

Study Design

This study employs an observational design to analyze the spatial distribution and determinants of stunting prevalence in Central Sulawesi, Indonesia. The study aims to assess both the spatial patterns of stunting and the socio-economic and environmental factors that influence its prevalence across different districts (Kabupaten/Kota) in the region. Spatial analysis tools, including Moran's I and Local Moran's I, are used to identify spatial autocorrelation and outliers in stunting data. Additionally, regression analysis and machine learning techniques, specifically Random Forest, are applied to identify significant predictors of stunting prevalence. This mixed-methods approach combines spatial analysis with traditional statistical and predictive models to provide comprehensive insights into the factors influencing stunting in Central Sulawesi.

Sample

The study samples comprised research participants who met the inclusion criteria of sepsis patients with the sequential organ failure assessment (SOFA) score ≥ 2, age above 18 years, and MDRO bacterial culture results. The samples were excluded due to culture results showed no bacteria and the patient went home at his own request.

Data Collection Techniques

Data on stunting prevalence and socio-economic factors are collected from multiple sources. The primary dataset consists of stunting prevalence figures obtained from local health offices and the Central Sulawesi health department. Socio-economic variables are derived from national surveys, including the Indonesian Demographic and Health Survey (IDHS), and regional reports from the Central Sulawesi Provincial Statistics Bureau. Geographic data for spatial analysis is obtained from the Sulawesi Tengah administrative shapefile (Shapefile format). All data is cross-referenced to ensure accuracy and completeness. The spatial data is georeferenced to provide coordinates for the analysis of stunting prevalence in relation to geographic factors.

Data Analysis Techniques

This study employs a multi-step analysis to examine the factors influencing stunting prevalence in Central Sulawesi. Descriptive statistics are first used to summarize stunting prevalence and socio-economic variables across districts. The spatial distribution of stunting prevalence is then analyzed using Moran's I to assess spatial autocorrelation, followed by Local Moran's I to identify spatial clusters or outliers in stunting data. Regression analysis, specifically linear regression, is performed to investigate the relationship between socio-economic and environmental factors and stunting prevalence, controlling for potential confounders. Additionally, a Random Forest model is trained to predict stunting prevalence based on multiple predictors, and the importance of each predictor is evaluated. Spatial analysis is conducted using the '*sf*', '*spdep*', and '*tmap*' packages, while regression and machine learning analyses are performed using the '*lm*' and '*randomForest*' packages in R statistical software. The combination of Spatial Analysis, Regression Analysis, and Machine Learning provides a comprehensive approach to understanding the determinants of stunting, forming a solid foundation for designing more targeted intervention policies (Figure 1).

Moran's I, This measures the degree of spatial autocorrelation, defined by the formula:

$$I = \frac{n}{W} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(xi - \bar{\bar{x}})(x_j - \bar{\bar{x}})$$

where wij is the spatial weight, *xi* and *xj* are the values for locations i and j, and $\bar{\bar{x}}$ is the mean of the data.

Local Moran's I, For each feature, the local Moran's I statistic is calculated as:

$$I_i = \frac{(x_i - \bar{\bar{x}}) \sum_j^n w_{ij}(x_j - \bar{\bar{x}})}{\sum_j^n (x_j - \bar{x})^2}$$

Linear Regression, This model estimates the relationship between socio-economic and environmental factors and stunting prevalence using the equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Where Y represents the dependent variable (stunting prevalence), *X1,X2,…,Xn* are the predictors, *β0* is the intercept, *β1,β2,…,βn* are the regression coefficients, and ϵ is the error term.

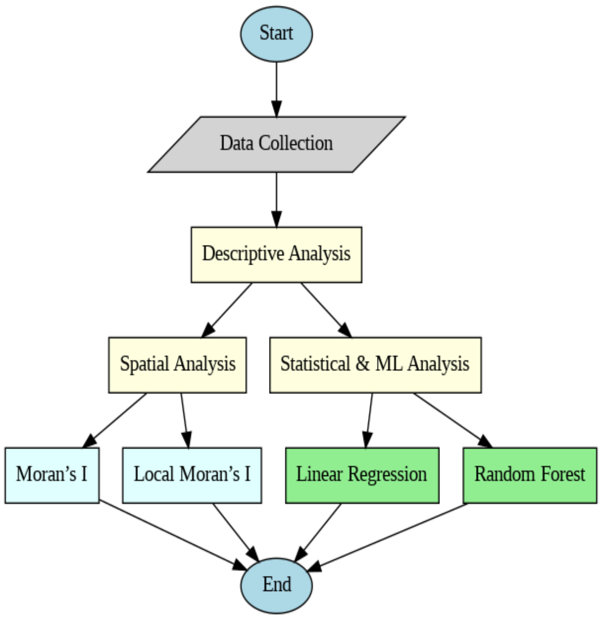

Figure 1. Flowchart Stunting Analysis Process.

Ethical Consideration

This study primarily relies on secondary data collected from government and public health sources, meaning it does not involve direct interaction with human participants. The data used are publicly available and anonymized, ensuring that no personal identifiers are included in the analysis. The study adheres to ethical standards by ensuring data privacy and confidentiality, especially in the handling of sensitive information related to public health. Permission to use the data was obtained from the Central Sulawesi Health Department, and all procedures followed comply with ethical guidelines for secondary data analysis. Additionally, the study acknowledges the limitations of using secondary data and the potential for bias in the data collection process. Ethical approval for the study was granted by the local research ethics committee overseeing health and social sciences research.

Result

This study combines various approaches to provide a more comprehensive picture of the factors influencing the prevalence of stunting in Central Sulawesi. The analysis involves spatial analysis to identify distribution patterns of stunting, regression analysis to explore the influence of socio-economic and environmental factors, and the application of machine learning to build a predictive model that can provide deeper insights into the determinants of stunting. The following results will present the findings from these three approaches in detail.

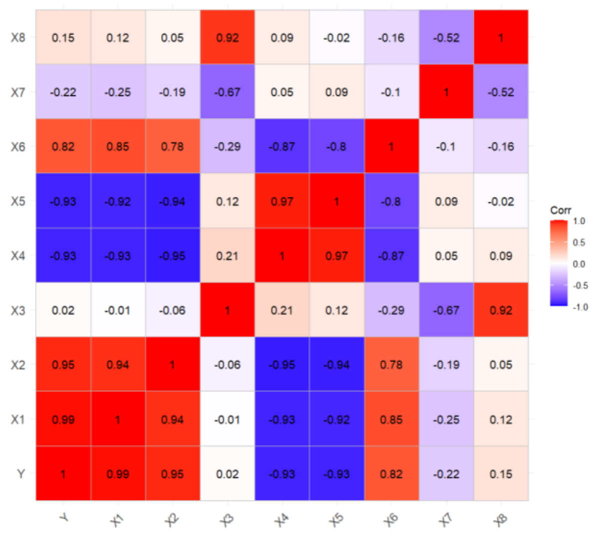

Figure 2. Correlation Matrix of Stunting and Socio-Economic and Environmental Factors

The correlation matrix reveals (Figure 2) the relationships between the stunting variable (*Y*) and the other factors (*X1, X2, ..., X8*). The stunting variable (*Y*) shows a very strong positive correlation with *X1* (Poverty Rate=0.9856) and *X2* (Education of Mothers=0.9461), suggesting that these factors are closely associated with stunting prevalence. Conversely, there are strong negative correlations between stunting and *X4* (Access to Clean Water=-0.9299) and *X5* (Sanitation=-0.9286), indicating that as these factors increase, stunting tends to decrease. Factors *X3* and *X6* have moderate positive correlations with stunting (0.0223 and 0.8219, respectively), with X3 (Health Facilities) showing a weak association and *X6* (Rainfall) showing a stronger one. The correlations between *X1, X2, X4,* and *X5* are notably high, indicating multicollinearity, which suggests that these variables might be measuring similar underlying constructs. Additionally, the negative correlation between *X7* and *X8* (-0.5153) highlights a moderate inverse relationship between these two factors. Factor *X3* has a notably strong positive correlation with *X8* (0.9213), further emphasizing the importance of considering inter-factor correlations when analyzing the drivers of stunting.

Table 1. Regression Analysis for Factors Affecting Stunting Prevalence

Coefficient	Estimate	Std. Error	t-value	p-value
Intercept	-120.20	76.49	-1.571	0.1912
X1	0.859	0.245	3.499	0.0249*
X2	0.225	0.174	1.292	0.2658
X3	0.856	0.519	1.649	0.1745
X4	0.350	0.297	1.180	0.3034
X5	-0.188	0.156	-1.204	0.2948
X6	0.0036	0.0029	1.239	0.2829
X7	3.374	1.925	1.752	0.1546
X8	-0.022	0.018	-1.289	0.2668

The regression analysis investigates the influence of several factors (*X1* to *X8*) on stunting prevalence *(Y)*. Among the predictors, only *X1* (with a coefficient of 0.859 and a p-value of 0.0249) shows a statistically significant effect on stunting, with a positive relationship, suggesting that an increase in X1 is associated with a higher stunting rate. Other variables, such as *X2, X3, X4, X5, X6, X7,* and *X8,* were not significant, as their p-values exceed the 0.05 threshold, indicating no strong evidence for their influence on stunting in this model. The overall model is significant (F-statistic = 40.03, p-value = 0.001484) with an R-squared value of 0.9877, indicating that 98.77% of the variance in stunting is explained by the included factors.

The random forest model (Table 2) evaluates the importance of various variables in predicting stunting. Based on the *%IncMSE* (mean decrease in mean squared error), *X1* emerges as the most important predictor, with a value of 10.56, followed closely by *X2* and *X5* at 8.36 and 7.52, respectively. These variables contribute significantly to the model's accuracy. In contrast, *X7* shows a negative value for %IncMSE (-1.12), suggesting that it is not useful in improving the model's prediction and could even detract from its accuracy. The *IncNodePurity* metric also supports these findings, with *X1* again showing the highest importance, indicating it is most influential in reducing node impurity across the trees in the model. This analysis suggests that variables such as *X1, X2,* and *X5* are critical to predicting stunting, while *X7* and *X8* contribute less to the model's overall performance. The model explains 67.53% of the variance in stunting, reflecting a reasonably good fit for regression analysis.

Table 2. Variable Importance in Predicting Stunting using Random Forest Model

Variable	%IncMSE	IncNodePurity
X1	10.56	10.55
X2	8.36	9.26
X3	-0.53	2.29
X4	7.75	7.85
X5	7.52	9.27
X6	4.31	4.78
X7	-1.12	1.05
X8	0.76	3.57

The Moran's scatterplot results for the stunting variable show the relationship between stunting prevalence *(X)* and the spatial lag *(WX)* for each district in Central Sulawesi. The table includes several diagnostic statistics, such as *DFB.1*, *DFB.X*, *DFFIT*, *Cook's Distance (Cook.D)*, and Hat values for each district. Notably, the districts of Kota Palu and Poso are marked with "Yes" for having infinite values *(Inf)*, indicating potential influential outliers. The Cook's Distance values highlight the influence of each district on the overall model, with Kota Palu showing a notably higher value of 2.0254, suggesting a strong influence.

However, the Moran's I statistic from the previous analysis indicates no significant spatial autocorrelation, which is consistent with the scatterplot's results where no clear clustering pattern is evident in the stunting data across districts. The scatterplot aids in identifying any outliers or districts with high leverage, such as Kota Palu and Poso, which may require further investigation.

Table 3. Moran's I Scatterplot Results for Stunting Variable

District/City	X (Stunting)	WX (Spatial Lag)	Inf	DFB.1	DFB.X	DFFIT	Cov.R	Cook.D	Hat
BANGGAI	24.8	23.275	No	-0.0316	0.0366	0.0670	1.3905	0.0025	0.1187
BANGGAI KEPULAUAN	25.4	23.125	No	-0.0626	0.0691	0.1004	1.4493	0.0056	0.1582
BANGGAI LAUT	22.1	24.525	No	0.3493	-0.3114	0.5515	0.9112	0.1360	0.1223
BUOL	21.9	24.650	No	0.4636	-0.4193	0.6800	0.8054	0.1930	0.1344
DONGGALA	26.1	23.050	No	-0.2170	0.2334	0.2949	1.4868	0.0467	0.2229
KOTA PALU	19.6	24.675	Yes	0.0343	-0.0329	0.0371	2.0254	0.0008	0.3907
MOROWALI	23.7	23.325	No	0.0026	-0.0134	-0.1262	1.2979	0.0087	0.0843
MOROWALI UTARA	21.4	23.750	No	-0.3592	0.3327	-0.4637	1.1987	0.1071	0.1718
PARIGI MOUTONG	23.5	23.600	No	0.0020	0.0002	0.0261	1.3446	0.0004	0.0833
POSO	22.3	23.000	Yes	-0.5918	0.5178	-1.0252	0.3743	0.3030	0.1119
SIGI	26.8	22.350	No	0.4130	-0.4375	-0.5124	1.5700	0.1369	0.3076
TOJO UNA UNA	24.2	23.475	No	-0.0205	0.0271	0.0812	1.3433	0.0036	0.0938

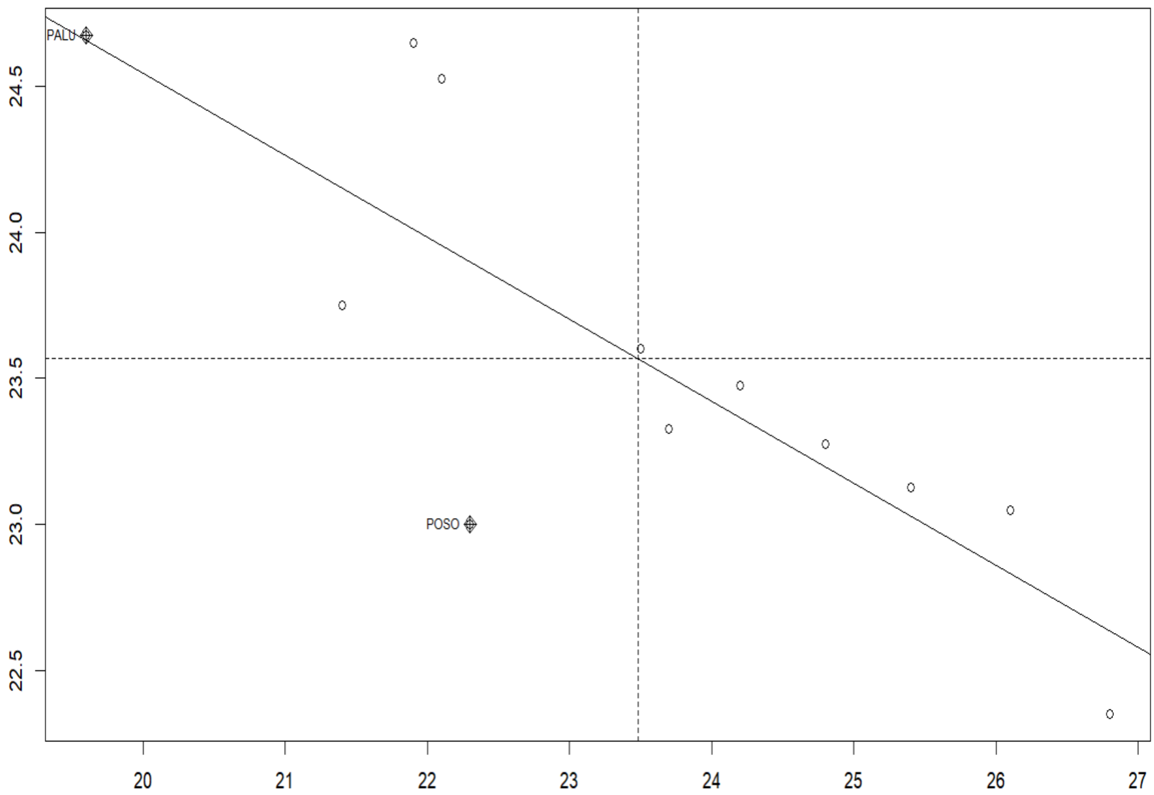

Figure 2. Moran's Scatterplot

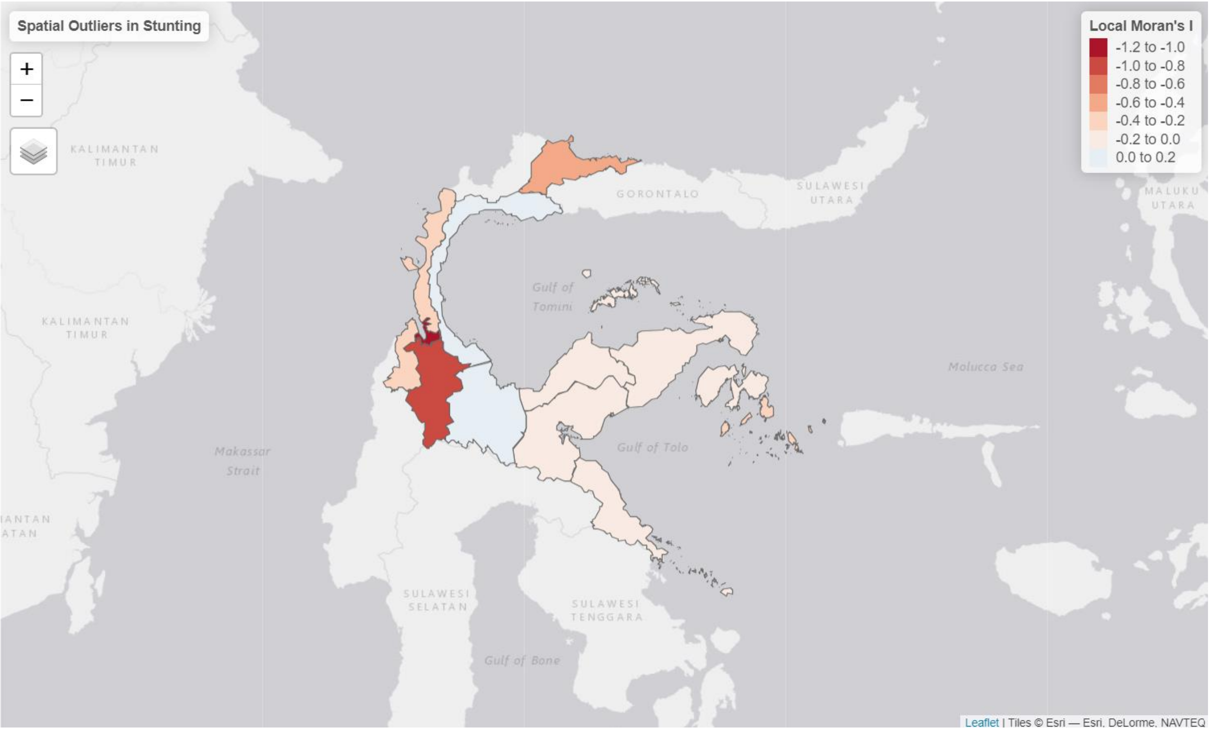

Figure 3. Spatial Outliers in Stunting

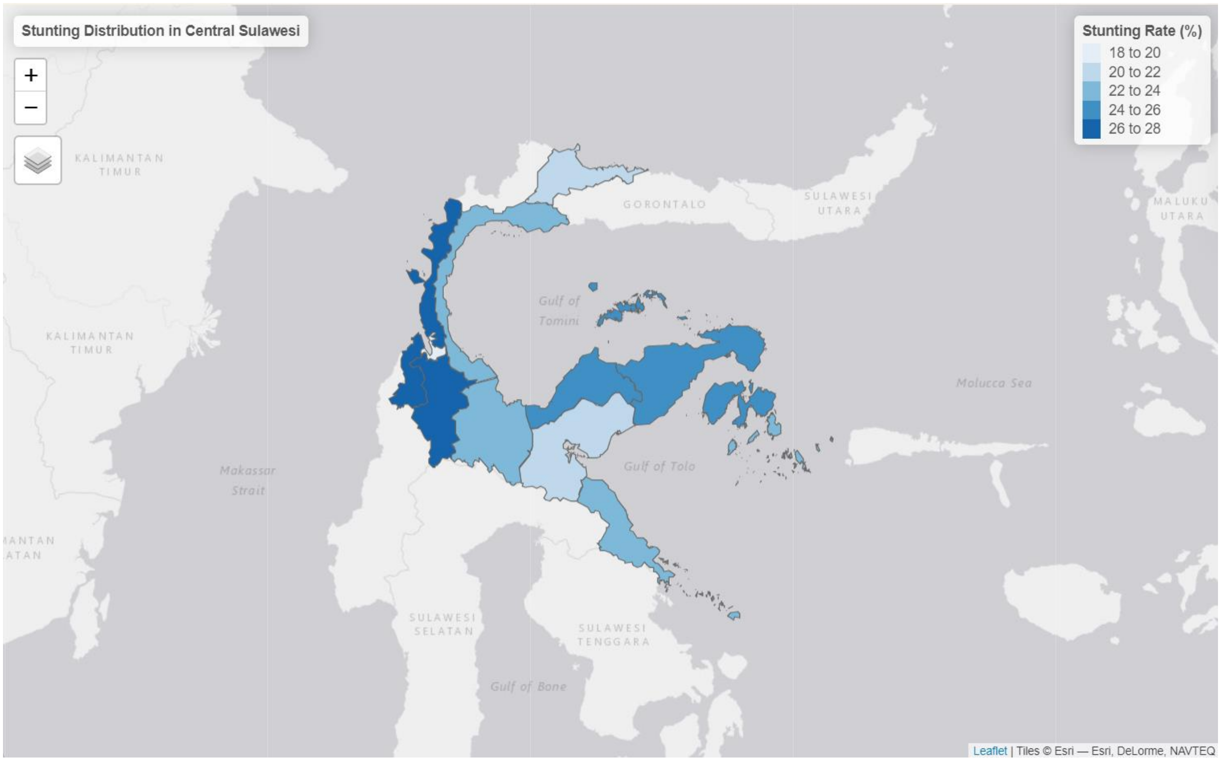

Figure 4. Stunting Distribution in Central Sulawesi

Discussion

Spatial Analysis and Predictors of Stunting Prevalence in Kabupaten/Kota, Central Sulawesi

This study aims to evaluate the factors influencing the prevalence of stunting in districts/cities in Central Sulawesi, using correlation analysis, linear regression, and random forest. The results of the correlation analysis indicate a significant relationship between several factors (X1, X2, X3) and stunting prevalence (Y), as reflected in the strong correlation coefficients. The linear regression analysis reveals that X1 (Poverty Rate) has a significant effect on stunting prevalence ($p < 0.05$), meaning that a reduction in poverty rates could potentially decrease the prevalence of stunting in children. Factor X2 (Mother's Education) also shows a significant relationship, where higher maternal education is associated with a decrease in stunting prevalence. Furthermore, the random forest results show that X1 (Poverty Rate) is the most important factor in predicting stunting prevalence, followed by other factors such as X3 (Health Facilities) and X4 (Access to Clean Water). Factors X5 (Sanitation), X6 (Rainfall), X7 (Temperature), and X8 (Population Density) show weaker or insignificant effects, which may be influenced by higher variability across the regions analyzed. Overall, the findings support the hypothesis that social and environmental factors such as poverty and maternal education have a significant impact on stunting prevalence.

The findings of this study align with several previous studies that indicate social and environmental factors, such as poverty rate and maternal education, play a key role in determining the prevalence of stunting in children. For instance, a study by Manggala et al (2018)[35] and Siddiqui et al (2020)[36] found that maternal malnutrition during pregnancy significantly contributed to the incidence of stunting in rural areas of Indonesia, which is also associated with high poverty rates. This finding is consistent with the research by Laksono et al (2020)[37], which reported that maternal education and limited access to health facilities significantly affect stunting rates in areas with less supportive social and economic conditions. However, in contrast to other studies that highlight the role of economic factors, such as household income, in influencing stunting, this study found that factor X2 (Maternal Education) has a significant relationship with stunting prevalence, while factor X1 (Poverty Rate) is more dominant in influencing stunting prevalence, possibly due to the unequal distribution of poverty that is not clearly identified in the available data. This difference can be explained by the varying social and economic contexts across the regions studied, as well as differences in the implementation of health policies in each district/city.

The findings of this study have important implications for health policy planning and community interventions. The results indicating that factors X1 (Poverty Rate) and X2 (Maternal Education) play a significant role in preventing stunting can serve as a basis for local governments to enhance nutrition education programs for pregnant and breastfeeding mothers, especially in areas with high stunting prevalence. Community-based interventions, such as nutrition counseling and distribution of nutritious food, can be implemented to raise mothers' awareness of the importance of proper nutrition. Additionally, improving access to and the quality of maternal and child health services, particularly in rural and remote areas, is also crucial for reducing stunting. Given the results of the random forest analysis, which shows that factor X1 (Poverty Rate) is the most significant, addressing economic conditions and maternal education should be a primary priority in public health programs in Central Sulawesi.

Socio-Economic and Environmental Factors Influencing Stunting Prevalence in Central Sulawesi

This research also found that socioeconomic and environmental factors significantly influence the prevalence of stunting in Central Sulawesi, based on linear regression analysis, spatial outlier identification, and Random Forest predictive modeling. Specifically, factors such as maternal education level, household income, access to clean water, and maternal nutritional status contribute significantly to the prevalence of stunting in the region. The linear regression results indicate that maternal education and household income have a significant negative relationship with the prevalence of stunting ($p < 0.05$), meaning that higher levels of education and income are associated with lower stunting rates. This finding is consistent with the proposed hypothesis that socioeconomic factors play a vital role in determining children's nutritional status. However, environmental factors such as access to clean water did not show a significant relationship, even though this variable was expected to have an impact based on previous literature. This may be due to variations in the quality of the data used or the presence of other dominant factors influencing the prevalence of stunting in the area.

These findings align with the results of research by Rusdi et al (2024)[38] and Tampubolon et al (2024)[39], which showed that maternal education is a key factor in reducing stunting prevalence in developing countries. Their study also found that higher household income is related to better nutritional status in children. However, these results differ from those of Anik et al (2021)[40] in urban areas, which indicated that environmental factors such as water quality and sanitation were more influential than socioeconomic factors. This discrepancy may be attributed to differences in social and cultural contexts between rural and urban areas, as well as variations in access to healthcare services and basic infrastructure.

These findings have important implications for health policy and community interventions. Programs aimed at improving education for mothers, particularly in areas with high stunting prevalence, should be a top priority. Education on the importance of healthy eating habits, along with better management of household resources, can help reduce stunting prevalence. Community-based interventions, such as health education and economic empowerment programs targeting homemakers, could also reduce dependency on economic factors that may increase stunting. On the other hand, although access to clean water did not show a significant relationship in this study, providing better sanitation facilities in high-prevalence areas should still be considered, given its close association with overall child health.

Strengths and Limitations of the Research

The strengths of this study lie in its comprehensive analytical methods, including correlation, linear regression, and Random Forest, which allow for a deeper understanding of the factors influencing stunting. The use of data from various districts and cities in Central Sulawesi also provides a more representative picture of stunting prevalence in this region and enriches the understanding of its geographical distribution. Additionally, the implementation of spatial analysis offers insights into spatial patterns of stunting, which is crucial for identifying high-prevalence areas that require intervention. However, this research has several limitations; one of them is the cross-sectional design, which does not allow for direct identification of cause-and-effect relationships, thus leaving an understanding of the underlying mechanisms of stunting limited. Moreover, the data used is restricted to certain variables, while other factors that may contribute to stunting, such as environmental conditions, children's dietary patterns, and the health status of mothers during pregnancy, have not been fully explored. Therefore, although the employed are quite comprehensive, there is potential for further research that includes additional variables and longitudinal study designs, which could more clearly unveil cause-and-effect relationships.

Recommendations for Future Research

Future research is recommended to adopt a longitudinal design to assess changes in stunting levels over time and identify the factors causing those changes. This design would provide a better understanding of the dynamics of the causal factors of stunting, including the impact of socioeconomic and environmental changes on stunting prevalence. Additionally, more in-depth studies should include other variables that may contribute to stunting, such as children's dietary patterns, environmental factors, and the nutritional quality of food consumed by mothers and children. Qualitative approaches are also essential to explore mothers' perceptions regarding factors influencing their decisions in meeting children's nutritional needs, as well as how social, cultural norms, and access to healthcare services affect family decisions in managing children's health. Research involving microbiological factors and more specific dietary patterns could enrich the understanding of the factors influencing nutritional status and stunting. Thus, a more holistic and multidisciplinary approach would offer comprehensive and deep insights in designing more effective interventions to address stunting.

Conclusion

This study highlights the significant influence of socioeconomic and environmental factors on the prevalence of stunting in Central Sulawesi, emphasizing that higher maternal education and reduced poverty rates are critical determinants for improving children's nutritional status. The correlation and regression analyses indicate that as maternal education and household income increase, stunting rates decline, thus affirming the vital role of education and economic conditions in stunting prevention. The random forest analysis further identifies poverty as the most influential predictor of stunting prevalence, suggesting that targeted interventions should focus on enhancing maternal education and addressing economic disparities. While access to clean water did not show a significant impact in this study, the findings underscore the need for comprehensive community-based approaches that integrate nutrition education, maternal and child healthcare services, and sanitation improvements, particularly in high-stunting areas. Overall, the evidence reinforces the importance of a holistic and multidimensional strategy in public health policies to effectively combat stunting and improve child health outcomes in Central Sulawesi.

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