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Moran's I Index and KKN-Based LISA

Spatial Analysis of Toddler Stunting in Indonesia 2024

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Abstract: Stunting in toddlers is a significant nutritional issue that may negatively impact the quality of Indonesia's future human resources. This study aims to analyze the spatial patterns of stunting prevalence in toddlers in Indonesia as a basis for developing region-based policy interventions. A quantitative approach was used through spatial autocorrelation analysis using Moran's I Index and Local Indicators of Spatial Autocorrelation (LISA), which is based on the K-Nearest Neighbors (KNN) method. Stunting prevalence data were obtained from 514 districts/cities in Indonesia and analyzed to detect clustering patterns in high-risk areas. The results showed a Moran's I of 0.315 (P-value <), indicating positive spatial autocorrelation among regions. Also, these results indicate that areas with high stunting prevalence tend to be geographically clustered, particularly in areas outside Java, such as Nusa Tenggara, Kalimantan, Sulawesi, and Papua. The results of this study emphasize the importance of a region-based approach to stunting management that accounts for spatial factors. High-high cluster areas are highly vulnerable to stunting, as indicated by low nutrition coverage, access to sanitation, and protein consumption, as well as high poverty rates. This situation highlights the importance of more focused and effective policy interventions that include improving nutrition, increasing access to food and sanitation, health education, and strengthening welfare and education aspects.

Keywords: Spatial Analysis; Moran's I Index; Policy Intervention; LISA; Stunting.

1. Introduction

Reducing stunting has become a top priority on the global health agenda and is part of six global nutrition targets set by World Health Organization (2014). Furthermore, stunting has been proposed as a key indicator in the post-2015 development agenda. In Indonesia, stunting in toddlers remains a crucial challenge to health development. Stunting results from inadequate nutritional intake during pregnancy and early childhood. Stunted children are at risk of not reaching their ideal height, and their brain development is also impaired, thus hindering their full cognitive potential. This condition can lead to difficulties in school, lower incomes as adults, and limitations in social participation (UNICEF et al., 2023).

The prevalence of stunting in Indonesia shows a downward trend. In line with the Sustainable Development Goals (SDGs), Indonesia is committed to eliminating all forms of malnutrition, including stunting, by 2030. Based on data from Kementerian Kesehatan RI (2024), the national stunting prevalence rate according to the 2024 National Nutritional Status Survey (SSGI) was recorded at 19.8 percent, down 1.7 percent from 21.5 percent in 2023. The government is targeting a reduction in stunting prevalence to 14.2 percent by 2029 through the 2025–2029 National Medium-Term Development Plan (RPJMN).

Addressing stunting requires a comprehensive, multisectoral approach. To effectively reduce stunting, interventions must span various sectors, including improving food and nutrition security, access to education, sanitation and environmental hygiene (WASH), health services, and poverty reduction (de Onis & Branca, 2016). Other factors that need attention to reduce stunting are not providing exclusive breastfeeding during the first six months, premature birth, short baby height, and the mother's height (Beal et al., 2018). The results of research conducted by Simamora et al. (2023) showed that the majority of respondents who experienced stunting had cognitive impairment. Therefore, stunting prevention is necessary, especially in children under 2 years of age, given the impacts that are difficult to reverse if the condition persists for a long time.

In addition to the mother's educational level, research by Atamou et al. (2023) found that maternal parenting patterns were significantly associated with stunting prevalence. Parenting patterns were the second-highest risk factor after maternal knowledge. This is because mothers play a key role in regulating children's diets based on household food availability. Mothers are the closest figures to children from an early age, so appropriate parenting patterns will help children develop into adults with healthy lifestyles.

On the other hand, the maternal mortality rate (MMR) in Indonesia is recorded at 189 per 100,000 live births. Despite a downward trend, this figure remains the highest among ASEAN countries (Kementerian Kesehatan RI, 2023). Therefore, nutritional interventions during pregnancy are very important, not only to reduce MMR and neonatal mortality, but also as part of a stunting prevention strategy (UNICEF et al., 2023).

Saputri and Tumangger (2019) stated that the obstacles to stunting reduction are diverse. From the government's perspective, challenges include suboptimal implementation of prevention programs, limited resources and budget allocation, and insufficient campaign intensity and advocacy on stunting. Meanwhile, at the individual level, particularly for mothers, there is still a low level of understanding about stunting and minimal involvement in integrated health service post (Posyandu) activities.

Nirmalasari (2020) also identified a number of factors contributing to stunting, including maternal age being too young (under 20) or too old (over 35), teenage pregnancy, and maternal height below standard. From a child development perspective, boys, children with a history of infectious diseases, and those who have not received immunizations tend to have a higher risk of stunting. Furthermore, environmental factors such as the use of untreated drinking water, high exposure to pesticides, and inadequate sanitation (such as the lack of adequate latrines) also contribute to the increased risk of stunting.

In general, stunting is influenced by multiple determinants, both directly and indirectly. Therefore, efforts to address stunting require a cross-sectoral, integrated, and region-specific approach. In this context, measuring and analyzing stunting spatially is a crucial element in planning targeted interventions, particularly in areas with high levels of vulnerability.

Stunting significantly impacts an individual's quality of life and potential for human resource development, both in the short and long term. Some of the serious impacts include an increased risk of morbidity and mortality in early childhood, impaired cognitive and intellectual development in adolescence, and an increased risk of non-communicable (degenerative) diseases in adulthood (Aryastami, 2017; Saputri & Tumangger, 2019; Sumartini, 2020; Widanti, 2016). The complexity of these impacts confirms that stunting is not only a health issue, but also a major challenge in the national development agenda.

The implementation of the accelerated stunting reduction program until 2024 provided valuable lessons, particularly regarding the effectiveness of multisectoral interventions, the strategic role of local governments, and the importance of integrating data into determining target groups. The Indonesian government's commitment to gradually reducing stunting prevalence is emphasized in the 2025–2045 National Long-Term Development Plan (RPJPN), with targets of reducing stunting rates to 14.4% by 2029 and to 5% by 2045. This target demonstrates the need for a more structured, focused, and evidence-based approach.

One relevant approach to supporting such policy formulation is to understand the spatial dimension of stunting prevalence. Spatial phenomena demonstrated in various studies indicate that stunting rates in a region tend to correlate with those in surrounding areas. This means that regions with high stunting prevalence tend to be geographically close to other regions with high stunting rates, and vice versa. Therefore, this study aims to identify whether there is spatial autocorrelation in the distribution of stunting prevalence in Indonesia in 2024, as a basis for more contextual and region-based policy decision-making. Therefore, this study aims to analyze the spatial autocorrelation of stunting prevalence among toddlers in Indonesia in 2024 using Moran's I Index and LISA approaches based on the K-Nearest Neighbors (KNN) algorithm, in order to identify clustering patterns of high-risk areas as a basis for contextual and region-based intervention policies. In addition, this study also analyzes the characteristics of regions that form stunting clusters in terms of nutrition, welfare, food security, sanitation, and education as a basis for formulating contextual and region-based policies.

2. Methods

This study uses a quantitative approach based on spatial analysis to map the distribution patterns of stunting prevalence in toddlers across Indonesia. The analytical method used is spatial autocorrelation analysis using the K-Nearest Neighbors (KNN) algorithm. Spatial autocorrelation analysis using the KNN approach is used to determine the Moran's I Index and the Local Indicator of Spatial Autocorrelation (LISA) values to map the distribution patterns of stunting prevalence in 2024 based on the proximity of districts/cities in Indonesia. This can serve as a basis for formulating more targeted, region-specific intervention policies.

The variables used in the analysis are the 2024 stunting prevalence rates for 514 districts/cities in Indonesia, sourced from the Directorate General of Regional Development, Ministry of Home Affairs. Several variables related to stunting are used to identify the characteristics of each cluster, as shown in Table 1.

Table 1. Research Variables

Aspect	Variable	Unit	Data Source
Nutrition	Babies under 6 months of age receive exclusive breast milk (ASI).	Percent	Directorate General of Regional Development, Ministry of Home Affairs
	Low birth weight (LBW) babies	Percent	Statistics Indonesia
Welfare	Percentage of poor population	Percent	Statistics Indonesia
	Monthly Per Capita Expenditures on Food	Percent	Statistics Indonesia
Food security	Average Protein Consumption per Capita	Grams/Day	National Food Agency
Sanitation	Households with Access to Adequate Sanitation	Percent	Statistics Indonesia
Education	Average Years of Schooling (RLS)	Year	Statistics Indonesia

2.1. Spatial Autocorrelation

In spatial analysis, geographically dispersed observations are generally not statistically independent. Observations that are geographically close together tend to have similar values compared to observations that are far apart, a pattern commonly referred to as spatial autocorrelation (Bivand et al., 2008). The presence of spatial autocorrelation in data means that it is not enough to just look at the value of a variable at one point, but it is necessary to consider the geographical context and the relationship between regions.

2.2. K-Nearest Neighbors Algorithm (KNN)

Classification is the process of constructing a model or function that is able to differentiate certain classes of data or concepts in order to predict the class of an object whose label is not yet known (Khan et al., 2002). One of the statistical methods widely used in classification is the k-nearest neighbors (KNN) algorithm. KNN searches for the k-nearest neighbors of data in space using a specific similarity or distance function.

In a spatial context, the KNN algorithm uses the nearest geographic neighbors to predict the class within a given region. Geographic proximity has significant predictive value because a region can act as a spatial indicator of class distribution, making this approach particularly relevant when data exhibits a high degree of positive spatial autocorrelation.

Considering Indonesia's geographical conditions, this analysis does not use the queen contiguity spatial weighting matrix in calculating the Moran Index but instead uses the KNN algorithm. Because the queen contiguity spatial weighting matrix relies on the physical boundaries of adjacent regions, it is less relevant for an archipelagic region like Indonesia. The use of the KNN algorithm is deemed appropriate for identifying spatial relationships, even though the regions do not directly border each other, by determining neighbors based on the geographic distance between the centroids of each region.

Khan et al. (2002) explain that one of the commonly used similarity functions is the Euclidean distance between two data tuples or one row of data in a multidimensional vector, which is used in calculating the distance or similarity between data. Suppose there are two tuples $X = (x_1, x_2, ..., x_{n-1})$ and $Y = (y_1, y_2, ..., y_{n-1})$, then the Euclidean distance is defined as follows.

$$d_2(X, Y) = \sqrt{\sum_{i=1}^{n-1} (x_i - y_i)^2} \tag{1}$$

This Euclidean function is a special case of the Minkowski similarity function, which is generally written as follows.

$$d_q(X, Y) = \left(\sum_{i=1}^{n-1} w_i |x_i - y_i|^q\right)^{1/q} \tag{2}$$

With q as the rank level parameter and w_i as the weight of each dimension. If $q = 1$, then the Manhattan distance is obtained as follows.

$$d_1(X, Y) = \sum_{i=1}^{n-1} |x_i - y_i| \tag{3}$$

And if $q \to \infty$, then the maximum distance function is obtained as follows.

$$d_\infty(X, Y) = {}_i^{max} |x_i - y_i| \tag{4}$$

The k value must be determined beforehand. Using a k value that is too large risks including samples that are not very similar, while using a k value that is too small can result in important samples being overlooked. The optimal k value depends largely on the characteristics and size of the data, with common values being 3, 5, or 7.

2.3. Moran's I Index

The Moran's I index is a method for measuring whether the values of a variable tend to be similar or different in adjacent regions. Moran's I value is calculated by comparing the extent to which a variable in a region correlates with the average value of the variable in the surrounding regions (spatial lag), then adjusting for a spatial weight that indicates the strength of the relationship between the regions (Bivand et al., 2008).

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{5}$$

Where y_i is the value of the i-th observation, $\bar{y}$ is the average of the observed variables, and w_{ij} is a spatial weight that represents the relationship between the i-th and j-th regions.

The expected value or expectation (E(I)) is obtained using the following formula.

$$E(I) = -\frac{1}{(n-1)} \tag{6}$$

The Moran's I Index ranges from -1 to +1, with values approaching -1 indicating strong negative spatial autocorrelation, while values approaching +1 indicate strong positive spatial autocorrelation. Values approaching 0 indicate the absence of a spatial pattern or a spatially random distribution (Wen et al., 2010).

Moran's I Index Test with the following hypothesis.

H_0 : I = E(I) (There is no spatial autocorrelation)

H_1 : I > E(I) (There is spatial autocorrelation)

Testing the Moran's I Index obtained a decision to reject H_0 if the Pvalue < α = 0,05.

2.4. Local Indicator of Spatial Association (LISA)

According to Anselin (1995), Local Indicator of Spatial Association (LISA) is a local spatial statistic designed to identify local clustering patterns or outliers in spatial data. LISA is used to identify local spatial patterns, both as clusters and outliers, by considering the contribution of each observation to the global indicator.

Mathematically, LISA for a region i is formulated as $L_i = f(y_i, yJ_i)$, where y_i is the value in region i and yJ_i are the values in neighboring areas J_i.

Through the LISA test, spatial characteristics in small areas are revealed and it is tested whether these patterns are statistically significant or just occur randomly.

3. Results and Discussion

Based on data from the Directorate General of Regional Development of the Ministry of Home Affairs, more than half of the total regencies/cities in Indonesia had stunting prevalence rates higher than the national rate (6.1%) in 2024. The highest stunting prevalence rate on the island of Sumatra was in West Nias Regency (North Sumatra Province) at 22.3%, while the lowest was in Medan City and Binjai City (North Sumatra Province) at 0.2%. On the island of Java, the highest prevalence rate was 17.3% in Banjarnegara Regency (Central Java Province). In comparison, the lowest was 0.7% in East Jakarta City (Jakarta Province) and Surabaya City (East Java Province). Turning to the islands of Nusa Tenggara and Bali, the highest stunting prevalence rate was in Southwest Sumba Regency (NTT Province) at 28.6%, and the lowest in Denpasar City (Bali Province) at 0.6%. Meanwhile, on the island of Kalimantan, the highest stunting prevalence rate is in Berau Regency (East Kalimantan Province) at 33.7%, and the lowest is in Ketapang Regency (West Kalimantan) at 1.6%. Majene Regency (West Sulawesi Province) has the highest prevalence rate on the island of Sulawesi at 34.4%. In comparison, Siau Tagulandang Biaro and Bolaang Mongondow Regencies (North Sulawesi Province) have the lowest

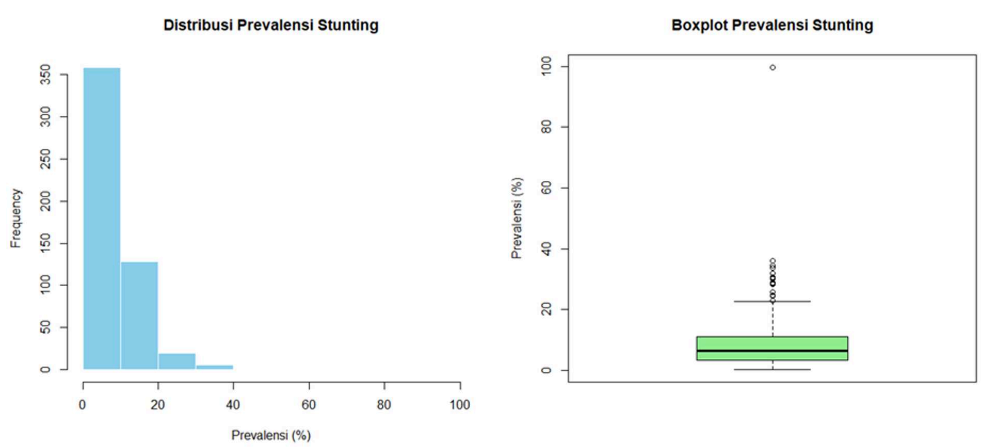

Figure 1. Overview of Stunting Prevalence in Indonesia in 2024 Based on Histogram and Boxplot Visualization

prevalence rate at 0.4%. Finally, on the islands of Maluku and Papua, Deiyai Regency (Central Papua Province) has the highest prevalence rate (99.7%), and Nduga Regency (Papua Mountains Province) has the lowest stunting prevalence rate at 0.5%.

The distribution of stunting prevalence in Indonesia in 2024, as shown in a histogram, is right-skewed. This means that the majority of data is concentrated on the left side, indicating that stunting prevalence in districts/cities is relatively low to moderate (ranging from 0% to 15%). Several districts/cities have stunting prevalence above 20%, which is also indicated by the boxplot graph through outlier points, such as Polewali Mandar Regency (21.9%), North Central Timor Regency (22.6%), Kapuas Hulu Regency (30.0%), and the most distant outlier, Deiyai Regency (99.7%). The large number of outliers indicates disparities in stunting prevalence across districts/cities in Indonesia. While most districts/cities are in the low range, a small number have very high stunting prevalence.

The prevalence value of 99.7% in Deiyai Regency is statistically far outside the distribution range of most regions and can be categorized as an extreme outlier. In the context of administrative data, very high values may be influenced by variations in reporting quality across regions, limited recording coverage, and possible entry errors in the reporting system. Nevertheless, these data were retained in the analysis to maintain consistency with the official sources used. Therefore, interpretation of the analysis results, particularly in regions with extreme values, should be carried out with caution, given the possibility of administrative bias.

Having identified disparities in stunting prevalence across districts/cities in Indonesia, it is necessary to determine whether the distribution of stunting prevalence follows a random pattern or is clustered based on geographic proximity. Therefore, a spatial autocorrelation analysis was conducted to determine whether there is a relationship/link between stunting prevalence based on geographic location in 514 districts/cities in Indonesia using the K-Nearest Neighbors (KNN) approach. This approach is particularly useful in a geographic context like Indonesia, an archipelagic country where many regions are physically separated but remain spatially adjacent due to geographic proximity.

The following are the results of spatial autocorrelation analysis using Moran's I index and the Local Indicator of Spatial Autocorrelation (LISA).

Table 2. Moran Index Test Results

Moran's Index (I)	Expectation (E(I))	Pvalue
0.315	-0.002	< 0.001

Based on Table 2, the Moran index value for stunting prevalence in districts/cities in Indonesia is 0.315, which is greater than the expected value of -0.002 (I > E(I)). This value reflects moderate positive spatial autocorrelation, meaning that the prevalence of stunting in toddlers in districts/cities in Indonesia has a clustering pattern. Districts/cities with high stunting prevalence tend to be close to those with high prevalence, and those with low prevalence tend to be close to those with low prevalence. This can be proven statistically through a significance test on Moran's I index with the following hypothesis.

Hypothesis:

H_0 : There is no spatial autocorrelation or no relationship between the prevalence of stunting in toddlers in one district/city and other districts/cities that are located nearby)

H_1 : There is spatial autocorrelation or there is a relationship between the prevalence of stunting in toddlers in one district/city with other districts/cities that are located nearby.

Rejection Area: Reject H_0 if Pvalue < $\alpha = 0.05$

The test results showed a P-value of <0.001, which is smaller than the significance level $\alpha = 0.05$, so H_0 was rejected, indicating the test results are statistically significant. Therefore, it can be concluded that there is spatial autocorrelation between the prevalence of stunting in toddlers in one district/city and other districts/cities in Indonesia that are geographically close.

To identify local cluster patterns, the analysis continued using Moran's scatterplot and mapping based on the Local Indicators of Spatial Association (LISA) significance test. The LISA map was constructed using a K-Nearest Neighbor (KNN)-based spatial weight matrix with k = 6. The selection of this number of neighbors was based on spatial connectivity and the stability of local autocorrelation estimates. In initial testing with k = 4, the resulting weight structure did not fully produce an optimally connected network, resulting in less stable cluster patterns. Therefore, k = 6 was chosen to ensure each district/city has an adequate number of neighbors and to form a more connected spatial weights matrix, thus more robustly representing spatial interactions between regions without obscuring local variations.

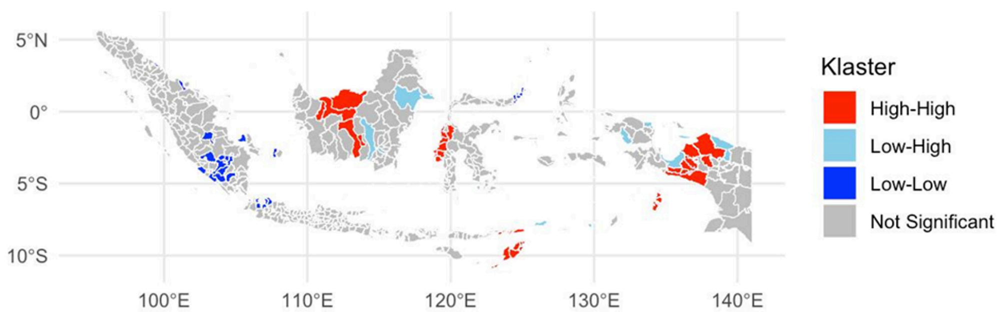

Figure 2. Hotspot Areas for Stunting Prevalence in Indonesia in 2024

The LISA (KNN) cluster map in Figure 2 shows a significant spatial autocorrelation pattern in certain regions, where the analysis results only identified three cluster types: High-High, Low-High, and Low-Low, while the High-Low quadrant did not appear in the test results. There are 32 regencies/cities in Indonesia that have a high stunting prevalence and are surrounded by areas with a high stunting prevalence (High-High), 12 districts/cities in Indonesia that have a low stunting prevalence but are surrounded by areas with a high stunting prevalence (Low-High), and 39 districts/cities in Indonesia that have a low stunting prevalence and are surrounded by areas with a low stunting prevalence (Low-Low). These findings indicate the existence of spatial clustering of stunting prevalence in Indonesia, making areas in the High-High cluster a top priority for stunting reduction interventions.

3.1. Regencies/Cities within High-High Cluster

The distribution of the High-High cluster shows a concentration of districts/cities with a high prevalence of stunting, predominantly in eastern Indonesia, particularly in East Nusa Tenggara, Papua, and Central Papua, and West Sulawesi. Districts/cities within this cluster are generally geographically close to each other and form a clear regional pattern, while a small number are spread across Kalimantan and Maluku, as shown in Table 3.

This clustering pattern is reflected in the 2024 stunting prevalence data by district/city sourced by the Directorate General of Regional Development, Ministry of

Table 3. List of Regencies/Cities With High-High Stunting Prevalence Clusters in Indonesia

No.	Regencies/Cities	Province	No.	Regencies/Cities	Province
1	Kapuas Hulu	West Kalimantan	17	Kota Kupang	East Nusa Tenggara
2	Sekadau	West Kalimantan	18	Kupang	East Nusa Tenggara
3	Sintang	West Kalimantan	19	Lembata	East Nusa Tenggara
4	Katingan	Central Kalimantan	20	Malaka	East Nusa Tenggara
5	Palangkaraya City	Central Kalimantan	21	Rote Ndao	East Nusa Tenggara
6	Sigi	Central Sulawesi	22	Timor Tengah Selatan	East Nusa Tenggara
7	Central Buton	Southeast Sulawesi	23	Timor Tengah Utara	East Nusa Tenggara
8	Wakatobi	Southeast Sulawesi	24	Kepulauan Aru	Maluku
9	Majene	West Sulawesi	25	Deiyai	Central Papua
10	Mamasa	West Sulawesi	26	Dogiyai	Central Papua
11	Mamuju	West Sulawesi	27	Intan Jaya	Central Papua
12	Central Mamuju	West Sulawesi	28	Mimika	Central Papua
13	Pasangkayu	West Sulawesi	29	Paniai	Central Papua
14	Polewali Mandar	West Sulawesi	30	Puncak Jaya	Central Papua
15	Alor	East Nusa Tenggara	31	Mamberamo Raya	Papua
16	Belu	East Nusa Tenggara	32	Waropen	Papua

Home Affairs. Central Papua recorded the highest average stunting prevalence at 28.53%, followed by West Sulawesi at 23.43% and East Nusa Tenggara at 13.54%. The relatively higher average prevalence in these regions compared to most other provinces indicates a concentration of stunting problems in Eastern Indonesia.

This finding is in line with the results of the 2024 Indonesian Nutritional Status Survey (SSGI), which showed a spatial clustering of higher stunting prevalence in Eastern Indonesia, and is consistent with the results of spatial modeling using the Bayesian spatial Conditional Autoregressive (CAR) approach, which identified Eastern Indonesia as the region with the highest stunting risk nationally. A study conducted by Azis and Aswi (2023) also shows that approximately 56% of provinces in Indonesia are at high risk of stunting, with West Sulawesi, East Nusa Tenggara, and West Papua having the highest relative risk (RR) values. The convergence of findings from several sources and approaches indicates that stunting problems in Eastern Indonesia are spatially clustered and influenced by interconnected regional conditions, thus requiring an integrated and cross-regional approach.

3.2. Regencies/Cities within Low-High Cluster

The Low-High Cluster consists of regencies/cities with relatively low stunting prevalence, surrounded by areas with higher prevalence. Districts/cities in this cluster are spread across several regions in Indonesia, with the largest concentrations in Papua and West Papua, as well as parts of Sulawesi and Kalimantan, as shown in Table 4. Based on regencies/cities stunting prevalence data for 2024, districts in this cluster performed better than their surrounding areas but remain within a regional context with relatively high stunting rates.

Table 4. List of Regencies/Cities With Low-High Stunting Prevalence Clusters in Indonesia

No.	Regencies/Cities	Province	No.	Regencies/Cities	Province
1	South Hulu River	South Kalimantan	7	Yapen Islands	Papua
2	Kapuas	Central Kalimantan	8	Sarmi	Papua
3	East Kutai	East Kalimantan	9	Manokwari	West Papua
4	Palu City	Central Sulawesi	10	Sorong City	Southwest Papua
5	Bau Bau City	Southeast Sulawesi	11	South Sorong	Southwest Papua
6	Southwest Maluku	Maluku			

The spatial pattern of stunting prevalence in districts/cities within the Low-High cluster cannot be separated from the conditions of the surrounding areas. These regencies/cities are located within a regional environment with a relatively higher stunting prevalence, thus reflecting spatial disparities between adjacent regions. In this context, Low-High regions can be understood as transition areas that are relatively better off than their surrounding areas, likely supported by better access to services and infrastructure, but still face potential regional pressures (spillover effects) from areas with a high stunting prevalence. Therefore, even though they are not areas with a high stunting prevalence, regencies/cities within the Low-High cluster still require ongoing prevention efforts to maintain existing achievements.

3.3. Regencies/Cities within Low-Low Cluster

Regencies/cities included in the low-low cluster have low stunting prevalence and are surrounded by areas with similarly low stunting prevalence. This cluster is concentrated in the provinces of South Sumatra, Jakarta, and North Sulawesi. Regencies/cities in this cluster generally share similar proximity-based intervention programs for addressing or reducing stunting prevalence.

Table 5. List of Regencies/Cities With Low-Low Stunting Prevalence Clusters in Indonesia

No.	Regencies/Cities	Province
1	West Bangka	Bangka Belitung Islands
2	Batanghari	Jambi
3	Batu Bara	North Sumatra
4	Bekasi	West Java
5	Belitung	Bangka Belitung Islands
6	Bogor	West Java
7	East Bolaang Mongondow	North Sulawesi
8	Karawang	West Java
9	Kaur	Bengkulu
10	Siau Tagulandang Biaro Islands	North Sulawesi
11	Sangihe Islands	North Sulawesi
12	West Jakarta Administrative City	DKI Jakarta
13	Administrative City of Central Jakarta	DKI Jakarta
14	Administrative City of South Jakarta	DKI Jakarta
15	City Administration of North Jakarta	DKI Jakarta
16	Bekasi City	West Java
17	Bitung City	North Sulawesi
18	Bogor City	West Java
19	Depok City	West Java
20	Dumai City	Riau
21	Kotamobagu City	North Sulawesi
22	Manado City	North Sulawesi
23	Palembang City	South Sumatra
24	Prabumulih City	South Sumatra
25	Tangerang City	Banten
26	Tomohon City	North Sulawesi
27	Minahasa	North Sulawesi
28	South Minahasa	North Sulawesi
29	Southeast Minahasa	North Sulawesi
30	North Minahasa	North Sulawesi
31	Muara Enim	South Sumatra
32	Musi Rawas	South Sumatra
33	Ogan Ilir	South Sumatra
34	Ogan Komering Ulu	South Sumatra
35	South Ogan Komering Ulu	South Sumatra
36	Penukal Abab Lematang Ilir	South Sumatra
37	Seluma	Bengkulu
38	Tangerang	Banten
39	Way Kanan	Lampung

Based on stunting prevalence data at the district/city level in 2024 from the Directorate General of Regional Development of the Ministry of Home Affairs, a pattern of clustering of regions with positive achievements was observed, with the lowest average prevalence of 1.30% in districts/cities in North Sulawesi, followed by South Sumatra (1.75%) and DKI Jakarta (2.02%). The low-low cluster formed in the South Sumatra region, including the cities of Palembang, Prabumulih, and the OKU region and its surroundings is scientifically supported by findings of the geographical characteristics of the region using multivariate analysis with the Prevalence Ratio

(PR) association measure, that the majority of these districts/cities have swamp areas that significantly have a stunting risk that is not higher than swamp areas after controlling for other variables (Sadiq et al., 2023).

Areas with a relatively low average prevalence can be used as a benchmark or good example for other areas, for example, the average prevalence of stunting in the DKI Jakarta area (2.02%) is an implementation of the Equality Strategy approach reviewed in the study by Taufiqurokhman (2023), namely through the effectiveness of regulations, the Foster Parents for Stunting Children (BAAS) program and cross-sector collaboration carried out by the DKI Jakarta Provincial Government so that there is an even distribution of interventions in administrative areas.

3.4. Regional Characteristics Based on Cluster Results in Each Aspect

Intervention steps to reduce the prevalence of stunting in Indonesia based on the characteristics of regional groups can be reviewed from several variables related to stunting in each aspect, namely the nutritional aspect, welfare aspect, food security aspect, sanitation aspect and education aspect.

3.4.1. Nutritional Aspects

Exclusive breastfeeding and low birth weight (LBW) are two factors related to infant nutrition from birth. Nutritional interventions from pregnancy through early childhood, including nutritional support and strengthening integrated health post (Posyandu) services, contribute significantly to the reduction in stunting (Arieffiani & Ekowanti, 2024). Babies born with low birth weight are often more susceptible to growth problems due to limited nutritional reserves. Exclusive breastfeeding is crucial to help meet the baby's nutritional needs, especially for babies with low birth weight (LBW). If babies do not receive adequate nutrition in early life, the risk of stunting increases.

(1) Babies under 6 months of age receive exclusive breastfeeding

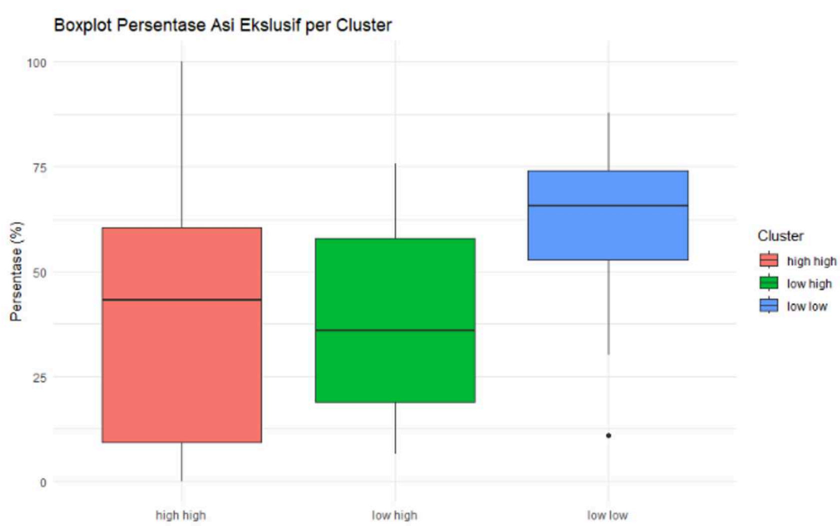

Figure 3. Boxplot of Percentage of Babies Receiving Exclusive Breastfeeding

Figure 3 shows a boxplot of the distribution of the percentage of infants under 6 months of age who are exclusively breastfed. The low-low group had the highest median exclusive breastfeeding coverage, at 65.7 percent, with a data distribution ranging from 10.8 percent to 87.9 percent. This means that in areas with a relatively low risk of stunting, exclusive breastfeeding practices are relatively good. Conversely, the high-high group, which has the highest risk of stunting, only had a median exclusive breastfeeding coverage of 43.2 percent. The distribution of values is quite wide, ranging from 0% to 100%, indicating that there are still areas with very low coverage. The low-high group had the lowest median, at 36 percent, with coverage ranging from 6.4 percent to 75.8 percent.

(2) *Low Birth Weight (LBW) Babies*

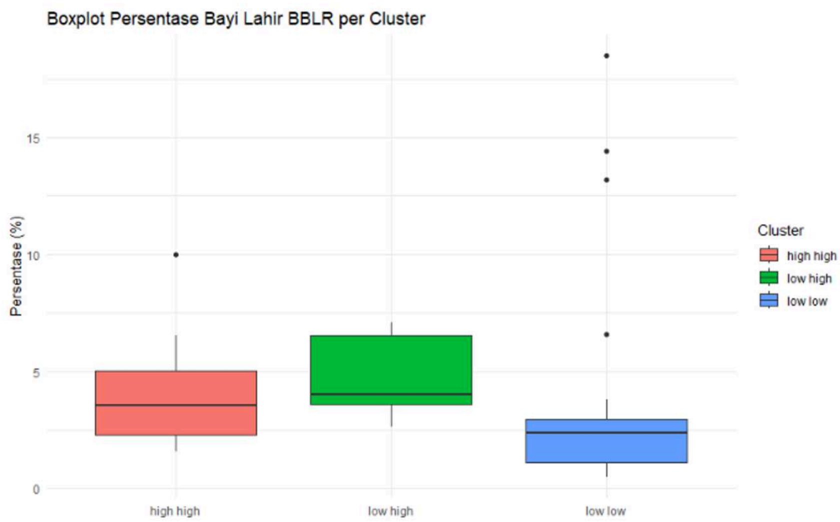

Figure 4. Boxplot of Percentage of LBW

Low birth weight (LBW) is a significant risk factor for growth disorders, including stunting. Figure 4 shows a boxplot of the distribution of LBW infants per cluster. The low-low group had the lowest mean and median LBW percentages, at 3.55 and 2.36 percent, respectively, with a minimum value of 0.49 percent and a maximum of 18.5 percent. Despite the low mean, the distribution of values is quite large, indicating regional disparities within this cluster. The high-high group had a mean LBW of 4.27 percent and a median of 3.56 percent, with a narrower distribution (1.57-10 percent). This indicates that although this cluster has a high risk of stunting, the proportion of LBW tends to be in the moderate range. Meanwhile, the low-high group had the highest average LBW rate, at 4.77 percent, although the range was relatively narrow (2.64 to 7.1 percent) and the median was lower (3.56 percent) than in the low-high group. This suggests that in some moderately affected areas, there are still challenges in preventing low birth weight babies.

3.4.2. Welfare Aspects

In terms of welfare, the characteristics of each regional group can be identified from the variables of poverty levels and per capita expenditure on food.

(1) *Percentage of Poor Population*

Poverty has a direct impact on infant nutritional deficiencies due to limited access to nutritious food and healthcare. Women who experience stunting during childhood are at risk of giving birth to children who also suffer from stunting, thus contributing to an intergenerational cycle of poverty (de Onis & Branca, 2016). Poor families tend to have low nutritional knowledge, often leading to inappropriate infant feeding practices, which can lead to stunting in

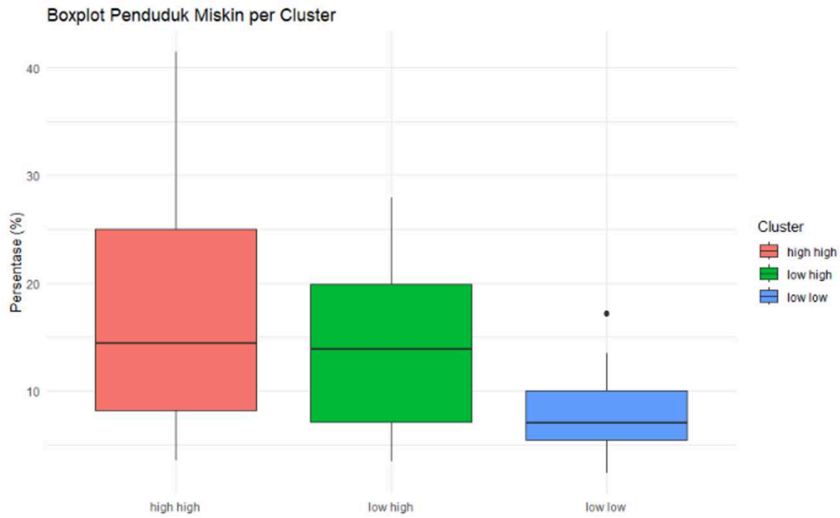

Figure 5. Boxplot of Percentage of Poor Population

toddlers. This is demonstrated by the comparison of the boxplot of the percentage of the poor population in Figure 5 across regional groups.

It is known that high-high stunting areas tend to have higher poverty rates than other areas. In the high-high area group, the median value and data distribution appear wider, indicating that poverty variation in poverty within this group is quite large, suggesting the presence of areas with extreme poverty levels. Meanwhile, the low-low area group shows lower poverty rates that are relatively homogeneous. The most severe poverty conditions in areas with high stunting and surrounded by areas with high stunting, such as districts/cities in Kalimantan, Nusa Tenggara, Sulawesi, and Papua, must be a top priority for accelerating poverty alleviation through concrete interventions to achieve the stunting reduction target.

(2) *Percentage of Per Capita Expenditure on Food*

Monthly per capita food expenditure is often used as an indirect indicator of a household's ability to meet nutritional needs, including those of toddlers. Households with a high percentage of food expenditure may allocate more funds to meet their food needs. Still, this indicator does not directly reflect the quality or adequacy of the nutrients they consume.

Figure 6, a boxplot comparing per capita food expenditure across regional groups, shows that the high-high region group has higher median and average expenditure than the other groups. However, the high expenditure in the high-high region group, which is mostly located in eastern Indonesia, is geographically relatively remote. These regions have limited distribution infrastructure, and high transportation costs can make staple food prices higher than in other regions. Therefore, the high food expenditure in these regions may reflect high prices and the cost of living, rather than solely increase in the quantity or quality of food consumption.

Furthermore, the significant variation in expenditure distribution within the high-high group indicates heterogeneity in household economic capacity. In low-income households, the proportion of food expenditure tends to be high because the majority of income is used to meet basic needs, limiting the amount of non-food expenditures that support quality of life. This condition

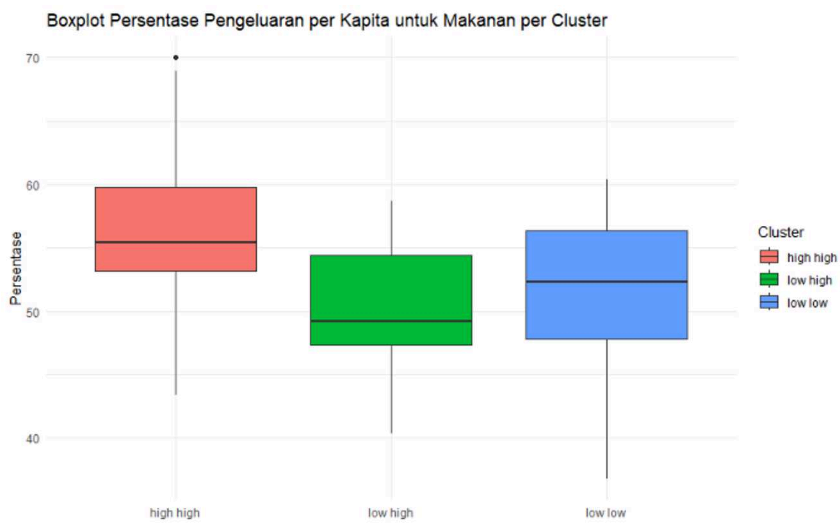

Figure 6. Boxplot of Percentage of Food Expenditure

can contribute to the persistence of stunting, despite relatively high nominal food expenditures.

In the low-high region group, the lower median and expenditure distribution indicate relatively consistent, limited purchasing power in regions with low stunting prevalence but surrounded by high-stunting areas. Meanwhile, the low-low group shows a slightly higher median expenditure than the low-high group, which may reflect relatively more stable economic conditions.

Overall, high per capita food expenditure does not automatically reflect the adequacy and quality of nutritional intake, as variations in price levels across regions also influence these indicators. Therefore, formulating policies to reduce stunting needs to consider not only the amount of food expenditure, but also aspects of affordability, access to food distribution, and the quality of nutritional consumption of toddlers.

3.4.3. Food Security Aspects

Food security is directly related to the availability and affordability of nutritious food at the household level. Consistent with the findings of the Productivity Safety Net Program (PSNP) study in Ethiopia, food security is a key factor in child development (Bahru et al., 2020). One important indicator of food security is protein consumption. If families have adequate access to protein sources, especially animal protein, children's nutritional needs will be more easily met. Conversely, low protein consumption can reflect weak food security, which ultimately impacts growth and the risk of stunting in children.

(1) Average protein consumption per capita

Descriptive analysis can be performed by comparing the boxplots between groups, as illustrated in Figure 7. This shows that per capita protein consumption differs across clusters. The low-low group had the highest average protein consumption, at 65.9 grams per day, with a median of 63.6 grams and a range of 55-97.9 grams per day. This indicates that areas with a low risk of stunting tend to have better protein consumption patterns. The low-high group had an average of 57.5 grams per day and a median of 59.8 grams, with a range of 40.5 to 71.7 grams. Meanwhile, the high-high group, with the

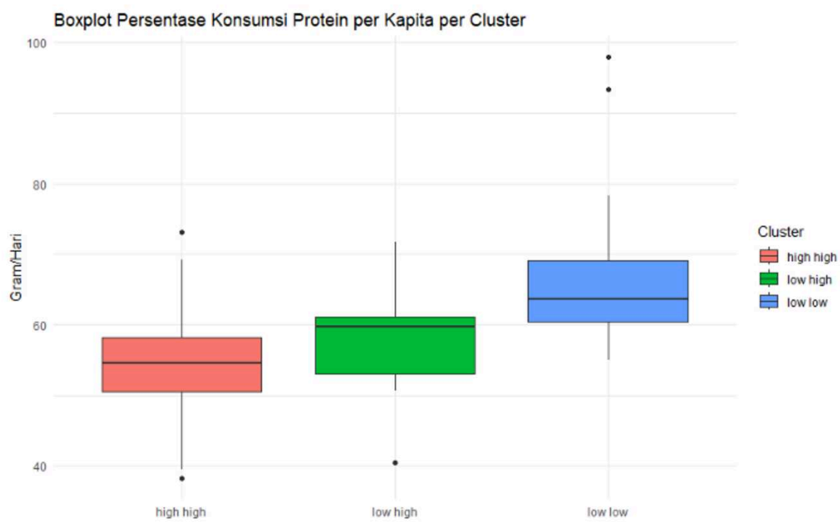

Figure 7. Boxplot of Average Protein Consumption per Capita

highest risk of stunting, had the lowest average protein consumption, at 54.2 grams per day, with a median of 54.6 grams and a range of 38.3 to 73.1 grams.

3.4.4. Sanitation Aspects

Sanitation plays a significant role in stunting, as inadequate sanitation increases the risk of infection, which can hinder the absorption of essential nutrients in toddlers. Access to inadequate sanitation facilities increases the risk of stunting due to repeated exposure to infections and other health problems (Fenske et al., 2013). Findings related to sanitation are as follows.

(1) Households with access to adequate sanitation

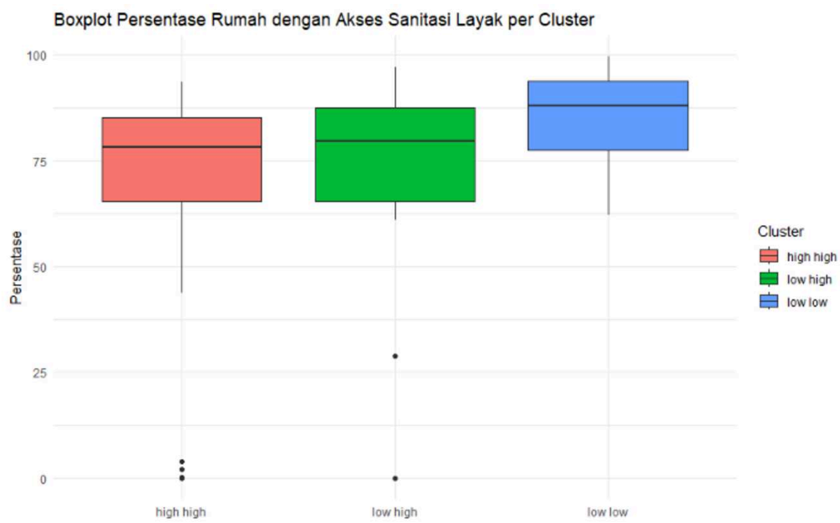

Figure 8. Boxplot of the Percentage of Households With Access to Adequate Sanitation

Figure 8 shows that the highest average number of households with access to adequate sanitation is in the low-low category, indicating areas with low stunting rates surrounded by areas with low stunting prevalence. This suggests that areas with good nutritional conditions also have better and more equitable access to sanitation.

3.4.5. Educational Aspects

Improving parental education, particularly maternal education, significantly contributes to child growth and in reducing stunting prevalence. This is due to its association with increased nutritional knowledge, improved childcare practices, greater utilization of maternal and child health services, and the adoption of clean, healthy lifestyles (Brar et al., 2020). In terms of education, the characteristics of each regional group can be identified from the average years of schooling of its population. A person's educational level, as measured by years of schooling, particularly maternal education, is a significant factor influencing the risk of stunting in toddlers.

(1) Average length of schooling

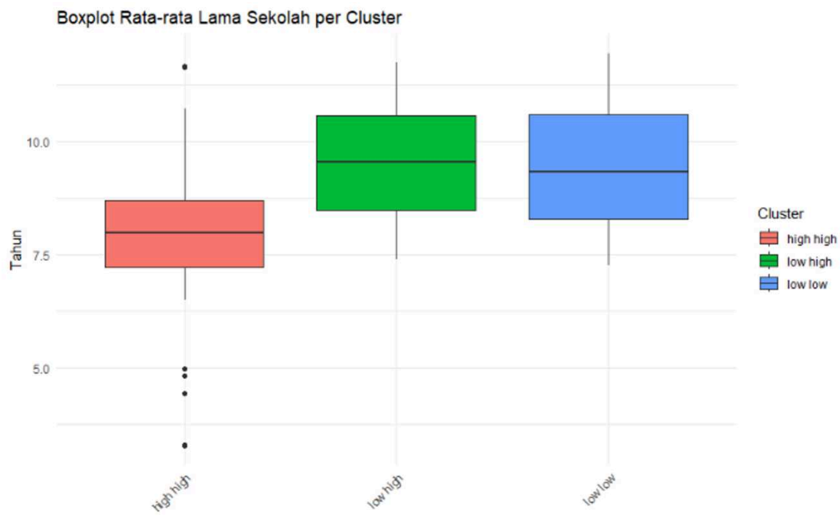

Figure 9. Boxplot of Average Years of Schooling

The average length of schooling in Figure 9 shows the highest average in the high-high category, indicating that areas with high stunting prevalence surround areas with low stunting rates. However, this distribution differs slightly from the low-low category, where areas with low prevalence surround areas with low stunting rates. Meanwhile, the lowest average length of schooling (8 years) and the most extreme value is in the high-high category, where areas with high stunting rates surround areas with high stunting rates. This suggests that low levels of education can influence the high prevalence of stunting.

4. Conclusion and Recommendations

4.1. Conclusion

A spatial analysis of stunting prevalence in Indonesia in 2024 revealed a significant positive spatial autocorrelation pattern between districts/cities. This finding indicates that areas with high stunting prevalence tend to be geographically close to other areas with high stunting rates. Based on the Local Indicators of Spatial Autocorrelation (LISA) analysis, 32 districts/cities were identified as falling into the "high-high" cluster category, meaning areas with high stunting prevalence are surrounded by similarly high prevalence. This cluster spans several key geographic regions, particularly in areas outside Java, including Kalimantan, Nusa Tenggara, Sulawesi, and Papua.

This situation indicates a significant spatial concentration of stunting in Indonesia. This underscores the importance of implementing place-based policy strategies that respond to specific local and spatial characteristics. This approach is believed to be more effective because it considers the unique geographic, social, and economic contexts of each region, thereby increasing the efficiency and accuracy of interventions in reducing stunting prevalence.

Areas in the high-high cluster are highly vulnerable to stunting, characterized by low exclusive breastfeeding coverage, low protein consumption, low sanitation access, and high poverty rates. Although food expenditures in these areas are relatively high, this does not guarantee the quality of nutritional intake.

4.2. Recommendations

Based on the conclusions, policy recommendations for stunting reduction in Indonesia need to be directed towards a region-based approach. First, the central government needs to prioritize the high-high cluster when determining intervention loci. Furthermore, cross-ministerial/institutional policy integration is needed, simultaneously targeting improvements in nutritional status, economic welfare, food security, sanitation, and education.

Based on the conclusions, policy recommendations for stunting reduction in Indonesia need to be directed towards a region-based approach. First, the central government needs to prioritize the high-high cluster when determining intervention loci. Furthermore, cross-ministerial/institutional policy integration is needed, simultaneously targeting improvements in nutritional status, economic welfare, food security, sanitation, and education.

Second, at the local government level, particularly in high-high districts/cities, cross-sectoral coordination is needed in the planning and implementation of stunting reduction programs. Specific and sensitive nutrition interventions need to be tailored to local conditions by increasing exclusive breastfeeding coverage, increasing protein intake, expanding access to proper sanitation, and strengthening social protection for poor households.

Third, village governments in high-high areas need to allocate village funds to support stunting reduction interventions, including improving access to proper sanitation, strengthening household food security, providing assistance to families at risk of stunting, and strengthening the role of integrated health post (Posyandu) cadres and family support teams.

Fourth, the private sector needs to be involved through corporate social responsibility programs, prioritizing stunting management in high-high cluster areas. The role of the private sector can be focused on supporting financing and providing supporting facilities for interventions in nutrition, sanitation, maternal and child health, as well as strengthening community health cadres and workers.

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