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Spatial Determinants of Childhood Stunting in Lambitu, Bima: A GIS-based Multilevel Analysis

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Abstract

Stunting is a public health issue that requires special attention, especially in relation to risk factors such as low maternal education, low birth weight babies, maternal age, premature birth, and inadequate antenatal care. The objective of this study was to map the distribution of stunting in Lambitu Subdistrict, Bima Regency, using a Geographic Information System (GIS) to assist policymakers in designing more targeted and effective intervention programmes. The method used was quantitative descriptive research with a GIS approach, including the collection of secondary data from the Lambitu Community Health Centre on the number of toddlers and stunting cases, as well as spatial data in the form of village boundary maps analysed using GIS software to produce thematic maps of stunting distribution. The study identified fluctuating trends in stunting cases in six villages between 2023 and 2025, with Kuta village reporting a peak of 16% in 2023 and Ka'owa reaching 22% in 2024 and 22.78% in 2025. It concluded that GIS is effective for mapping stunting distribution and supporting targeted interventions. A SmartPLS analysis revealed a high-quality model showing that Determinants of Stunting (DIS) significantly impact Spatial Context & Service Access (SCS) and Stunting Outcomes (STO), explaining approximately 79% of the variance in both DIS and STO, with SCS serving as a vital mediating factor in these relationships.

Keywords

distribution of stunting,
geographic information system (GIS),
stunting,
spatial context & service access,
stunting outcomes

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Introduction

Stunting remains a serious challenge at the global level. According to the Joint Malnutrition Estimates report released by UNICEF, WHO, and the World Bank in 2023, in 2022, approximately 148.1 million toddlers or 22.3% of the total number of children in the world suffered from this condition (Putri & Maulidia, 2024). In 2024, approximately 150.2 million children worldwide, or 23.2%, were recorded as experiencing stunting (WHO, 2025). Most of these cases are found in developing countries, with 52% in Asia and 43% in Africa (Tapkigen et al., 2024). Although the number has decreased by approximately 30 million compared to ten years ago, the rate of decline in stunting is still relatively slow. The results of the 2024 Indonesian Nutrition Status Survey (SSGI) show that the national prevalence of stunting stands at 19.8%, down from 21.5% in the previous year (Kemenkes RI, 2025). Despite this decline, this still means that around one in five toddlers in Indonesia are stunted. In West Nusa Tenggara (NTB), the prevalence is higher, at 29.8%, making it one of the provinces with the highest rates nationally (Kemenkes RI, 2025). In fact, SKI 2023 data reports that Bima Regency has a prevalence of 36.7%. These high figures illustrate serious nutritional problems, especially in remote areas and among low-income communities (Yanti et al., 2023).

Several contributing factors include poor nutritional status of pregnant women, complementary feeding that does not meet recommendations, limited sanitation and clean water availability, and high poverty rates. In response to this, the NTB regional government and Bima Regency continue to strengthen maternal and child nutrition intervention programmes, optimise complementary feeding, and improve the environment as part of efforts to accelerate the reduction of stunting (Wardah, 2022).

A Geographic Information System (GIS) is a technology that functions to manage, analyse, and present data linked to geographical or spatial locations. Through this approach, data can be processed based on specific coordinates, making it very useful in mapping health issues, including stunting, which is unevenly distributed across regions (Merzi & Aktas, 2000; Yuspita Sari et al., 2025). Through this approach, data can be processed based on specific coordinates, making it very useful in mapping health issues, including stunting, which is unevenly distributed across regions (Febriana et al., 2022; Gustin et al., 2023; Nolte et al., 2008; Novriyanti et al., n.d.; Paula Bria et al., 2025; Sari et al., 2025; Yushananta & Ahyanti, 2025).

The high prevalence of stunting in Bima Regency indicates nutritional inequality between regions. This situation highlights the need for a deeper understanding of how cases are distributed and the environmental factors that may influence this. Thus, a geographical approach is important to provide a more realistic picture of stunting in the region. In line with this, this study aims to map the distribution of stunting in Lambitu Subdistrict using a Geographic Information System (GIS). Through spatial analysis, it is hoped that useful information can be generated as a basis for decision-making, particularly for policy makers and related parties, in designing more targeted intervention programmes to reduce stunting rates

Materials and Methods

This study utilised a quantitative descriptive method with a Geographic Information System (GIS) (Febriyanthi, 2025) approach conducted in Lambitu Subdistrict, Bima Regency, covering six villages, namely Kaboro, Ka'owa, Kuta, Londu, Sambori, and Teta. The research population consisted of all toddlers registered in the Lambitu Community Health Centre working area, with 516 toddlers in 2023, 594 toddlers in 2024, and 574 toddlers in 2025. The research sample consisted of all children under five years of age who were stunted, namely 56 children in 2023, increasing to 86 children in 2024, and remaining high at 84 children in 2025.

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Further analysis using multivariate analysis with SmartPLS (Marko Sarstedt, Christian M. Ringle, 2020) to review the spread of stunting in Lambitu sub-district, Bima Regency includes Determinants of Stunting (DIS), Spatial Context & Service Access (SCS), Stunting Outcomes (STO) including:

Table 1
Indicators of the determinant dimensions of stunting in Lambitu sub-district, Bima district, West Nusa Tenggara.

Factor	Dimensions	Indicator
Determinants of Stunting (DIS)	Maternal & Perinatal Factors (DIS 1)	1 and 2
	Child Feeding & NutritioN (DIS 2)	3 and 4
	Child Illness (DIS 3)	5 and 6
	Household Food Security (DIS 4)	7 and 8
	WASH (Water, Sanitation, Hygiene) (DIS 5)	9,10 and 11
Spatial Context & Service Access (SCS)	S1: Distance from home to integrated health post/community health center (km, GIS data) S2: Travel time to health services (minutes) S3: Stunting hotspots (Moran's I/Getis-Ord Gi analysis results) S4: Regional population density (GIS/census data) S5: Regional vulnerability index (combined access & density)	1,2,3,4 and 5
Stunting Outcomes (STO)	Anthropometric Indicators (STO 1)	1 and 2
	Nutritional Status Classification (STO 2)	3
	Morbidity Correlates (STO 3)	4 and 5
	Long-term Risks (STO 4)	6

Results and Discussions

The analysis was conducted by compiling secondary data from the Lambitu Community Health Centre on the number and percentage of stunted children in six villages, namely Kaboro, Ka'owa, Kuta Londu, Sambori, and Teta, for the period 2023 to 2025. All of this data was then visualised through a map of stunting cases so that patterns and trends in each village could be seen more clearly and readers could more easily understand the distribution of cases in the Lambitu District. The following is a map of stunting cases in the Lambitu District for the period 2023-2025:

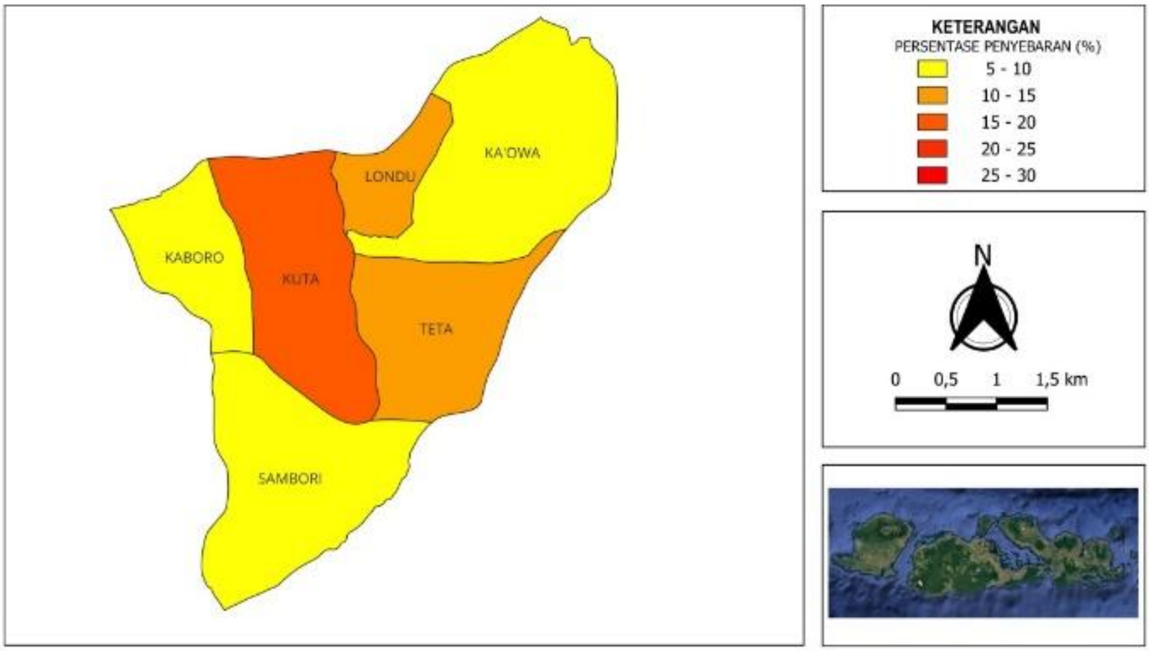

Figure 1. *Map of Stunting Cases in Lambitu Subdistrict in 2023*

Figure 1 shows the results of stunting case mapping in Lambitu Subdistrict in 2023, classified based on proportional class distribution using the QGIS application. On the map, the prevalence rate is indicated by colour gradation, where darker colours indicate higher stunting rates. Of the six villages mapped, Kuta Village has the highest prevalence of 16%, marked in orange, followed by Teta Village at 15% and Londu Village at 14%, marked in light orange. Meanwhile, lower prevalence rates were observed in Kaboro Village and Ka'owa Village, at 8% each, and Sambori Village at 6%, which are shown in yellow.

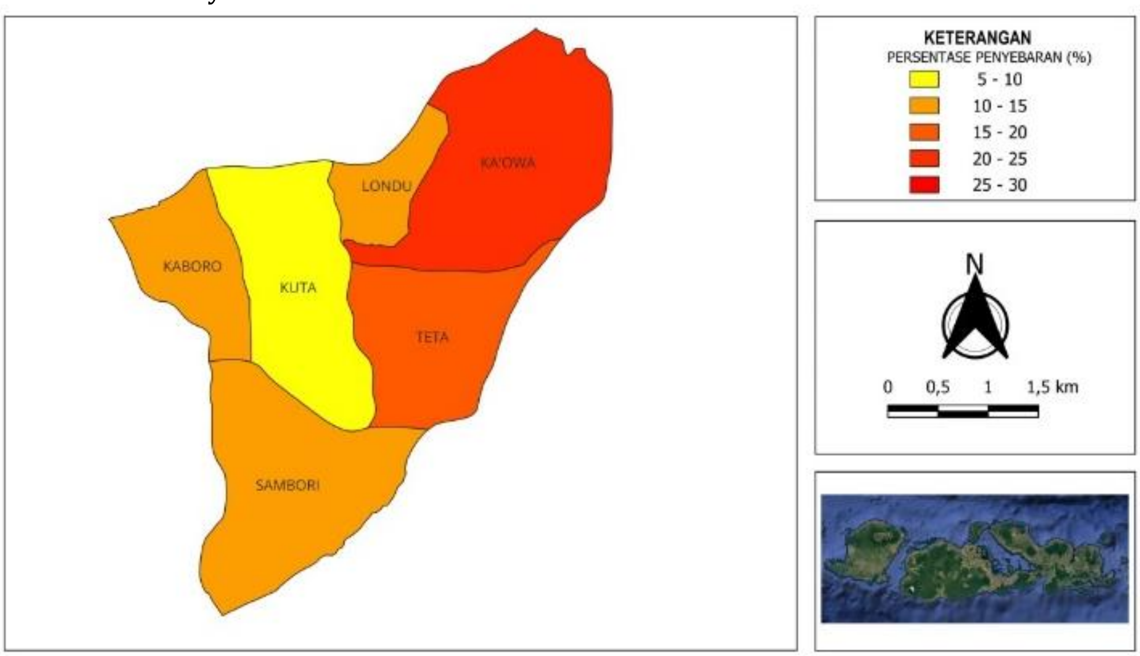

Figure 2. *Map of Stunting Cases in Lambitu Subdistrict in 2024*

Figure 2 shows the mapping of stunting cases in Lambitu District in 2024, with different colours representing the prevalence rate in each village. Ka'owa Village has the highest prevalence rate of 22%, marked in bright red. Teta Village follows with 19% in orange, while Londu Village has a rate of 13% in light orange. Sambori and Kaboro villages each have a prevalence of 11% and are marked in light orange, while Kuta village has a prevalence of 10% and is marked in yellow.

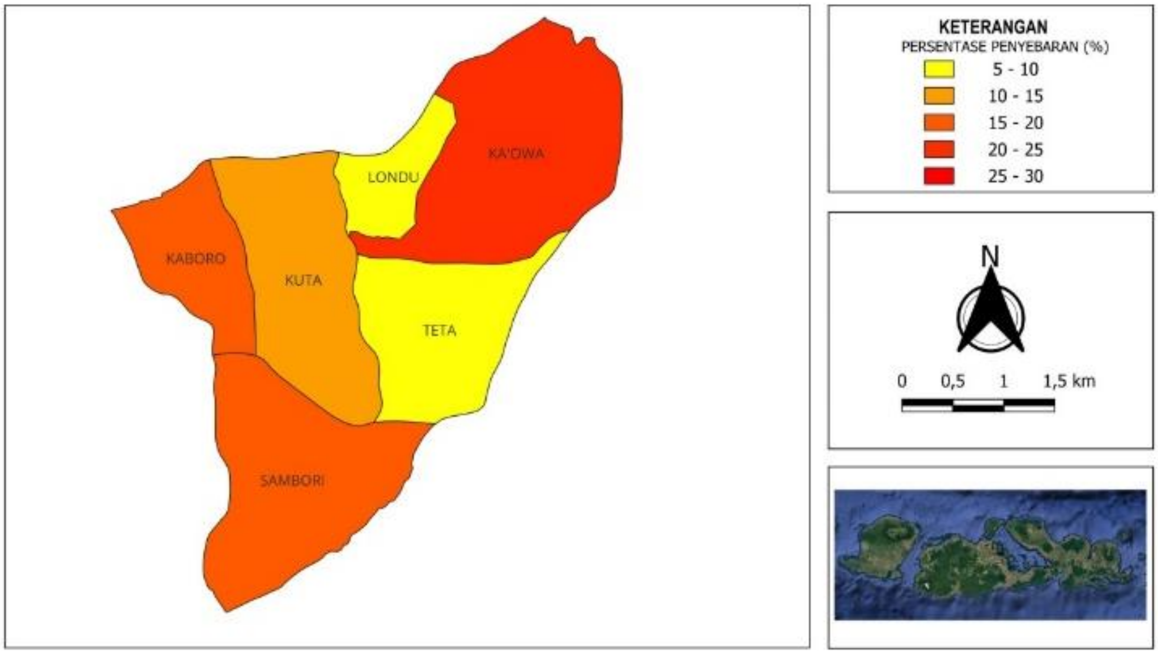

Figure 3. *Map of Stunting Cases in Lambitu Subdistrict in 2025*

Figure 3 shows the prevalence of stunting in Lambitu District in 2025. Ka'owa Village has the highest rate at 22.78%, marked in bright red. Sambori Village follows with 17.91% and Kaboro Village with 16.92%, both marked in orange. Meanwhile, Kuta Village stands at 11.61% and is coloured light orange. Teta Village stands at 10% and Londu Village at 9.69%, both of which are coloured yellow

Mapping stunting in Lambitu Subdistrict reveals significant spatial dynamics from 2023 to July 2025. In 2023, Kuta Village (16%), Teta Village (15%), and Londu Village (14%) stood out as the areas with the highest prevalence of stunting, while Sambori Village (6%) and Kaboro Village (8%) had lower levels. In 2024, attention shifted to Ka'owa Village (22%) and Teta (19%), while Kuta showed a decline to 10%. Data from July 2025 shows consistency in Ka'owa at 22.78%, an increase in prevalence in Sambori (17.91%) and Kaboro (16.92%), and a decrease in Teta (10%) and Londu (9.69%). In line with research by SPurwadi (2022), Research shows that birth weight <2.5 kg and early breastfeeding significantly affect stunting prevalence in North Padang Lawas Regency. Factors like health assistance, immunization, and iron tablets also impact stunting. Imam Faturrahman's 2022 study developed web-based software to map stunting locations in Gereneng Timur Village, improving accessibility and efficiency.

The changes in stunting rates indicate that their distribution is uneven and dynamic, requiring flexible management strategies tailored to the conditions of each region. These results are in line with research in (Yuspita Sari et al., 2025), which found that the application of spatial analysis can map the distribution patterns of stunting more clearly and support the improvement of health policy effectiveness (Annisa et al., 2025; Wang et al., 2009; Yanto et al., 2024a).

Geographic Information Systems (GIS) provide effective visual tools for identifying areas that require priority nutritional intervention. Dynamic changes in stunting patterns, such as an increase in cases in Ka'owa and the emergence of new clusters in Sambori and Kaboro, enable more targeted planning of interventions. Consistent with research findings (Islam et al., 2023; Mohammad et al., 2023), GIS has proven useful for mapping the distribution of stunting and determining strategic locations for intervention, including the role of community health centres and health facilities in response efforts. Thus, the use of GIS can strengthen intervention strategies tailored to the specific needs of each village.

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The use of colour-graded maps in mapping provides two main advantages, namely clarifying visual understanding and speeding up the decision-making process for policy makers. Research in (Kusrini et al., 2018; Yanto et al., 2024b) shows that GIS-based visualisation helps stakeholders work more efficiently and effectively, thereby contributing to a reduction in the prevalence of stunting (Yanto et al., 2024). The colour gradation from yellow to dark red makes it easier for health agencies and village officials to quickly assess conditions and determine the appropriate intervention measures.

Based on spatial distribution patterns and prevalence trends up to July 2025, several important intervention measures need to be taken. (1) Focus efforts on villages showing high or newly increasing prevalence, such as Ka'owa, Sambori, and Kaboro; (2) Utilise advanced spatial analysis, such as Local Indicators of Spatial Association (LISA) or spatial autocorrelation, to identify clusters and local risk factors such as sanitation conditions, economic status, and access to healthcare services (Fajri & Pertiwi, 2025). This approach is similar to that applied in a study in Sumedang in 2025. (3) Strengthening cross-sectoral cooperation, including in the fields of health, sanitation, education, and village administration, by utilising a GIS-based approach to design more targeted and needs-based nutrition interventions. In addition, the development of digital monitoring, such as through WebGIS or mobile applications, enables the integration of the latest data (Álvarez-Otero & de Lázaro y Torres, 2018). This approach has been implemented in Merbaun Village, Kupang District, which has succeeded in increasing user understanding from an average of 53.8 to 83.5 points through GIS training (Paula Bria et al., 2025).

In mountainous areas such as Lambitu District, access to clean water is often a challenge, especially during the dry season when springs dry up or are located far away. Lack of clean water makes children more susceptible to gastrointestinal infections, so that the body's energy is used more to fight disease than for growth. Research shows that access to adequate clean water has a significant relationship with the incidence of stunting ($p=0.001$) (Briguglio et al., 2020; Ilmiati et al., 2024a, 2024b; Jona et al., 2023; Mariana & Lestari, 2022; Puspitasari et al., 2024). Therefore, improving clean water facilities is a very important nutrition-sensitive intervention for mountain villages.

Access to animal protein such as meat, eggs, and fish is often limited in mountainous areas due to supply constraints, high costs, and poor transport infrastructure. This has an impact on low protein intake among children, which is an important factor in linear growth. Research in Pucak Village, (Nur et al., 2022; Sutrisminah et al., 2023), found a significant association between low animal protein intake and increased stunting incidence (p=0.007) (Oktorina, 2018; Saavedra, 2022). Furthermore, a study in the (Gassara et al., 2023),showed that low protein intake and poor hygiene practices have a significant impact on stunting.

In addition to poor sanitation and limited animal protein, there are several other significant risk factors that contribute to stunting. Among them is low maternal education, which increases the likelihood of children experiencing stunting by up to 1.6 times compared to mothers with higher education (Wahyuningrum et al., 2023). In addition, babies with low birth weight (LBW) are also a risk factor for stunting. Other factors include maternal age ≥ 30 years, premature birth, and inadequate antenatal care, which can contribute to stunting (Gusnedi et al., 2023; Nurdin et al., 2023).

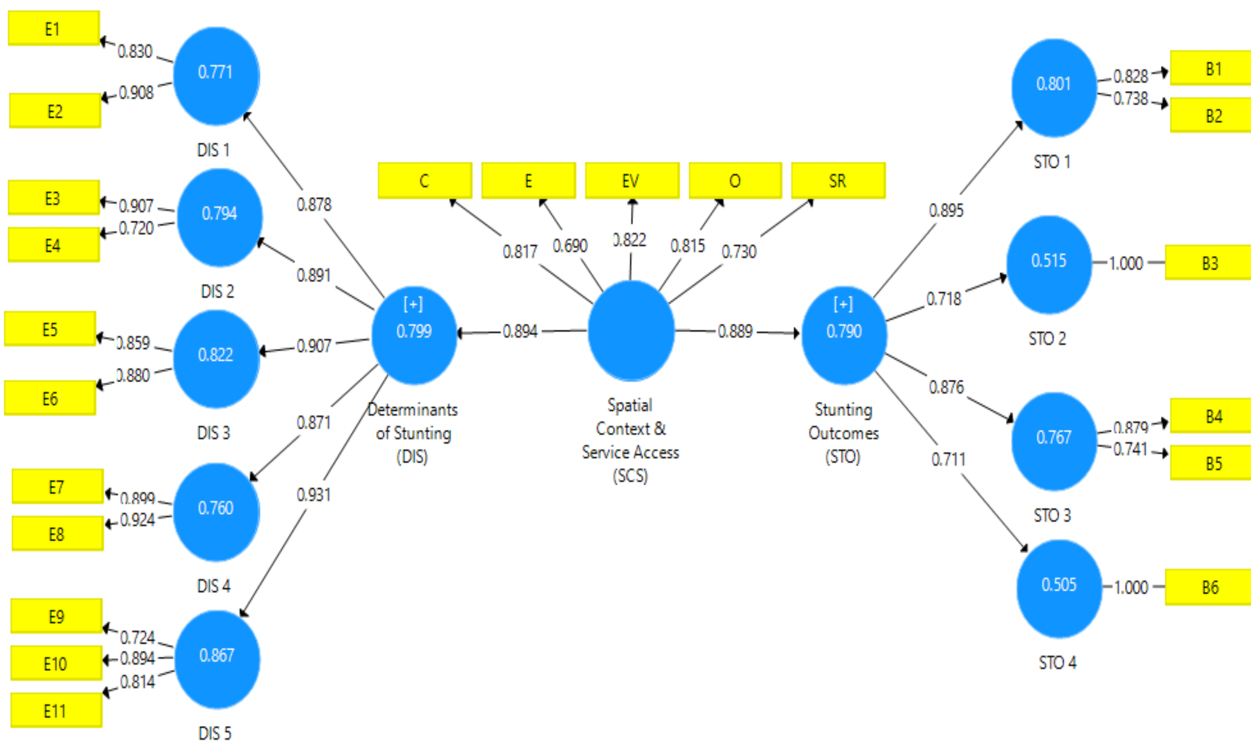

Figure 2. *Multivariate Partial Least Squares Structural Equation Modeling (SmartPLS) Analysis of the Causes of Stunting in Lambitu District, Bima Regency, West Nusa Tenggara.*

The structural model identified three main constructs: Determinants of Stunting (DIS), Spatial Context & Service Access (SCS), and Stunting Outcomes (STO). The DIS construct has five indicators with high reliability, while the SCS construct has five indicators with adequate reliability, but one requires interpretation. STO (Stunting Outcomes) konstruk adalah indikator (STO1–STO4) dengan nilai outer loading (0,505–0,801). STO2 dan STO4 memiliki loading sempurna, validitasnya dapat ditanyakan dalam konteks model. The study reveals that socioeconomic factors, nutrition, and household environment significantly influence spatial context and service access, while spatial access and public services significantly influence stunting outcomes. The model supports the conclusion that stunting management efforts in Lambitu should focus on improving underlying determinants (DIS) and increasing spatial access and services (SCS) to reduce stunting outcomes (Atamou et al., 2023; Maseta, 2022; Nsubuga et al., 2020; Nurdin et al., 2023; Pantiawati et al., 2023; Taqwin et al., 2023).

The total effects analysis reveals that childhood stunting in Lambitu is shaped by a strong interaction between individual-level determinants and spatial context. Spatial context and service accessibility exhibit a substantial influence not only on stunting outcomes (β = 0.889) but also on the underlying determinants of stunting (β = 0.779–0.832), highlighting the critical role of geographical disparities. These findings confirm that childhood stunting in Lambitu represents a multilevel and spatially clustered public health issue, requiring place-based and context-sensitive interventions.

Tabel 2.
Path Coefficients

Indicators	**Determinants of Stunting (DIS)**	**Spatial Context & Service Access (SCS)**	**Stunting Outcomes (STO)**
DIS 1	0.878		
DIS 2	0.891		
DIS 3	0.907		
DIS 4	0.871		
DIS 5	0.931		
Determinants of Stunting (DIS)		0.894	
STO 1			0.895
STO 2			0.718
STO 3			0.876
STO 4			0.711
Stunting Outcomes (STO)		0.889	

Based on the Path Coefficient Table, the model demonstrates a strong relationship between constructs. The Determinants of Stunting (DIS) construct indicators show high loading values, confirming convergent validity. The structural relationship between DIS and Spatial Context & Service Access (SCS) has a coefficient of 0.894, indicating a strong positive influence. In the Stunting Outcomes (STO) construct, indicators display acceptable loading values, with the correlation between SCS and STO at 0.889. Overall, the results highlight that stunting determinants influence both spatial conditions and service access directly and strengthen their impact on stunting outcomes indirectly through SCS.

Tabel 3.
Specific Indirect Effects

Spatial Context & Service Access (SCS) -> Determinants of Stunting (DIS) -> DIS 1	0.785
Spatial Context & Service Access (SCS) -> Determinants of Stunting (DIS) -> DIS 2	0.796
Spatial Context & Service Access (SCS) -> Determinants of Stunting (DIS) -> DIS 3	0.810
Spatial Context & Service Access (SCS) -> Determinants of Stunting (DIS) -> DIS 4	0.779
Spatial Context & Service Access (SCS) -> Determinants of Stunting (DIS) -> DIS 5	0.832
Spatial Context & Service Access (SCS) -> Stunting Outcomes (STO) -> STO 1	0.796
Spatial Context & Service Access (SCS) -> Stunting Outcomes (STO) -> STO 2	0.638
Spatial Context & Service Access (SCS) -> Stunting Outcomes (STO) -> STO 3	0.779
Spatial Context & Service Access (SCS) -> Stunting Outcomes (STO) -> STO 4	0.632

The findings highlight that the Spatial Context & Service Access (SCS) construct significantly influences the Determinants of Stunting (DIS) and Stunting Outcomes (STO) through strong indirect effects. The indirect effects on DIS range from 0.779 to 0.832, with DIS5 at 0.832 being the highest. For STO, the values vary between 0.632 and 0.796, with STO1 achieving the highest at 0.796. These results indicate that SCS acts as a crucial mediating mechanism, underscoring the importance of spatially based interventions and improved access to health services in reducing stunting prevalence.

Tabel 4.
R Square

Indicators	R Square	R Square Adjusted
DIS 1	0.771	0.769
DIS 2	0.794	0.792
DIS 3	0.822	0.820
DIS 4	0.760	0.757
DIS 5	0.867	0.866
Determinants of Stunting (DIS)	0.799	0.797
STO 1	0.801	0.799
STO 2	0.515	0.510
STO 3	0.767	0.765
STO 4	0.505	0.500
Stunting Outcomes (STO)	0.790	0.788

Based on R^2 and Adjusted R^2 values, the model shows strong explanatory power for the Determinants of Stunting (DIS) and Stunting Outcomes (STO), with values of 0.799 and 0.790 respectively. This indicates that approximately 79% of the variation can be explained by predictor variables. At the indicator level, certain indicators like DIS5 (0.867) and DIS3 (0.822) reflect their constructs well, while others like STO2 (0.515) and STO4 (0.505) show moderate contribution. The close values of R^2 and Adjusted R^2 suggest model stability and lack of overfitting, confirming the model's predictive quality regarding stunting determinants and outcomes.

The results of this study indicate that stunting cannot be explained simply through individual determinants, but rather is the result of a complex interaction between social factors and spatial context. The developed PLS-SEM model shows that the determinants of stunting (DIS) have a very strong influence on spatial context & service access (SCS), which in turn significantly mediates this influence on stunting outcomes (STO). The high path coefficient value and strong R^2 (0.79) indicate that the model has substantial explanatory power in capturing the variability of stunting at the regional level. These findings strengthen the argument that stunting is a multidimensional phenomenon determined not only by individual characteristics but also by structural factors inherent in the spatial and distribution of health services (Black et al., 2013).

The findings enhance the social determinants of health framework by incorporating spatial inequality as a significant mediating factor. While prior research identifies maternal education, economic status, and birth conditions as crucial for stunting, this study reveals that their effects vary significantly with geographic context and access to health services(Wahyudi et al., 2023). According to health geography, space actively influences health risk distribution and service accessibility, suggesting that spatial disparities in service availability can amplify or mitigate the effects of these social determinants on stunting(Amoah et al., 2021; Chae et al., 2022; Mohapatra & Wiley, 2019).

The study emphasizes that SCS serves as a crucial link between social determinants and stunting, indicating structural mediation through health service access and spatial disparities. It aligns with prior research highlighting the relationship between limited access to health services and stunting rates in underdeveloped regions. The authors argue that interventions aimed at modifying individual behavior, without addressing spatial factors, may not suffice. Notably, this study innovatively combines Geographic Information System (GIS) and Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze stunting, contrasting with earlier works that employed GIS descriptively and overlooked spatial dimensions in structural analyses.

Conclusion

This study shows that the use of Geographic Information Systems (GIS) is highly effective in mapping and 07/05/2026analysing the distribution of stunting in Lambitu Subdistrict, Bima Regency. Data from the Community Health Centre shows a fluctuating trend in the prevalence of stunting in six villages from 2023 to 2025. In 2023, Kuta village had the highest prevalence of 16%, depicted in orange, followed by Teta village at 15% and Londu village at 14%, both also in bright orange, indicating a fairly high level of stunting. In 2024, Ka'owa village had the highest prevalence of 22%, marked in bright red, while Teta village also showed an increase to 19%, marked in orange, and Kuta village decreased to 10%, marked in yellow. In 2025, Ka'owa village continues to show the highest rate at 22.78%, coloured bright red, followed by Sambori village at 17.91% and Kaboro village at 16.92%, both coloured orange, while Teta and Londu villages decreased to 10% and 9.69%, coloured yellow. This data indicates that the distribution of stunting is uneven and dynamic, requiring adaptive and spatial data-based management strategies.

The SmartPLS analysis demonstrates that the model constructed shows excellent quality regarding measurement and structure. The Determinants of Stunting (DIS) and Stunting Outcomes (STO) constructs exhibit high loading values, satisfying convergent validity and effectively representing the constructs. A significant relationship exists where DIS strongly influences Spatial Context & Service Access (SCS) (0.894), which in turn considerably affects STO (0.889). The R Square values for DIS (0.799) and STO (0.790) indicate that the model explains approximately 79% of the variance in each endogenous construct. Additionally, SCS serves as a significant mediating variable, enhancing the impact on DIS and STO with a notable indirect effect. Thus, the SmartPLS model demonstrates robust explanatory and predictive power, effectively elucidating the connections between stunting determinants, spatial context and service access, and stunting outcomes.

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References

Álvarez-Otero, J., & de Lázaro y Torres, M. L. (2018). Education in sustainable development goals using the spatial data infrastructures and the TPACK model. *Education Sciences*, *8*(4). https://doi.org/10.3390/educsci8040171

Amoah, P. A., Nyamekye, K. A., & Owusu-Addo, E. (2021). A multidimensional study of public satisfaction with the healthcare system: a mixed-method inquiry in Ghana. *BMC Health*

Services Research, *21*(1). https://doi.org/10.1186/s12913-021-07288-1

Annisa, N. N., Setiadi, D., Radiati, A., & Sukawan, A. (2025). Spatial Analysis of Stunting Incidents in Toddlers in The City of Tasikmalaya 2023. *JIKO (Jurnal Informatika Dan Komputer)*, *9*(1), 60. https://doi.org/10.26798/jiko.v9i1.1329

Atamou, L., Rahmadiyah, D. C., Hassan, H., & Setiawan, A. (2023). Analysis of the Determinants of Stunting among Children Aged below Five Years in Stunting Locus Villages in Indonesia. In *Healthcare* (Vol. 11, Issue 6, p. 810). MDPI AG. https://doi.org/10.3390/healthcare11060810

Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., de Onis, M., Ezzati, M., Grantham-McGregor, S., Katz, J., Martorell, R., & Uauy, R. (2013). Maternal and child undernutrition and overweight in low-income and middle-income countries. *The Lancet*, *382*(9890), 427–451. https://doi.org/10.1016/s0140-6736(13)60937-x

Briguglio, M., Vitale, J. A., Galentino, R., Banfi, G., Dina, C. Z., Bona, A., Panzica, G., Porta, M., Dell'osso, B., & Glick, I. D. (2020). Healthy eating, physical activity, and sleep hygiene (HEPAS) as the winning triad for sustaining physical and mental health in patients at risk for or with neuropsychiatric disorders: Considerations for clinical practice. *Neuropsychiatric Disease and Treatment*, *16*, 55–70. https://doi.org/10.2147/NDT.S229206

Chae, D., Kim, H., Seo, M., Asami, K., & Doorenbos, A. (2022). Public Health Center Service Experiences and Needs among Immigrant Women in South Korea. *Journal of Korean Academy of Community Health Nursing*, *33*(4), 385–395. https://doi.org/10.12799/JKACHN.2022.33.4.385

Fajri, R. N., & Pertiwi, T. S. (2025). Prevalensi Stunting di Kabupaten Sumedang Menggunakan LISA (Local Indicators of Spatial Association). *Syntax Literate ; Jurnal Ilmiah Indonesia*, *10*(1), 540–550. https://doi.org/10.36418/syntax-literate.v10i1.17361

Febriana, R. W., Kom, S., & Kom, M. (2022). Sistem Prediksi Risiko Stunting Menggunakan Bayesian Network Berbasis GIS. In *Eksplorasi …*. download.garuda.kemdikbud.go.id. http://download.garuda.kemdikbud.go.id/article.php?article=3591214&val=31175&title=Sistem Prediksi Risiko Stunting Menggunakan Bayesian Network Berbasis GIS

Febriyanthi, F. (2025). *PEMETAAN SEBARAN KASUS STUNTING MENGGUNAKAN APLIKASI Q-GIS DI KABUPATEN KUNINGAN TAHUN 2024*. repo.poltekkestasikmalaya.ac.id. http://repo.poltekkestasikmalaya.ac.id/5993/

Gassara, G., Lin, Q., Deng, J., Zhang, Y., Wei, J., & Chen, J. (2023). Dietary Diversity, Household Food Insecurity and Stunting among Children Aged 12 to 59 Months in N'Djamena—Chad. *Nutrients*, *15*(3). https://doi.org/10.3390/nu15030573

Gusnedi, G., Nindrea, R. D., Purnakarya, I., Umar, H. B., Andrafikar, Syafrawati, Asrawati, Susilowati, A., Novianti, Masrul, & Lipoeto, N. I. (2023). Risk factors associated with childhood stunting in Indonesia: A systematic review and meta-analysis. *Asia Pacific Journal of Clinical Nutrition*, *32*(2), 184–195. https://doi.org/10.6133/apjcn.202306_32(2).0001

Gustin, R. K., Ramadanti, T., Ediana, D., & ... (2023). Analisis pemetaan faktor resiko kejadian stunting menggunakan aplikasi GIS di Kabupaten Pasaman. In *Human Care …*. pdfs.semanticscholar.org. https://pdfs.semanticscholar.org/6361/62afee55d4ed5de127a17e690803cebed76b.pdf

Ilmiati, F., Syauqy, A., Noer, E. R., Margawati, A., & Kartini, A. (2024a). Energy Intake, Protein Intake, and Toddler Hygiene with the Incidence of Stunting in 24-59 Months Toddlers in Mentawai Islands. *JURNAL INFO KESEHATAN*, *22*(4), 724–734. https://doi.org/10.31965/infokes.vol22.iss4.1738

Ilmiati, F., Syauqy, A., Noer, E. R., Margawati, A., & Kartini, A. (2024b). Energy Intake, Protein Intake, and Toddler Hygiene with the Incidence of Stunting in 24-59 Months Toddlers in Mentawai Islands. *Jurnal Info Kesehatan*, *22*(4), 724–734. https://doi.org/10.31965/infokes.vol22.iss4.1738

Islam, M. S., Islam, M. S., Chowdhury, R., & Zaman, M. M. (2023). Stunting and its associated factors in under-five children: evidence from Bangladesh Demographic and Health Survey 2014. In *Bangabandhu Sheikh Mujib Medical University Journal* (Vol. 15, Issue 4, pp. 22–31). Bangladesh Journals Online (JOL). https://doi.org/10.3329/bsmmuj.v15i4.63893

Jona, R. N., Juwariyah, S., & Ovikariani, O. (2023). Pemberdayaan Masyarakat sebagai Upaya untuk Pencegahan dan Penanganan Kondisi Kegawatan Kasus Hepatitis A melalui Program HEHO (Healty Environment Healty Food). In *Jurnal Pengabdian Perawat* (Vol. 2, Issue 2, pp. 55–59). Persatuan Perawat Nasional Indonesia Jawa Tengah. https://doi.org/10.32584/jpp.v2i2.2382

Kusrini, K., Kirana, K. C., Purwanto, M. I., & Laksito, A. D. (2018). GIS-based decision support system for cash waqf distribution. *Journal of Theoretical and Applied Information Technology*, *96*(3), 701–711. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85042373382&partnerID=40&md5=6d8b09c9cba8a34e30ecf60326a3d496

Mariana, P. P., & Lestari, K. S. (2022). Analisis Faktor Personal Higiene dan Akses pada Sanitasi terhadap Kasus Stunting pada Balita di Asia : Literature Review. In *Promotif : Jurnal Kesehatan Masyarakat* (Vol. 12, Issue 2, pp. 116–130). Universitas Muhammadiyah Palu. https://doi.org/10.56338/promotif.v12i2.2661

Marko Sarstedt, Christian M. Ringle, and J. F. H. (2020). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (Issue September). https://doi.org/10.1007/978-3-319-05542-8

Maseta, E. J. (2022). Factors associated with stunting among children in Mvomero district Tanzania. In *Nutrition and Health* (p. 2147483647). SAGE Publications. https://doi.org/10.1177/02601060221129004

Merzi, N., & Aktas, M. T. (2000). Geographic information systems (GIS) for the determination of inundation maps of Lake Mogan, Turkey. *Water International*. https://doi.org/10.1080/02508060008686856

Mohammad, M. I., Hermanda, A. M., Karmanto, B., & Khasanah, L. (2023). Pemetaan Distribusi Prevalensi dan Faktor Risiko Stunting dengan Sistem Informasi Geografis Kota Cirebon: Laporan Data. *Health Information : Jurnal Penelitian*, *15*(3), e925. https://doi.org/10.36990/hijp.v15i3.925

Mohapatra, S., & Wiley, L. F. (2019). Feminist Perspectives in Health Law. *Journal of Law, Medicine and Ethics*, *47*(4_suppl), 103–115. https://doi.org/10.1177/1073110519898047

Nolte, K., Palumbo, J., Brown, J., & ... (2008). Integrating GIS in the epidemiology and management of the cucurbit yellow stunting disease virus (CYSDV). In …. … SCIENCE 113 S WEST ST, STE 200 ….

Novriyanti, P. H., Oktaviani, D., & Latief, K. (n.d.). Determinan Faktor Risiko Kejadian Stunting Berdasarkan Pemetaan Kasus Stunting pada Balita dengan Geographic Information System (GIS). In *academia.edu*. https://www.academia.edu/download/109147599/149.pdf

Nsubuga, E. J., Muzafaru, S., Isunju, J. B., & Mayega, R. W. (2020). *Determinants of stunting and underweight among children aged 6 to 59 months in Bussi Islands of Wakiso District, Uganda: a cross-sectional study*. Research Square Platform LLC. https://doi.org/10.21203/rs.2.23751/v1

Nur, A., Sine, J. G. L. S., & Nita, M. H. D. (2022). Differences in Development of Gross Motor and Fine Motor Skills of Stunting and Non-Stunting Toddlers Aged 36-59 Months. In *Jurnal Ilmiah Kesehatan (JIKA)* (Vol. 4, Issue 3, pp. 470–478). LPPM Akper Yapenas 21 Maros. https://doi.org/10.36590/jika.v4i3.294

Nurdin, A., Masrul, M., Gusnedi, G., Umar, H. B., Purnakarya, I., Syafrawati, S., Andrafikar, A., Novianti, N., Susilowati, A., Nindrea, R. D., & Lipoeto, N. I. (2023). *Prevalence and Determinants of Stunting Risk Factors among Children Under Five Years Old: An Analysis of the Indonesian Secondary Database*. Springer Science and Business Media LLC.

https://doi.org/10.21203/rs.3.rs-3019263/v1

Oktorina, S. (2018). Key Factors Related to Stunting in Indonesia. In *International Conference on Sustainable Health Promotion* (pp. 15–19). Fakultas Sains dan Teknologi UINSA. https://doi.org/10.29080/icoshpro.v1i0.6

Pantiawati, I., Widianawati, E., & Fani, T. (2023). Determinants of Stunting Based on Ecological Approach in Stunting Locus Area in Banyumas District. In *Jurnal Ilmu Kesehatan Masyarakat* (Vol. 13, Issue 3, pp. 376–384). Faculty of Public Health of Sriwijaya University. https://doi.org/10.26553/jikm.2022.13.2.376-384

Paula Bria, Y., Andrianus Nani, P., Carmeneja Hoar Siki, Y., Selia Metkono, B., & Putry Bria, Y. M. (2025). Penerapan dan Pelatihan Sistem Informasi Geografis untuk Pemetaan Penyebaran Stunting di Desa Merbaun, Kabupaten Kupang, Nusa Tenggara Timur. *BERNAS: Jurnal Pengabdian Kepada Masyarakat*, *6*(3), 1919–1929. https://doi.org/10.31949/jb.v6i3.13664

Puspitasari, A., Abdullah, N., & Alimuddin, H. (2024). Sanitasi Lingkungan dan Tingkat Asupan Protein Hewani Terhadap Kejadian Stunting Pada Balita di Desa Pucak Kabupaten Maros. *An Idea Health Journal*, *4*(02), 45–50. https://doi.org/10.53690/ihj.v4i02.239

Putri, A. D., & Maulidia, S. (2024). Pengelompokan Kejadian Stunting di Indonesia pada Tahun 2022 dan Faktor-faktor yang Memengaruhinya: Sebuah Gambaran. *Seminar Nasional Official Statistics*, *2024*(1), 449–458. https://doi.org/10.34123/semnasoffstat.v2024i1.1972

Saavedra, J. M. (2022). The Changing Landscape of Children's Diet and Nutrition: New Threats, New Opportunities. *Annals of Nutrition and Metabolism*, *78*, 40–50. https://doi.org/10.1159/000524328

Sari, A. D. L., Rohman, H., & Salsabila, A. (2025). Geographic Information Systen (GIS) Mapping of Toddler Cases Stunting Cases in Bantul Regency in 2022. *Procedia of Engineering and …*. https://pels.umsida.ac.id/index.php/PELS/article/view/2212

Sutrisminah, E., Surani, E., Yuniarti, H., & Syofa, A. N. (2023). Pengentasan Stunting Menuju Gondang Bebas Stunting. In *Jurnal Abmas Negeri (JAGRI)* (Vol. 4, Issue 1, pp. 16–21). LPPM Akper Yapenas 21 Maros. https://doi.org/10.36590/jagri.v4i1.516

Taqwin, T., Pont, A. V., & Iskandar, Y. (2023). Determinan Stunting Balita di Wilayah Kerja Puskesmas Moutong, Kabupaten Parigi Moutong, Sulawesi Tengah. In *Jurnal Bidan Cerdas* (Vol. 5, Issue 1, pp. 43–50). Poltekkes Kemenkes Palu. https://doi.org/10.33860/jbc.v5i1.1809

Wahyudi, M., Pardita, G., & Sari, A. (2023). Upaya Pemerintah Kota Tanjungpinang Dalam Percepatan Penurunan Angka Kasus Stunting Berdasarkan Indeks Khusus Penanganan Stunting Provinsi Kepulauan Riau. In *Journal of Research and Development on Public Policy* (Vol. 2, Issue 4, pp. 199–204). Lembaga Pengkajian dan Pengembangan Sumberdaya Pembangunan (LPPSP). https://doi.org/10.58684/jarvic.v2i4.111

Wahyuningrum, S. N., Asturiningtyas, I. P., Martiyana, C., & Mirzautika, A. (2023). Low birth weight and low mother education as dominant risk factors of stunting children in Magelang Regency, Central Java. *AcTion: Aceh Nutrition Journal*, *8*(1), 111. https://doi.org/10.30867/action.v8i1.859

Wang, X., Höjer, B., Guo, S., Luo, S., Zhou, W., & Wang, Y. (2009). Stunting and 'overweight' in the WHO Child Growth Standards – malnutrition among children in a poor area of China. *Public Health Nutrition*, *12*(11), 1991–1998. https://doi.org/10.1017/s1368980009990796

Wardah. (2022). Keluarga Bebas Stunting. In *InfoDATIN: Pusat Data Teknologi Informasi Kementerian Kesehatan RI* (pp. 1–12).

WHO. (2025). Children aged 5-17 years who are overweight (including obese), latest available estimates. *National Institutes of Health (NIH)*. https://doi.org/10.1787/888932523994

Yanti, Y., Susilawati, E., Alza, Y., & Santhariana, L. (2023). Pendampingan Tim Percepatan Penurunan Stunting melalui Inisiasi dan Implementasi Dashat (Dapur Sehat Atasi Stunting) di Desa

Pancuran Gading Kabupaten Kampar. In *SEGANTANG LADA : JURNAL PENGABDIAN KESEHATAN* (Vol. 1, Issue 2, pp. 86–93). Poltekkes Kemenkes Tanjungpinang. https://doi.org/10.53579/segantang.v1i2.137

Yanto, D., Susanto, H., Darmanto, H., Saputra, A. B., & Andika, F. D. (2024a). Penerapan Sistem Informasi Geografis Pada Pemetaan Dan Monitoring Balita Stunting. *Journal of Electrical Engineering and Computer (JEECOM)*, *6*(2), 494–507. https://doi.org/10.33650/jeecom.v6i2.9598

Yanto, D., Susanto, H., Darmanto, H., Saputra, A. B., & Andika, F. D. (2024b). Penerapan Sistem Informasi Geografis Pada Pemetaan Dan Monitoring Balita Stunting. *Journal of Electrical Engineering and Computer (JEECOM)*, *6*(2), 494–507. https://doi.org/10.33650/jeecom.v6i2.9598

Yushananta, P., & Ahyanti, M. (2025). Determining Stunting Risk Areas Using a Combined AHP-GIS approach: A Case Study of Pesawaran Regency, Lampung, Indonesia. *Ruwa Jurai: Jurnal Kesehatan …*. http://ejurnal.poltekkes-tjk.ac.id/index.php/JKESLING/article/view/5046

Yuspita Sari, R., Nurhayati, S., Dwi Raharjo, U., Haniyah Sary, idah, Kesehatan, F., Rekam Medis dan Informasi Kesehatan, P., Jenderal Achmad Yani, U., & Studi Kebidanan, P. (2025). Pemanfaatan Sistem Informasi Geografis Untuk Memetakan Distribusi Stunting Menggunakan Metode Autokorelasi Morans'I. *Terapan Informatika Nusantara*, *5*(10), 585–593. https://doi.org/10.47065/tin.v5i10.5756