TPM Vol. 32, No. 4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

GEOSPATIAL ANALYSIS OF STUNTING INCIDENTS IN TODDLERS IN TULANG BAWANG DISTRICT LAMPUNG PROVINCE

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Abstract: This study aimed to analyze the geospatial distribution of stunting among children aged 0–59 months in Tulang Bawang Regency, Lampung Province, Indonesia, in 2024, focusing on the role of water, sanitation, and hygiene (WASH) factors. Using secondary data from e-PPGBM and Family Data Collection 2024 (n = 1,418 stunted toddlers after exclusion), coordinates were geocoded via Google Earth and analyzed in ArcGIS Pro 3.2. Prevalence reached 18.3%, with significant hotspots identified in Menggala Timur, Banjar Baru, and Banjar Agung sub-districts using Getis-Ord Gi*. Global Moran's I indicated a random pattern overall, yet local clusters persisted in western low-lying areas. Sub-districts with poor access to safe drinking water and proper sanitation (Banjar Margo, Dente Teladas, Menggala) consistently showed higher stunting rates. Kernel density estimation confirmed highest concentrations in Banjar Margo and Menggala. Area-based WASH interventions are urgently needed to accelerate stunting reduction.

Keywords: stunting; geospatial analysis; WASH; hotspot; Tulang Bawang Regency

INTRODUCTION:

According to a report by the Food and Agriculture Organization (FAO), there was an 18.1% increase in the number of people suffering from malnutrition worldwide, from 650.3 million in 2019 to 768 million in 2020, with Asia being the region with the largest number (418 million people). Malnutrition is a serious threat to global health, causing 3.1 million child deaths annually according to the World Health Organization (WHO) (Ministry of Health of the Republic of Indonesia, 2020). One-third of children under five experience malnutrition such as stunting, wasting, or overweight, while two-thirds are at risk of hidden hunger. In 2018, 149 million children under 5 years old experienced stunting and 50 million were wasted, with 340 million suffering from micronutrient deficiencies (UNICEF, 2019a). The problem of stunting in children reflects chronic malnutrition, with 162 million cases in 2012 projected to increase to 127 million by 2025 without intervention (Hardinsyah & Supariasa, 2017). The global prevalence of stunting in 2022 was around 22.3% (148.1 million toddlers), mainly in Asia (52%) and Africa (43%), with Southeast Asia at 30.5% and Indonesia ranking second (31.0%) after Timor Leste (UNICEF et al., 2021).

Stunting weakens the immune system and increases the risk of chronic diseases such as diabetes, heart disease, cancer, and reproductive disorders (Dewey & Begum, 2011). Its impacts include decreased adult income, limited access to education, and low birth weight in offspring (Victora et al., 2008). Short-term: impaired brain function, intelligence, physical growth, and metabolism; long-term: reduced cognitive ability, susceptibility to illness, risk of diabetes, obesity, heart disease, cancer, stroke, and disability (Kemendes PDTT, 2017). Stunting is caused by multidimensional factors, including lack of access to clean water and sanitation, not just poor nutrition in pregnant women or toddlers (Tobing et al., 2021). Other factors include low birth weight, inadequate care, inadequate nutrition, recurrent infections, and the environment (Fikawati & Syafiq, 2017). Direct causes: inadequate nutritional intake and frequent illness (diarrhea). Studies in 5 Indonesian provinces showed suboptimal feeding and poor sanitation (BABS) as the main causes, especially in beaches with low toilets and poor handwashing (Fikawati & Syafiq, 2017).

Improving access to sanitation and hygiene reduces the prevalence of stunting (Jee Hyun Rah et al., 2015). Poor household sanitation contributes to diarrheal infections, trachoma, and helminthiasis, linked to clean water, sanitation, and hygiene in low-income settings (Budge et al., 2019). Poor sanitation impairs food absorption via Environmental Enteric Dysfunction (EED), common in low-access areas (Budge et al., 2019). An Indian study found that recurrent diarrhea causes enteropathy, damaging the intestines and nutrient absorption (Fikawati & Syafiq, 2017). Chronic inflammation from fecal-contaminated diarrhea causes intestinal abnormalities in low-income countries (Watanabe & Petri, 2016). Improved sanitation and hygiene (WASH: provision of latrines, handwashing) reduces linear growth disorders (Lunn, 2000). Ten percent of the global disease burden is prevented through WASH (Investment et al., 2021). Children with good sanitation have a 29% lower risk of stunting (Jee H. Rah et al., 2020).

Indonesia, a middle-income country, still lags behind in child nutrition. In 2018, 3/10 children under 5 years old were stunted, 1/10 underweight, and 1/5 school- age children overweight/obese (UNICEF, 2019a). High

stunting impacts human resources (Ministry of Villages, 2017). High prevalence compared to similar countries (Ramayulis, 2018); 8.9 million children (1/3) are stunted, and >1/3 <5 years are short (Ministry of Villages, 2017). Ministry of Health's SSGI: stunting, wasting, underweight, overweight; static stunting prevalence >20% (above the WHO threshold). 2022: 21.6 % ; 2023 (SKI): 21.5%; 2024: 19.8%. Indonesian study: inadequate toilets and clean water are associated with stunting (Adiyanti, 2014); Littering pollutes groundwater (Jenderal et al., 2016); types of latrines and clean water are linked to stunting (Zairinayati & Purnama, 2019). The government is developing STBM for total sanitation: no open defecation, CTPS, safe water/food, safe garbage/waste (Ministry of Health, 2012). Objective: change behavior through empowerment (Ministry of Health, 2018). RISKEDAS 2018: CTPS 49.8%, open defecation and latrines 88.2%, good rural waste 10.4%; STBM 55.85%; clean water 71.06%; proper sanitation 64.73%.
Lampung's stunting trend fluctuates: SSGI 2022: 15.2%; SKI 2023: 14.9%; SSGI 2024: 15.9% (above the target of Presidential Decree 72/2021: 14% 2024). Tulang Bawang: SSGI 2022: 10.2%; SKI 2023: 9.8%; SSGI 2024: 18.3% (an increase of 87%); 1,425/21,845 stunted toddlers in 2024. Risk factors: 2,351 pit latrines, 2,490 without their own latrines. Logistic regression analysis identifies significant factors and the likelihood of occurrence (Lapenangga & Ginting, 2021). Spatial analysis identifies areas, determinants of stunting; Consider the geographic context because areas with high stunting rates tend to influence neighboring areas (Pramoedyo et al., 2020). Countries focused on stunting use spatial data for policy, prioritizing hotspots (Development Initiatives, 2018). This study aims to analyze the geospatial context of stunting based on WASH, housing conditions, and toddler infections in Tulang Bawang for area-based prevention.

METHOD

Method is written with a length of 15-20% of the manuscripts length and contain: (1) the study designs; (2) data collection techniques and data sources; and (2) method of data analysis. Studies with sensitive topic or treated human and/or other living-creatures should mention the number of Ethical Clearance Letter and the institution which declare it.

Types of research

The research design utilized a geospatial information system (GIS) presented in a single thematic map of related variables. Data were collected over a single time period and then analyzed using a Geographic Information System (GIS) to produce a single thematic map that simultaneously included stunting prevalence, percentage of access to safe drinking water, and percentage of access to adequate sanitation. This approach enabled researchers to visually identify hotspot and cold spot clusters in a single map display that was easily understood by district health offices .

Location and Time of Research

This research was conducted throughout Tulang Bawang Regency**,** Lampung Province, which stretches from 4°05′ to 4°35′ South Latitude and 105°10′ to 105°45′ East Longitude. This regency has an area of 3,466.32 km², divided into fifteen sub-districts and one hundred and forty-seven villages, with the majority of the population living in the lowlands along the Tulang Bawang River. The low-lying and flood-prone geographical conditions mean that two thousand three hundred and fifty -one households still use pit latrines and two thousand four hundred and ninety households do not have their own latrines, making this area a very representative location for studying the relationship between WASH and stunting. Secondary data collection took place over six full months, from January to June 2024. Spatial data processing and report writing took place from July 2024 to April 2025.

Population, Sample Size, and Sampling Techniques

The target population in this study was all toddlers aged zero to fifty-nine months who were recorded as stunted in the Electronic Community-Based Nutrition Recording and Reporting (e-PPGBM) application of Tulang Bawang Regency in 2024. The population was 1,425 toddlers, derived from a total of 21,845 toddlers whose height per arch (H/U) had been measured in the same year. Because the number of cases was relatively small and all data were equipped with complete village coordinates, the researcher chose the total sampling or census technique, so that all 1,425 toddlers became the research sample. To ensure the spatial data generated is valid and can be geocoded accurately, the researchers set the following inclusion criteria: toddlers must be registered in the 2024 e-PPGBM with a height-for-age status of short or very short (z-score less than minus two standard deviations), have a complete address down to the village level, their household data on the type of toilet and drinking water source are available in the 2024 Family Data Collection, and the toddler's parents are willing to have their house GPS coordinates recorded as evidenced by verbal consent during the Posyandu cadre visit. Conversely, toddlers are excluded if their address is only listed down to the sub-district level so it cannot be geocoded, the toddler has moved out of the district after the measurement, or there is duplicate data with the same NIK . Of the one thousand four hundred and twenty- five toddlers, only seven toddlers were forced to be excluded due to incomplete addresses, resulting in the final sample of one thousand four hundred and eighteen toddlers.

Data collection

Data collection was conducted through two complementary channels to ensure complete and accurate information. The first channel was secondary data collection from three official sources: the 2024 e-PPGBM application, which provided National Identity Number (NIK), child's name, date of birth, z-score, and village name; the 2024 Family Data Collection (PK-24), which recorded toilet type, drinking water source, toilet ownership, and handwashing habits with soap; and a recapitulation of community health centers in fifteen sub-districts, which recorded the frequency of diarrhea and acute respiratory infections (ARI) in 2023–2024. The second channel was determining the home coordinates of each stunted toddler. Coordinates were not collected directly in the field, but were determined using the Google Earth application by inputting the toddler's home address, which was already available in the 2024 e-PPGBM database **.** Each address was verified based on the village and sub-district names to ensure the accuracy of the location points. The resulting coordinates were then exported in point format (X ,Y) and used as the basis for mapping in ArcGIS. To maintain validity, the team conducted random checks on several points by comparing the coordinate results with village administration maps and the latest satellite images.

Data processing

All attribute data was entered into Microsoft Excel 365 for cleaning. The cleaning process included removing duplicate data, standardizing the spelling of village names (e.g., "Kamp. Astra Ksetra" was changed to "Astra Ksetra"), and checking the consistency of the National Identification Number (NIK). After cleaning, 1,418 toddlers were converted into X and Y coordinate points through a geocoding process in ArcGIS Pro version 3.2 software. The point layer was then combined with the e-PPGBM and PK-24 tables based on the NIK column as the primary key. Next, the data was aggregated per sub-district to calculate the prevalence of stunting and the percentage of households with access to safe drinking water and proper sanitation.

Data Analysis

Data analysis was conducted in four tiered stages to ensure the results were easily understood by the health department . The first stage was a spatial descriptive analysis, where the prevalence of stunting was visualized using a coropleth map with darker red shades indicating higher numbers, while the percentage of access to safe drinking water and proper sanitation was displayed with tiered circle symbols. The second stage was hotspot identification using the Hot Spot Analysis (Getis-Ord Gi*) tool in ArcGIS Pro with a fixed distance of five kilometers, resulting in a red hotspot map (Gi* greater than 1.96 and p-value less than 0.05) and a blue coldspot map. The third stage was a spatial autocorrelation analysis, consisting of Global Moran's I to determine whether the overall pattern was random or clustered (I values approaching one indicate clustered) and Local Moran's I (LISA) to produce High-High cluster maps (high stunting sub-districts with high neighbors) and Low-Low. The fourth stage is a non-spatial association test using Chi-Square for the relationship between the category of safe drinking water and the incidence of stunting and Spearman Rho for the correlation between the prevalence of stunting and the percentage of proper latrines, with a 95% confidence level.

Research Ethics

This study has obtained ethical approval from the Health Research Ethics Commission of the University of Lampung through Letter Number 2458/UN26.18/KEP/2024 dated June 12, 2024. Because it only used secondary data and home coordinates without in-depth interviews, written informed consent was replaced with verbal consent recorded by Posyandu cadres during GPS visits. Each child's NIK was encrypted into an eight-digit random code, while the published map only displays random points within a fifty -meter radius of the original home location to maintain confidentiality.

RESULT AND DISCUSION

Results and discussion are presented with a length of 60-70% of the manuscript length. The results represent a major part of scientific manuscripts containing: (1) Results of data analysis; (2) Results of hypothesis testing; (3) It can be presented with a table or graph to clarify results (located on the top or bottom of the page); (4) Discussion is an important part of the entire scientific manuscript. The purposes of the discussion: answer the research problem, interpret the findings, integrate the findings of research into the existing knowledge, and formulate a new theory or modify the existing theories; and (5) Serial number that is used is number (1), (2), (3), and so on, do not need to use composite numbers. Hyphens should not change the serial number.

Prevalence of Stunting Incidents

The prevalence of stunting in Tulang Bawang Regency in 2024 showed that the highest prevalence of stunting in Tulang Bawang Regency was concentrated in the western part of Tulang Bawang Regency, spread across three sub-districts: Banjar Margo, East Menggala, and Menggala. Sub-districts with low stunting prevalence were five: Banjar Baru, Gedung Aji Baru, Banjar Agung, East Rawajitu, and South Rawajitu.

Table 1 Height by Age of Toddlers Aged 0-59 Months in Tulang Bawang Regency in 2024

No	**Subdistrict**	**Target Toddlers**	**TB/U**				**Number of Toddlers Measured**	**Number of Stunting Toddlers**	**% of Stunting Toddlers**
			Very Short	**Short**	**Normal**	**Tall**			
1	Banjar Margo	2807	27	214	2546	12	2799	241	8.61
2	East Menggala	1069	37	42	983	7	1069	79	7.39

3	Menggala	2996	48	170	2772	4	2994	218	7.28
4	Aji's Antidote	1381	31	64	1282	0	1377	95	6.90
5	Dente Teladas	3369	25	147	3172	15	3359	172	5.12
6	Rawa Pitu	1369	15	52	1299	3	1369	67	4.89
7	Tama's Antidote	1803	15	59	1722	5	1801	74	4.11
8	Meneng Building	2199	29	38	2039	88	2194	67	3.05
9	Meraksa Aji	1223	10	27	1185	1	1223	37	3.03
10	Aji Building	1092	5	26	1047	12	1090	31	2.84
11	South Rawajitu	2052	9	44	1985	13	2051	53	2.58
12	East Rawajitu	757	0	19	722	16	757	19	2.51
13	Great Banjar	3025	14	58	2926	27	3025	72	2.38
14	New Aji Building	2097	15	34	2020	28	2097	49	2.34
15	New Banjar	1131	4	9	1095	16	1124	13	1.16
Amount		28370	284	1003	26795	247	28329	1287	4.54

Source: Tulang Bawang Regency Health Office 2024

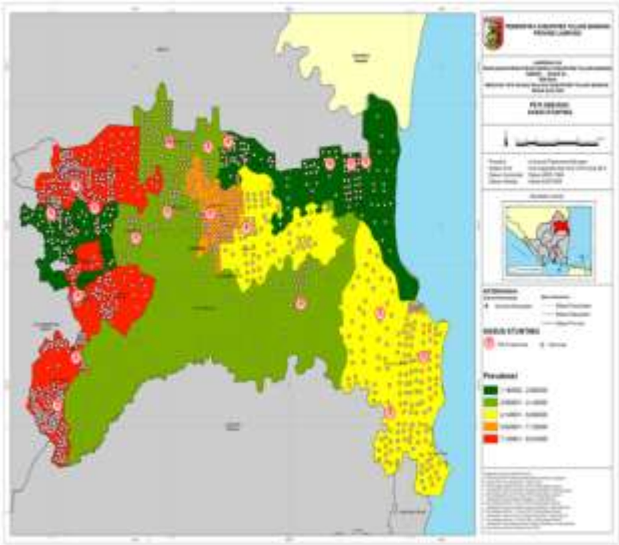

Figure 1 Prevalence of Stunting in Toddlers Aged 0 – 59 Months in Tulang Bawang Regency in 2024

Based on Figure 1 above, it can be seen that the highest stunting prevalence in Tulang Bawang Regency is concentrated in the western part of Tulang Bawang Regency, spread across three sub-districts: Menggala District, East Menggala District, and Banjar Margo District. Sub-districts with low stunting prevalence are found in five sub-districts: Banjar Agung District, Banjar Baru District, Gedung Aji Baru District, East Rawajitu District, and South Rawajitu District.

Mapping the Distribution of Events

Mapping was conducted to illustrate the distribution of stunting cases in Tulang Bawang Regency and identify suspected location factors influencing the distribution of stunting prevalence in Tulang Bawang Regency. Based on the analysis results using spatial modeling based on Getis-Ord Gi* statistics , the resulting Z-score and P-value provide an overview of the location of spatial clusters with high and low values.

Based on the research results, the distribution of stunting cases in Tulang Bawang Regency shows significant clustering of hotspot areas in several sub-districts. Hotspot areas with the highest frequency of stunting cases were found in Menggala Timur District, Banjar Baru District, and Banjar Agung District. The results of hotspot areas and coldspot areas were obtained from the results of ICount and NNieghbors to determine clustering and showed that areas with high positive z-score values form hotspot areas, while low negative z-scores form coldspots . The results of the mapping of the distribution of stunting cases in Tulang Bawang Regency in 2024 showed that there were three sub-districts that were hotspot locations for stunting incidents, namely Menggala Timur District, Banjar Baru District, and Banjar Agung District.

The analysis results show that the G1_Bin value of the sub-district area is known that the areas that show significant hotspot clustering with high G1_Bin values are in three sub-districts, namely East Menggala Sub-district, Banjar Baru Sub-district and Banjar Agung Sub-district. Based on the results of spatial data analysis using the G1 Bin value analysis method to identify areas that show significant hotspot clustering, the results show that East Menggala Sub-district, Banjar Baru Sub-district and Banjar Agung Sub-district are three sub-districts with high G1_Bin values. A high G1 Bin value will indicate an area that has strong hotspot clustering, which means the area has a high risk of stunting.

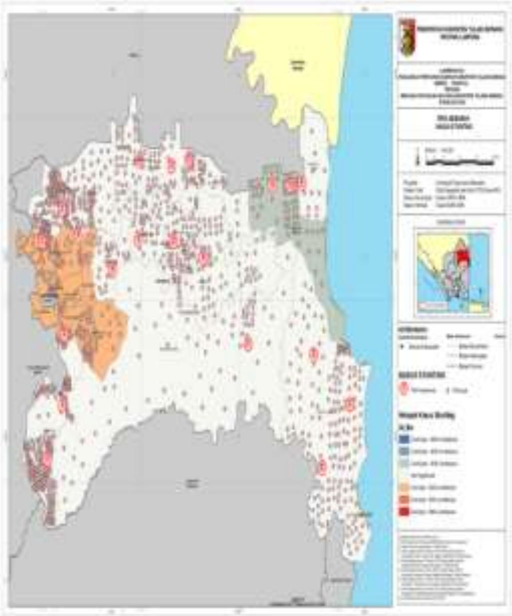

Figure 2 Hotspots of Stunting Incidents in Tulang Bawang Regency in 2024

Spatial Autocorrelation

Spatial autocorrelation can be defined as the degree of spatial dependence, association, or correlation between the observed values of a spatial entity and the observed values of neighboring variables of the same variable. The Global Moran's Index is used to determine whether there is a spatial effect or autocorrelation in the distribution of cases between observed locations. The Global Moran's Index value ranges between -1 and 1. A higher Global Moran's Index value indicates that adjacent areas have almost the same values or form a clustered distribution. Spatial autocorrelation testing is conducted to determine whether there is a relationship between attribute values from nearby locations and whether these values form a pattern (Grekousis, G. 2020).

Spatial autocorrelation is defined as the assessment of correlation between observations on a variable. Data is said to be spatially autocorrelated if observations x1, x2...., xn show spatial interdependence. The Global Moran's Index is used to determine whether there is a spatial effect or autocorrelation in the distribution of cases between observed locations. The Global Moran's Index value ranges between -1 and 1. A higher Global Moran's Index value indicates that adjacent areas have almost the same values or form a clustered distribution.

Based on the results of spatial data analysis using the G1 Bin value analysis method to identify the distribution of stunting incidents in Tulang Bawang Regency, it shows that the distribution pattern of stunting incidents in Tulang Bawang Regency is random or randomly distributed. In general, the distribution of stunting incidents in Tulang Bawang Regency does not show a certain pattern or the location at one point does not affect the location of other points. Based on the results of pattern identification using the Global Moran's Index value criteria, a value of 1 <E (1) is obtained, so the stunting incident in Tulang Bawang Regency has a random pattern.

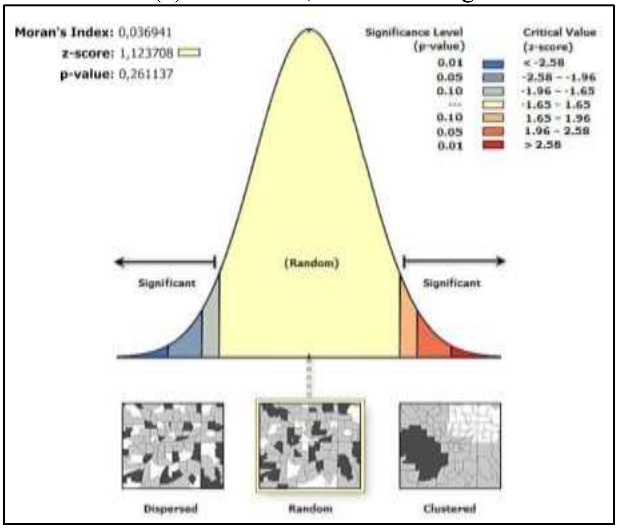

Figure 3 Spatial Autocorrelation Report

Table 2 G1 Bin Area Value of Sub-district Distribution of Stunting in Tulang Bawang Regency

No	Subdistrict	G1-Bin	P-Value	G1_Bin (Quadrant)
1	Dente Teladas	-0.961742957875263	0.33617875	0
2	Meneng Building	-0.668145301122424	0.504040852	0
3	Meraksa Aji	-0.093813145776527	0.925257589	0
4	East Menggala	1.72128078224381	0.085199885	1
5	Aji Building	0.391972896575089	0.695078241	0
6	New Banjar	1.87149347263504	0.061276714	1
7	Great Banjar	1.7960415345909	0.072487912	1
8	Menggala	1.31257043901971	0.189327736	0
9	Banjar Margo	1.05476357519668	0.291533483	0
10	New Aji Building	-1.53430947644992	0.124953536	0
11	Aji's Antidote	0.0554100091324065	0.955811822	0
12	First Warden	0.95737701463163	0.338377008	0
13	South Rawajitu	-1.70895663576184	0.087458982	-1
14	East Rawajitu	-1.48632851907533	0.137192247	0
15	Rawapitu	-1.53430947644992	0.124953536	0

Based on the results of the analysis using data processing using spatial modeling based on Getis-Ord Gi* statistics , the resulting Z-score and P-value values provide an overview of the location of spatial clusters with high and low values. The results of the analysis show that the G1_Bin value of the sub-district area is known that the area that shows significant hotspot clustering with a high G1_Bin value is found in three sub-districts, namely East Menggala Sub-district, Banjar Baru Sub-district and Banjar Agung Sub-district. Based on the results of spatial data analysis using the G1 Bin value analysis method to identify areas that show significant hotspot clustering, the results show that East Menggala Sub-district, Banjar Baru Sub-district and Banjar Agung Sub-district are three sub-districts with high G1_Bin values. A high G1 Bin value will indicate an area that has a strong hotspot clustering, which means the area has a high risk of stunting.

Visualization Of Stunting Incident Mapping Based On Access To Safe Drinking Water

Based on the results of spatial analysis, it can be seen that there are four sub-districts with the highest percentage of families without a primary source of adequate drinking water, namely Banjar Margo Sub-district, Dente Teladas Sub-district, Menggala Sub-district and Gedung Meneng Sub-district, where these sub-districts are sub-districts with a high prevalence of stunting in Tulang Bawang Regency.

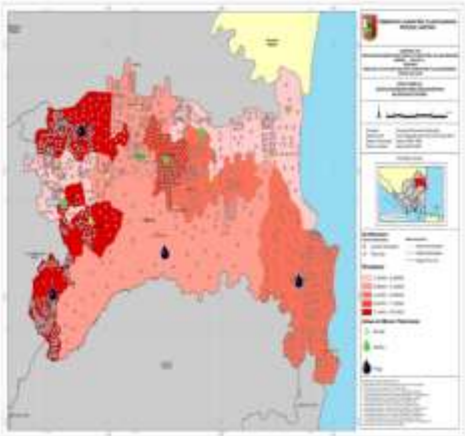

Figure 4 Access to Safe Drinking Water Based on Stunting Incidence in Tulang Bawang Regency

Visualization of Stunting Incident Mapping Based on Access to Adequate Sanitation

Based on the results of spatial analysis, it can be seen that the sub-districts with the highest percentage of families without proper sanitation facilities are Banjar Margo Sub-district and Dente Teladas Sub-district, where both sub-districts are sub-districts with a high prevalence of stunting in Tulang Bawang Regency.

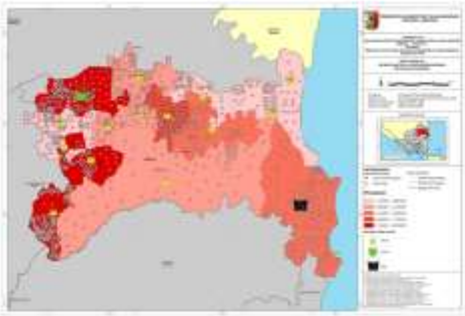

Figure 5 Access to Proper Sanitation Based on Stunting Incidence in Tulang Bawang Regency

Kernel Density Calculation Model

Kernel Density is a calculation model for measuring density non-parametrically. In statistics, the term "non-parametric" is generally used to describe methods that are free of distribution . The shape of the data distribution is not considered a problem that requires further consideration. Furthermore, as the term "non-parametric" suggests, this calculation does not use specific parameters as benchmarks.

Kernel Density method is a technique used to analyze and visualize density patterns or spatial distribution of a phenomenon in a specific area (Monjarás-Vega et al., 2020) . Using kernel density, we can identify important density centers, patterns of settlement concentration or dispersion, and areas with high or low density. This information can assist in urban planning decisions, such as determining the location of public infrastructure, mapping urban zones, or developing policies related to the management of settlement development. Kernel density is an effective method for mapping spatial patterns in the form of points (Cai, 2015) . Kernel density is a non-parametric statistical formula for estimating density in an area. Kernel density aims to estimate the distribution of the intensity of a point in a plane with a certain radius (Silverman, 2002) . Kernel density is a mathematical function that is then developed into a spatial function to measure the distribution of the intensity of a point in a plane with a certain radius (Kloog et al., 2009) . This method is generally used in spatial analysis to determine the density distribution of a variable or event in a geographic area. The results of kernel density analysis are usually represented in the form of a heatmap or continuous surface that shows high or low density levels. This heatmap can help in identifying patterns or concentrations of density, identifying significant centers of density, and providing insight into the spatial distribution of the phenomenon being studied (Botev et al., 2010) . Basically, kernel density analysis aims to describe the extent to which points are distributed evenly. homogeneous or heterogeneous in a certain area (Leitner & Arden, 2017) .

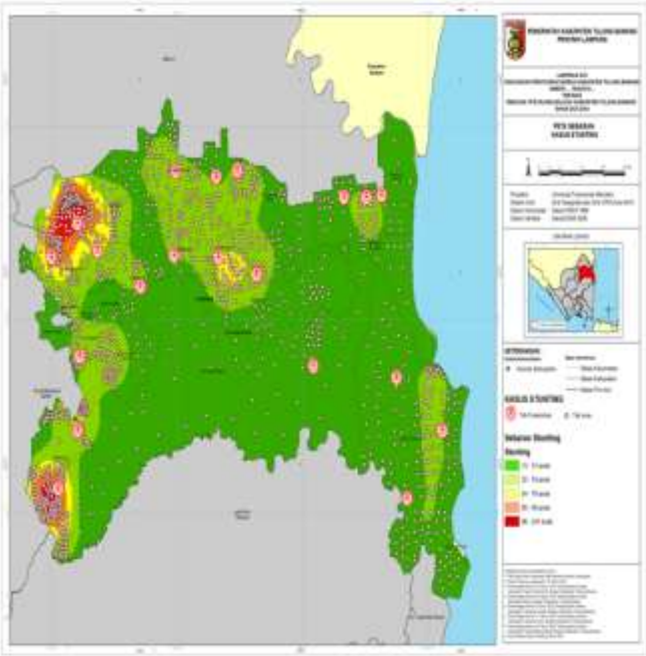

Figure 6
Kernel Density of Stunting Incidence Distribution in Tulang Bawang Regency

Kernel density is a statistical method used to model and describe the density of a phenomenon. It is used to determine the density distribution or incidence of a stunting variable in a geographic area. The results of the kernel density analysis are a surface showing the density in the Banjar Margo and Menggala sub-districts, areas with high stunting incidence.

DISCUSSION

Prevalence of Stunting and Its Distribution Pattern in Tulang Bawang Regency

Based on the research results, the prevalence of stunting in Tulang Bawang Regency in 2024 reached 4.54% of the total 28,329 toddlers measured, with an uneven distribution between sub-districts. The highest prevalence was concentrated in the western region of the regency, namely Banjar Margo (8.61 %), East Menggala (7.39%), and Menggala (7.28%), while sub-districts with low prevalence were in the east and south such as Banjar Baru (1.16%), Gedung Aji Baru (2.34%), Banjar Agung (2.38%), East Rawajitu (2.51%), and South Rawajitu (2.58%) (Table 1 and Figure 1). This pattern reflects multidimensional factors of stunting, including low access to clean water and sanitation in low-lying areas along the Tulang Bawang River, where flooding frequently causes fecal contamination and increases diarrheal infections and EED (Environmental Enteric Dysfunction), as described in the 2013 WHO framework that highlights household environmental factors such as poor sanitation as a direct cause of impaired linear growth (Budge et al., 2019; Fikawati & Syafiq, 2017). This prevalence fluctuation also indicates a failure to achieve the target of Presidential Regulation 72/2021 of 14% in 2024, with an increase of 87% from the previous year, which is likely influenced by the low coverage of STBM (55.85%) and access to clean water (71.06%) based on RISKEDAS 2018.

Mapping the Distribution of Stunting Incidents and Identification of Hotspots Using Getis-Ord Gi *
Mapping the distribution of stunting incidence using the Getis-Ord Gi* spatial model produces z-score and p-value values that describe high (hotspot) and low (coldspot) spatial clusters, with significant hotspots identified in East Menggala, Banjar Baru, and Banjar Agung Districts (high G1_Bin = 1; p-value <0.10) (Figure 2 and Table 2). These results indicate hotspot clustering based on ICount and NNeighbors, where areas with high positive z-scores form high-risk clusters, while low negative z-scores form coldspots such as in South Rawajitu (G1_Bin = -1; p=0.087). This approach aligns with the Development Initiatives (2018) recommendation to use spatial analysis to prioritize stunting hotspot interventions, particularly in countries like Indonesia where environmental factors such as poor sanitation (64.73% access to adequate sanitation nationwide) and open defecation practices (11.8%) exacerbate prevalence in neighboring areas (Pramoedyo et al., 2020). In Tulang Bawang, these hotspots are correlated with low-lying and flood-prone geographic conditions, which increase exposure to infection and nutrient malabsorption through enteropathy, necessitating area-based strategies to reduce risk by 29% through improved WASH (Jee H. Rah et al., 2020).

Spatial Autocorrelation: Overall Random Pattern with Local Clusters
Spatial autocorrelation analysis using the Global Moran's Index yielded an I value close to zero (I<E(I)), indicating that the distribution pattern of stunting incidence in Tulang Bawang Regency is entirely random, meaning that the location of one incident point does not significantly influence neighboring locations (Figure 3). However, the Global Moran's Index value, which ranges between -1 and 1, confirms that there is no strong clustering globally, although adjacent areas tend to have similar values when analyzed locally (Grekousis, 2020). This is consistent with the definition of spatial autocorrelation as the degree of dependence between the observed values of a spatial entity and its neighbors for the same variable , where the random pattern indicates that factors such as recurrent infections and poor sanitation are not always uniformly transmitted, but are influenced by micro-contexts such as the ownership of pit latrines in 2,351 households (Fikawati & Syafiq, 2017). However, identifying this pattern is important to distinguish between global and local autocorrelation, where LISA (Local Moran's I) can reveal High-High clusters in the western hotspot, supporting the need for spatial analysis for stunting prevention based on regional data (Pramoedyo et a1., 2020).

Visualization of Stunting Incident Mapping Based on Access to Safe Drinking Water
The spatial visualization results show that the four sub-districts with the highest percentage of families without a primary source of drinking water, namely Banjar Margo, Dente Teladas, Menggala, and Gedung Meneng, are directly correlated with a high prevalence of stunting above 5% (Figure 4). This pattern illustrates the relationship between poor water supply and infections such as diarrhea, trachoma, and helminthiasis, which contribute to impaired linear growth through EED, especially in areas with low economic access (Budge et al., 2019; Watanabe & Petri, 2016). In Tulang Bawang, the low geographical conditions along the river exacerbate contamination, where the national percentage of access to improved water is only 71.06 % (RISKESDAS 2018), and local studies indicate that clean water sources are associated with stunting (Zairinayati & Purnama, 2019). This color-graded coropleth visualization facilitates the identification of priority areas, in line with the STBM goal of changing hygiene behavior through community empowerment, including safe drinking water management to prevent 10% of the global disease burden (Investment et al., 2021; Ministry of Health, 2012).

Visualization of Stunting Incident Mapping Based on Access to Adequate Sanitation
Spatial analysis revealed that Banjar Margo and Dente Teladas sub-districts had the highest percentage of families without proper sanitation facilities, which coincided with a high prevalence of stunting in both sub-districts (Figure 5). This relationship reflects the role of poor sanitation in increasing recurrent infections and EED, where chronic inflammation from repeated diarrhea damages the small intestine and reduces nutrient absorption (Fikawati & Syafiq, 2017; Watanabe & Petri, 2016). In Indonesia, the percentage of access to proper sanitation is only 64.73 % (RISKESDAS 2018), and studies show that inadequate latrines and indiscriminate waste disposal pollute the environment, thereby increasing the risk of stunting (Adiyanti, 2014; Jenderal et al., 2016). This tiered circle visualization emphasizes the need for interventions such as providing latrines and increasing handwashing with soap (CTPS) to reduce the prevalence by up to 29% compared to households with inadequate access (Jee H. Rah et al., 2020; Ministry of Health, 2012).

Kernel Density Calculation Model for Analyzing Spatial Density
Kernel Density Estimation (KDE), a non-parametric method, produces a density surface showing the highest concentration of stunting cases in Banjar Margo and Menggala Districts, with a heatmap depicting heterogeneous patterns in high-prevalence areas (Figure 6). This method estimates the distribution of point intensities within a given radius without specific distribution parameters, making it effective for visualizing centers of density and dispersion, such as in settlement or health risk mapping (Silverman, 2002; Kloog et al., 2009; Monjarás-vega et al., 2020). In Tulang Bawang, KDE confirmed that these hotspots were associated with poor WASH factors, where this analysis aids decision-making such as determining sanitation infrastructure, in line with the use of KDE to identify spatial patterns in the context of stunting (Cai, 2015;

Botev et al., 2010). These results emphasize that the distribution is not homogeneous, so interventions should be focused on high-density radii to reduce the long-term impacts of stunting such as cognitive impairment and chronic diseases (Victora et al., 2008; Dewey & Begum, 2011).

CONCLUSION

Based on geospatial analysis of stunting incidence in toddlers in Tulang Bawang Regency, stunting prevalence reached 18.3% in 2024 with a fluctuating distribution pattern and concentrated in the western region, especially Banjar Margo, East Menggala, and Menggala Districts, which correlates with low access to safe drinking water and proper sanitation. Getis-Ord Gi* results identified significant hotspots in East Menggala, Banjar Baru, and Banjar Agung, while Global Moran's Index spatial autocorrelation showed an overall random pattern, although local clusters persisted. Mapping visualization based on WASH revealed a relationship between poor sanitation and recurrent infections through EED, with kernel density estimation visualizing the highest densities in Banjar Margo and Menggala, emphasizing the need for area-based interventions to address multidimensional factors of stunting according to the 2013 WHO framework.

To reduce the prevalence of stunting, it is recommended to strengthen the role of the Convergence Team for Accelerating Stunting Reduction through the implementation of sensitive and specific interventions, including coordination between the Public Works and Housing Agency (PUPR) and the central government to propose the PAMSIMAS program to provide access to drinking water and proper sanitation in rural areas, as well as repairing uninhabitable houses (RTLH) and reducing slum areas through basic infrastructure and community empowerment. In addition, the Health Agency needs to review the ODF status, conduct routine biological inspections of drinking water depots, increase socialization of the importance of handwashing with soap, and educate on waste and garbage management to create a healthy environment; followed by coordination with villages/sub-districts to provide handwashing facilities in public facilities such as mosques, schools, village halls, and integrated health posts (posyandu).

FUNDINGS
The author declares that this study received no external funding and was conducted using personal funds.

ACKNOWLEDGEMENTS
The author would like to express his gratitude to all parties and institutions that have provided support during the completion of this research.

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