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Spatial Autocorrelation Analysis of East Java Stunting Prevalence Cases in 2023

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ABSTRACT

Stunting is one of the chronic nutritional problems occur in East Java. In 2022, the percentage of stunting in East Java reached 19.2% and decreased to 17.7% in 2023. The less significant decrease occurred due to various factors, including malnutrition, poor sanitation, and environmental influences. This study will analyze the spatial influence on the prevalence of stunting in East Java, especially in 2023. The methods used include the Morans Index and the Local Indicator of Spatial Association (LISA). Spatial correlation analysis will help in determining the pattern of regional grouping based on stunting cases. This model works by testing whether the values of a variable at a location are related to the values of the same variable at neighboring locations, with the nature of the relationship being positive (clustering) or negative (dispersion). Using stunting prevalence data in 2023, the *Moran Index* = 0.3233 was obtained with a Z_{value} = -1.0776. This value indicates that there is positive spatial autocorrelation, but is not significant enough. Then, through the *Moran Scatterplot* analysis, there are indications of regional grouping in four spatial quadrants. The results of the LISA analysis show that there are five cities/regencies included in the High-High cluster (Jember, Probolinggo City, Lumajang, Malang, and Probolinggo), one area in the Low-High cluster (Situbondo), and one area in the Low-Low cluster (Gresik). These findings indicate the existence of a spatial concentration of stunting problems that can be used as a basis for developing appropriate handling strategies by the provincial government based on regions.

1. Introduction

Stunting is a condition of chronic malnutrition that occurs due to inadequate nutritional intake over a long period of time, usually caused by providing food that does not meet nutritional needs [1]. In addition to nutritional needs that are not met according to minimum standards, this case occurs due to malnutrition or infection in pregnant women, poor sanitation (air pollution and limited access to clean water), and socio-economic factors. Stunting cases are one of the international health problems that are being handled seriously by the World Health Organization (WHO); this is because the number of cases is still very high and there has been no significant decrease. Globally, in 2024, it is estimated that 150.2 million children aged 0-5 years will suffer from stunting. This figure represents 23.2% of the total children aged 0-5 years worldwide [2].

In cases of stunting, early symptoms can occur since the baby is in the womb, then physical characteristics will be increasingly visible when the baby is 2 years old [3]. Referring to WHO regulations, the main sign of stunting in children is when, at the age of 0-59 months, they have a height below X-2σ, where X is the standard value of child growth, and σ is the standard deviation value [4]. Stunting is an issue that needs attention from various parties because of the serious impact it causes, including being one of the causes of one million child deaths each year [5]. Stunting not only affects children's physical growth but can also affect their mental, cognitive, and intellectual development[6].

In Indonesia, stunting is still one of the main problems that has not been handled properly. Referring to a report from stunting.go.id, in 2022, there were around 4.7 million toddlers at risk of stunting in Indonesia [7]. This figure has not been able to decrease significantly in 2023. At the provincial level, East Java is one of the provinces experiencing high cases of stunting. Based on data from the National Population and Family Planning Agency (BKKBN) of East Java Province through the 2023 Indonesian Health Survey (SKI), the prevalence rate of stunting in East Java in 2023 was recorded at 17.7%, which is still below the national average. Probolinggo Regency recorded the highest prevalence of stunting in East Java, which was 35.4%, while Surabaya City had the lowest prevalence of 1.6% [8].

The problem of stunting needs to be handled seriously by the government. Without proper treatment, stunting can have worse impacts, such as death, weakened immune system, and complications of disease in the future (Sadida). In most areas in Indonesia, the prevalence of stunting in each region is indicated to have a spatial influence, where it is estimated that the high or low prevalence of stunting in a village will affect neighboring villages, such as malnutrition, which has a spatial effect in Central Java [9]. Thus, to identify the distribution pattern of stunting based on region, a spatial analysis approach can be used. The results of the analysis can be implemented to determine high-priority areas for stunting treatment so that treatment can be carried out on target [10]. Quantitative models that can be used for spatial analysis include the Moran Index and Local Indicators of Spatial Association (LISA). Referring to [11], the Moran Index is a value that can interpret spatial autocorrelation and can be used to analyze spatial relationships between adjacent regions related to a particular phenomenon/event. Moran's index can help determine whether there is a tendency for clustering or dispersion in the distribution of events in a region.

LISA is a local index used to evaluate trends in local patterns by showing some form of spatial relationship [12]. Global spatial autocorrelation, in this case, is the Moran index, which does not provide information on spatial patterns in a particular area. Therefore, information on the tendency of spatial relationships in each location with LISA is needed. Reference [13] defines LISA as a statistic that meets the following two criteria. 1) The LISA value of each region can be used to provide an indication of a significant spatial relationship grouping of the same values around the area. 2) The sum of the LISA values for the entire region is comparable to the Moran index value.

Several previous studies that examined the implementation of the Moran's Index and LISA for stunting cases include [10] using the Moran Index and LISA to analyze the distribution pattern of stunting. The results showed that although no spatial autocorrelation was found globally, there were significant clusters locally (high-high) in the Garut, Cianjur, and Bandung Regencies. This proves that the spatial approach is effective in identifying areas that are the focus of stunting problems. Then, [14] conducted a study on the distribution of stunting in the Bone Bolango Regency by implementing the Durbin Spatial model and further testing with the LISA method. Furthermore, the analysis was carried out using secondary data obtained from the Bone Bolango Health Office in 2019 regarding the number of stunting cases and the factors that influence them. The analysis variables include the percentage of exclusive breastfeeding (X1), the percentage of LBW (X2), the number of IDL (X3), the number of proper sanitation (X4), and the poverty rate (X5). Based on the analysis, it is known that the general factors that influence stunting cases in Bone Bolango Regency are the percentage of exclusive breastfeeding, the number of proper sanitation, and poverty.

Based on a review of previous studies, this study focuses on analyzing the spatial pattern of stunting prevalence in East Java Province in 2023. The analysis was carried out using a spatial autocorrelation approach using the Moran Index (Moran's I) to identify global patterns and the Local Indicator of Spatial Association (LISA) to detect local clusters [9]. This approach aims to identify regional grouping patterns based on stunting prevalence levels. Based on the spatial relationships formed through LISA, regions can be categorized into four types of clusters, namely cluster 1 (high-high), cluster 2 (low-low), cluster 3 (high-low), and cluster 4 (low-high) [15]. The results of the analysis obtained in this study are expected

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to help identify high-risk areas and become a basis for the government to form policies for handling stunting effectively, on target, and in accordance with spatial conditions in East Java Province.

2. Methods

2.1. Data and Data Source

This study utilizes stunting prevalence data from 2023 in East Java Province, obtained from the National Population and Family Planning Agency (BKKBN) of East Java, based on the outcomes of the 2023 Indonesian Health Survey (SKI). The dataset covers 38 districts/cities in East Java. In addition, spatial data in the form of administrative boundaries of districts/cities in East Java Province was obtained from the GeoBoundaries website in shapefile format (.shp). These data are accustomed to integrating stunting prevalence attributes with the geographic locations of each region, enabling spatial analysis to be executed. This study involves one variable, namely the number of stunting cases for each regency/city in East Java Province.

2.2. Tools and Software

The analysis in this study was executed utilizing the Python programming language. Several libraries were used, including Pandas and GeoPandas for tabular and spatial data management, Matplotlib for visualization, and PySAL (Python Spatial Analysis Library) for spatial autocorrelation calculations, including the Moran's Index and Local Indicators of Spatial Association (LISA). Python was chosen due to its flexibility, open-source nature, and comprehensive library support for spatial analysis.

2.3. Spatial Autocorrelation

Spatial autocorrelation is an analytical method accustomed to identifying patterns of association or relationships between locations within an area of observation [16]. This method offers valuable perspectives for understanding how the characteristics of a given area are influenced by its surrounding areas, allowing for a more comprehensive analysis of the spatial distribution of a phenomenon [17]. A positive spatial autocorrelation indicates that adjacent points share similar characteristics and exhibit a clustering pattern. Conversely, negative spatial autocorrelation suggests that adjacent points have differing characteristics. If the distribution is random, it means there is no significant spatial autocorrelation [18]. This concept serves as an important foundation in spatial measurement, particularly through methods, for instance, the Moran's Index and Local Indicators of Spatial Association (LISA) used in this study.

2.4. Spatial Weight Matrix

A spatial weight matrix is assembled to determine the relationship between regions based on geographic proximity, serving as the foundation for spatial autocorrelation analysis. In this study, weighting was carried out utilizing the Queen Contiguity method, where two regions are perceived as neighbors when they adjoin a boundary or a corner point [19]. In this method, the weight is assigned a value of one if the regions are contiguous and zero otherwise. Alternatively, point-based methods such as Euclidean Distance use the coordinates of each location to calculate proximity. The distance between points is calculated utilizing the following formula [20]:

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \tag{1}$$

Where u symbolizes the longitude and v the latitude of each point, the weights W_{ij} are then determined based on a threshold distance r, where locations are perceived neighbors if $d_{ij} < r$ and non-neighbors if $d_{ij} \geq r$.

2.5. Moran's Index

Moran's Index is a statistical indicator accustomed to ascertaining the level of spatial autocorrelation of a variable throughout a given area. It measures how the value of a variable at a specified location relates to values of the same variable in suburban areas based on the spatial weights between them. The formula accustomed to compute Moran's Index is as follows [21]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S_0\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{2}$$

Where I is the value of Moran's Index, n symbolizes the number of locations, x_i and x_j are the observed values at locations i and j, $\bar{x}$ is the mean of the observed values, w_{ij} is the element of the spatial weight matrix, and S_0 symbolizes the total sum of spatial weights. The value of Moran's Index lies between –1 and +1. A positive Moran's Index suggests positive spatial autocorrelation, meaning areas with similar values are grouped together. Conversely, a negative value signifies negative spatial autocorrelation, where areas with differing values are positioned near each other. An index value close to zero stipulates the deficiency of spatial autocorrelation, implying a random spatial distribution.

2.6. Moran's Scatterplot

Moran's scatterplot is a visualization tool accustomed to displaying the relationship between the normalized values of observations and the normalized average values of their neighboring regions. When accompanied by a regression line, this scatterplot can illustrate the strength of spatial relationships between regions and help uncover potential outliers. This plot is also useful for identifying spatial equilibrium patterns or the influence of surrounding areas on the value at a specified location [22]. Moran's scatterplot divides the regions into four quadrants, as shown in the following figure:

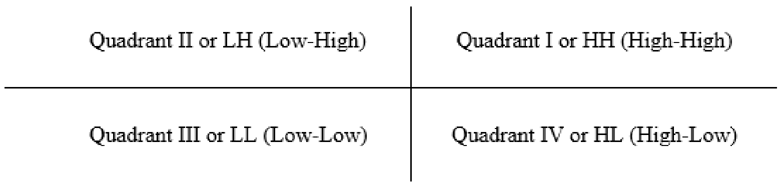

Figure 1. Moran's Scatterplot

Where Quadrant I (High-High) is the region with high values encircled by other high-value regions, Quadrant II (Low-High) is the region with low values encircled by high-value regions, Quadrant III (Low-Low) is the region with low values encircled by other low-value regions and Quadrant IV (High-Low): the region with high values encircled by low-value areas.

2.7. Local Indicator of Spatial Association (LISA)

As a global measure of spatial autocorrelation, Moran's Index cannot uncover localized spatial patterns within individual regions. Therefore, additional analysis utilizing LISA is needed to examine the spatial relationship tendencies at each location in more detail [23]. The Local Indicator of Spatial Association (LISA) is accustomed to measuring the contribution of each location to the overall spatial autocorrelation value [24]. The higher the LISA value, the stronger the indication that a region has similar values to its surrounding areas and forms a significant spatial clustering pattern. Mathematically, the LISA value is calculated utilizing the following formula [25]:

$$I_i = \frac{z_i\sum_j w_{ij}z_j}{m_2} \tag{3}$$

with $z_i = (x_i - \bar{x})$, $z_j = (x_j - \bar{x})$, and $m_2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$. Utilizing LISA, regions with significant spatial patterns such as high clusters (High-High) and low clusters (Low-Low), as well as anomalies like High-Low and Low-High, can be specifically identified.

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2.8. Research Flowchart

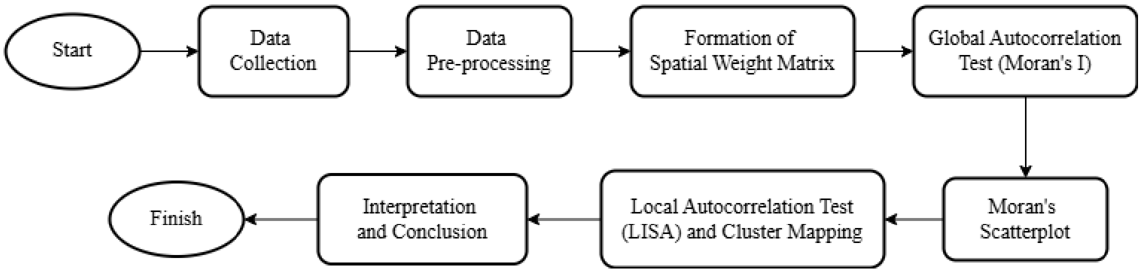

Figure 2. Research Flowchart

The flowchart of Figure 2 illustrates a comprehensive process for spatial data analysis using global and local autocorrelation methods. The process begins with data collection, where relevant spatial data is gathered from various sources such as surveys, sensors, or databases. Once collected, the data undergoes data pre-processing, which involves cleaning, normalizing, and transforming the data to ensure it is suitable for analysis. This step is critical for removing noise, handling missing values, and standardizing the dataset. After pre-processing, the formation of a spatial weight matrix is carried out. This matrix defines the spatial relationships between data points, such as proximity or connectivity, and serves as the foundation for spatial analysis. With the spatial weight matrix in place, a global autocorrelation test, such as Moran's I, is performed. This test evaluates the overall spatial dependence or clustering within the dataset, providing insights into whether similar values are spatially clustered or dispersed. To better visualize these results, a Moran's scatterplot is generated, illustrating the relationship between the variable of interest and its spatial lag.

The next step involves conducting a local autocorrelation test (LISA) to identify localized patterns and clusters within the dataset. This step is crucial for pinpointing areas of high or low values, often referred to as hotspots and cold spots, respectively. The identified clusters are then visualized through cluster mapping, which provides a spatial representation of the local patterns. Finally, the process concludes with the interpretation and conclusion step. Here, the results from both the global and local analyses are synthesized to draw meaningful insights. This step involves interpreting the patterns, understanding their implications, and relating them to the broader context or research questions. These findings can then inform decision-making, policy recommendations, or further research. This systematic approach ensures a thorough understanding of spatial relationships and dependencies within the data.

3. Results and Discussions

3.1. Overview of Stunting Prevalence in East Java

The initial analysis in this study was executed by evaluating the spatial pattern of stunting prevalence data across 38 regencies/cities in East Java Province in 2023. Table 1 presents a summary of the descriptive statistics for the stunting prevalence data used.

Table 1. Descriptive Statistics of Stunting prevalence in East Java in 2023

Minimum	Maximum	Mean	Standard Deviation	Q1	Median	Q3
1.6%	35.4%	17.7%	7.1%	14.1%	17.05%	20.75%

Based on the table, the average stunting prevalence across the 38 regencies/cities in East Java Province in 2023 was 17.7%, with a standard deviation of 7.1%. The minimum recorded prevalence was 1.6%, while the maximum reached 35.4%, indicating a significant disparity among regions. The median prevalence was 17.05%, with the first quartile (Q1) at 14.1% and the third quartile (Q3) at 20.75%. To provide a visual understanding of the geographical pattern of prevalence, the data was visualized in a thematic map, as shown in Figure 3. In this visualization, a gradient color scheme ranging from blue (low) to red (high) is accustomed to stipulate the stunting prevalence level in each regency/city.

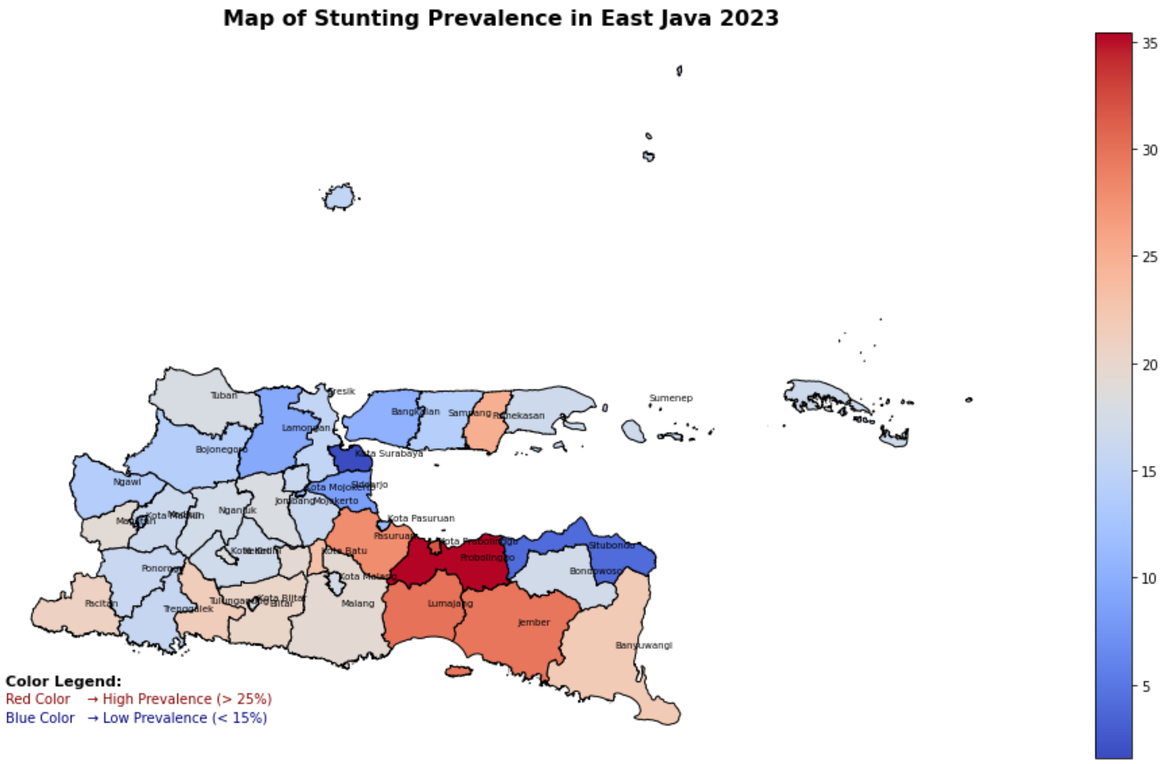

Figure 3. Stunting prevalence Map of East Java 2023

According to the map, it is observed that Probolinggo has a very high stunting prevalence (>25%), while Surabaya and several other major cities show lower prevalence rates (<15%). This map stipulates a concentration of stunting issues in specified areas, which requires more focused intervention policies, particularly in regions with high prevalence.

3.2. Spatial Weight Matrix

The spatial weight matrix was assembled utilizing the Queen Contiguity approach, whereas two areas are defined as neighbors if they adjoin either a boundary or a vertex. The matrix was then normalized using the row-standardized method to ensure uniform contribution of each region in the spatial analysis. Figure 4 presents a visual representation of the number of neighbors each region has, utilizing a histogram to illustrate the distribution of neighbor counts across areas in East Java Province.

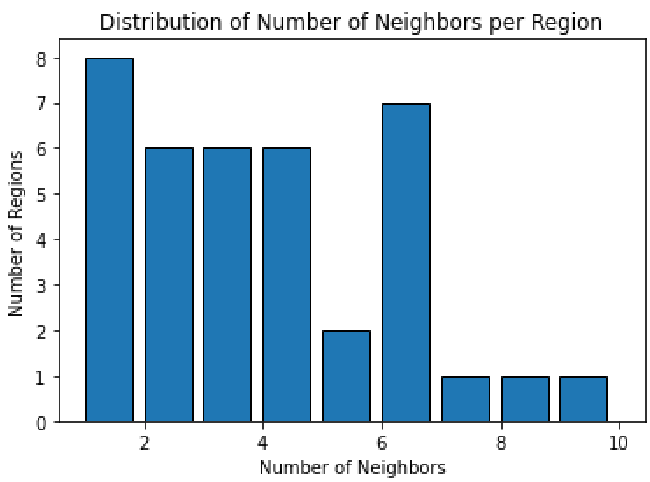

Figure 4. Distribution of Number of Neighbours per Region

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The histogram in Figure 4 shows that most regions in East Java have only one neighbor, suggesting isolation or border locations. Regions with 2 to 4 neighbors appear with relatively even frequency, while a peak at six neighbors reflects centrally positioned, well-connected areas. This variation in connectivity highlights the spatial diversity across the province and forms the basis for subsequent spatial autocorrelation analyses utilizing Moran's Index and LISA.

3.3. Moran's Index

The global spatial autocorrelation analysis of stunting prevalence in East Java in 2023 was executed utilizing Moran's Index. The test results are presented in Table 2 beneath.

Table 2. Moran's I Test Results for Stunting prevalence in East Java 2023

Moran's Index (I)	$E(I)$	$Var(I)$	Z_{value}
0.3233	-0.027	0.017	-1.0776

The Moran's Index value of 0.3233 stipulates a positive spatial autocorrelation in the distribution of stunting prevalence across districts/cities in East Java. This suggests that areas with high stunting prevalence favor to be positioned near other high-prevalence areas, and vice versa. However, based on the expected value $E(I)$ of -0.027 and a calculated Z_{value} of -1.0776, the Z_{value} does not exceed the critical threshold ($|Z| < 1{,}96$) at the 5% significance level. Therefore, there is no statistically significant global spatial autocorrelation. Nevertheless, the relatively high Moran's Index value still stipulates a potential clustering pattern, which warrants further local analysis utilizing LISA to identify regions with significant spatial clusters.

3.4. Moran's Scatterplot

Moran's scatterplot is accustomed to providing a visual representation of the spatial relationship between standardized stunting prevalence values and the average values of their neighboring areas (spatial lag). Figure 5. Displays the resulting scatterplot, which is separated into four quadrants, each reflecting a distinct spatial relationship pattern among the districts and cities in East Java Province.

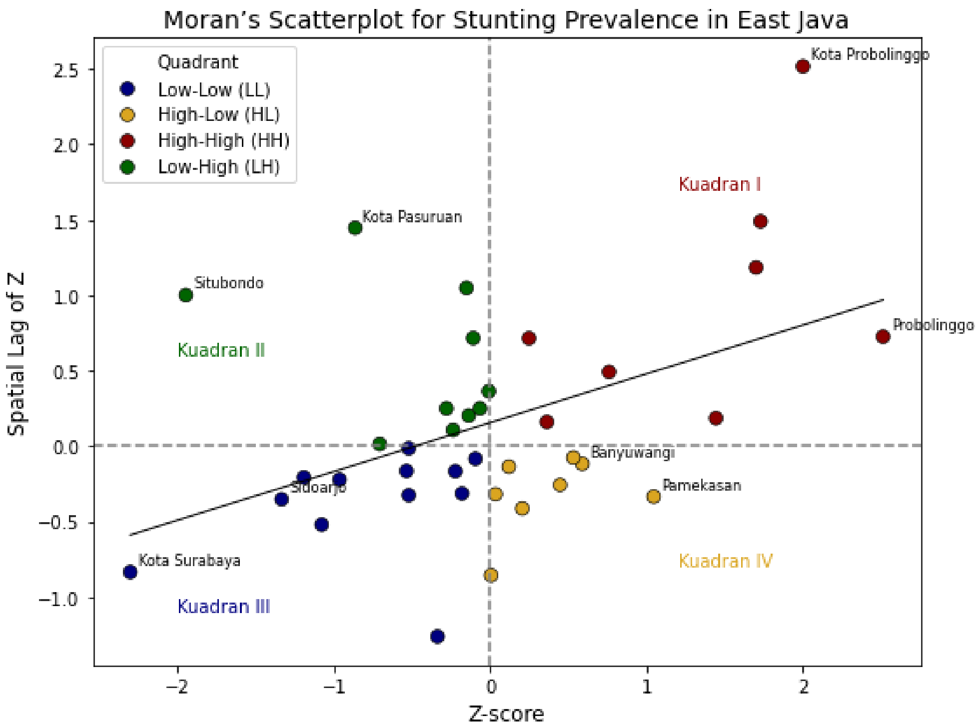

Figure 5. Moran's Scatterplot for Stunting prevalence in East Java

The outcomes of Moran's Scatterplot in Figure 5 show a clustering pattern of regions based on their z-scores and spatial lags. Regions such as Probolinggo (both the regency and the city) fall into Quadrant I (High-High), indicating high stunting prevalence encircled by neighboring areas with equivalently high prevalence. On the other hand, areas like Kota Surabaya and Sidoarjo are positioned in Quadrant III (Low-Low), showing consistently low prevalence values in their surrounding areas. Kota Pasuruan and Situbondo lie in Quadrant II (Low-High), meaning that although their prevalence is low, they are encircled by regions with high prevalence. Conversely, Banyuwangi and Pamekasan are in Quadrant IV (High-Low), indicating high prevalence in those areas but encircled by areas with low prevalence. The distribution of regencies/cities by quadrant is presented in Table 3 below:

Table 3. Distribution of Regencies/Cities in East Java Based on Moran's Scatterplot Quadrants

Quadrant	Regions
Quadrant I (HH)	Blitar, Jember, Batu City, Kota Probolinggo, Lumajang, Malang, Pasuruan, Probolinggo
Quadrant II (LH)	Bondowoso, Kediri, Blitar City, Madiun City, Malang City, Pasuruan City, Ponorogo, Situbondo, Sumenep, Trenggalek
Quadrant III (LL)	Bangkalan, Bojonegoro, Gresik, Mojokerto City, Surabaya, Lamongan, Madiun, Mojokerto, Nganjuk, Ngawi, Sampang, Sidoarjo
Quadrant IV (HL)	Banyuwangi, Jombang, Kediri City, Magetan, Pacitan, Pamekasan, Tuban, Tulungagung

3.5. Local Indicator of Spatial Association (LISA)

The LISA analysis was performed to identify local spatial clusters with statistical significance. The results revealed that five regencies/cities fall into the High-High cluster: Jember, Kota Probolinggo, Lumajang, Malang, and Probolinggo. These areas exhibit high stunting prevalence and are encircled by other areas with equivalently high prevalence, indicating a spatial concentration of stunting issues. On the other hand, Situbondo is classified in the Low-High cluster, meaning it has a low stunting prevalence but is encircled by regions with high prevalence. This may reflect either resilience or a potential risk of increasing prevalence in the future. Meanwhile, Gresik was identified in the Low-Low cluster, an area with low stunting prevalence encircled by other low-prevalence regions. Table 4 below presents the list of regencies/cities that are part of statistically significant spatial clusters based on LISA values.

Table 4. List of Regencies/Cities in Statistically Significant Spatial Clusters Based on LISA

LISA Cluster	Regions
High-High	Jember, Probolinggo City, Lumajang, Malang, Probolinggo Regency
Low-High	Situbondo
Low-Low	Gresik

The spatial distribution of LISA (Local Indicators of Spatial Association) clusters is effectively visualized in Figure 6, which provides a detailed mapping of the geographic distribution of spatial clusters across the study area. The map employs a color-coded scheme to highlight the various types of spatial clusters and their statistical significance. Red regions represent High-High clusters, indicating areas where high values of the analyzed variable are surrounded by other high values, suggesting strong positive spatial autocorrelation. Conversely, blue regions denote Low-Low clusters, where low values are clustered with other low values, signifying similar patterns of spatial concentration but at the lower end of the value spectrum.

In addition to these, green areas represent Low-High clusters, which indicate spatial outliers where a low value is surrounded by high values, and yellow areas symbolize High-Low clusters, where high values are situated among low-value neighbors. These two categories are particularly useful for identifying anomalies or irregularities in the data that deviate from overall spatial trends. Gray regions,

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on the other hand, correspond to areas that are not statistically significant ($p > 0.05$), suggesting that any observed spatial patterns in these areas could be attributed to random chance rather than meaningful spatial relationships. This visualization not only enhances the understanding of spatial dynamics within the dataset but also facilitates the identification of critical zones that may require further investigation or targeted interventions. By interpreting the spatial patterns and their significance, policymakers and researchers can derive actionable insights tailored to specific geographic contexts.

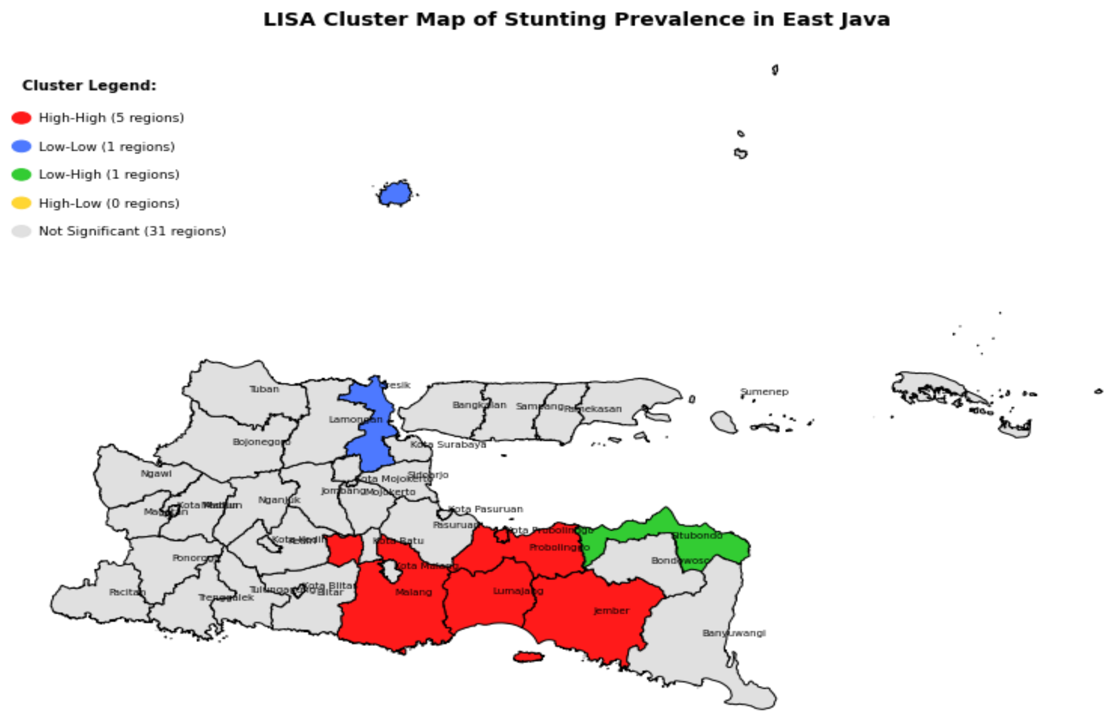

Figure 6. LISA Cluster Map of Stunting prevalence in East Java

4. Conclusion

The spatial analysis of stunting prevalence in East Java reveals that, globally, Moran's I Index value ($0{,}323$; $p > 0{,}05$) is not statistically significant. However, the Moran's Scatterplot visualization highlights clusters of high prevalence (High-High) in Blitar, Jember, Kota Batu, Kota Probolinggo, Lumajang, Malang, Pasuruan, and Probolinggo, as well as areas with low prevalence (Low-Low) in Bangkalan, Bojonegoro, Gresik, Kota Mojokerto, Kota Surabaya, Lamongan, Madiun, Mojokerto, Nganjuk, Ngawi, Sampang, and Sidoarjo. The LISA analysis further confirms five significant High-High hotspots in Jember, Kota Probolinggo, Lumajang, Malang, and Probolinggo, along with one Low-High outlier in Situbondo and one Low-Low cluster in Gresik. These findings highlight the importance of utilizing nutritional interventions and improvements in water and sanitation access in closely situated areas with high stunting prevalence (High-High clusters). Conversely, areas with low stunting prevalence but encircled by problematic regions (Low-High clusters) must be protected to prevent potential impacts. Meanwhile, areas in good condition (Low-Low clusters) can serve as best-practice models to be replicated in other regions to accelerate the reduction of stunting rates in East Java.

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