ILKOM Jurnal Ilmiah Vol. 18, No. 1, April 2026, pp. 151-164
Accredited 2nd by KEMDIKTISAINTEK No. 10/C/C3/DT.05.00/2025; E-ISSN 2548-7779| P-ISSN 2087-1716

Research Article

Optimization-Based Geospatial Clustering Using Fuzzy Geographically Weighted Clustering and Flower Pollination Algorithm for Stunting Risk Mapping

Ngatimin [a,1,*]; **Deden Istiawan** [a,2]; **Windyaning Ustyannie** [b,3]; **Rahmat Riyansyah** [a,4]; **Ameliatus Sholicah** [a,5]
[a] *Institut Teknologi Statistika dan Bisnis Muhammadiyah Semarang, Jl. Prof. Dr. Hamka Km. 01 Ngaliyan, Semarang, Indonesia*
[b] *Universitas Akprind Indonesia, Jl. Kalisahak No.28 Klitren, Yogyakarta, Indonesia*
[1]*ngatimin@itesa.ac.id;* [2]*deden.istiawan@itesa.ac.id;* [3]*wustyannie@akprind.ac.id;* [4]*rahmatriansyahpkp@gmail.com;* [5]*ameliatussholichah@gmail.com*
** Corresponding author*

Article history: Received November 05, 2025; Revised February 10, 2026; Accepted March 30, 2026; Available online April 20, 2026

Abstract

Stunting remains a major public health challenge in Indonesia, characterized by significant regional disparities and complex multidimensional determinants. Effective intervention strategies therefore require analytical approaches that are capable of capturing spatial heterogeneity and identifying region-specific vulnerability patterns. This study applies Fuzzy Geographically Weighted Clustering (FGWC) optimized using the Flower Pollination Algorithm (FPA) to map district-level stunting vulnerability and identify priority intervention areas. The analysis covers 514 districts using 21 multidimensional indicators representing health, nutrition, housing conditions, food security, social protection, and demographic characteristics derived from the Central Statistics Agency. The integration of FGWC with FPA enhances clustering performance by incorporating spatial dependence and metaheuristic optimization, enabling the algorithm to produce more stable and geographically sensitive clusters. Cluster validity indices confirm that a four-cluster solution provides the most optimal segmentation of stunting vulnerability. The results reveal distinct regional structures, socioeconomic-driven vulnerability associated with limited asset ownership, high dependence on social assistance and large household size, multidimensional deprivation concentrated primarily in eastern Indonesia, and nutrition-related vulnerability linked to breastfeeding duration and food security. These findings demonstrate that stunting patterns in Indonesia are spatially heterogeneous and influenced by diverse structural factors. The proposed FGWC–FPA framework offers a robust geospatial optimization approach that can support more precise, evidence-based, and region-specific strategies for accelerating stunting reduction.

Keywords: Geospatial; Intervention; Optimization; Mapping; Stunting

Introduction

Stunting remains one of the most persistent global public health challenges, reflecting structural inequalities in nutrition, health systems, sanitation, and socioeconomic conditions [1], [2]. Although substantial progress has been made worldwide, many low- and middle-income countries continue to experience high prevalence rates, with pronounced subnational disparities [2], [3]. Stunting has serious permanent and intergenerational impacts because it creates an intergenerational cycle in which women who were stunted as children tend to give birth to babies with low birth weight, thus perpetuating the risk of stunting [1].

Nationally, stunting is a major public health problem in Indonesia, with a prevalence of 21.5% in 2023 based on the results of the Indonesian Health Survey, which shows that nearly one in five toddlers suffer from chronic growth disorders [4]. Stunting not only affects children's physical condition, but also influences cognitive development [5], future productivity [6], and a nation's economic potential [7]. The factors that cause stunting are complex and interrelated, covering aspects of maternal and child health, sanitation, food access, and family socioeconomic status [8], [9], [10]. The problem of stunting also shows significant regional variations, reflecting differences in environmental, social, and economic conditions that have not been comprehensively mapped [11]. Therefore, understanding the spatial distribution of stunting and identifying high-risk areas is crucial for planning more targeted interventions.

Stunting reflects chronic malnutrition, which describes a community's limited access to the basic necessities for child growth, such as nutrition, health services, sanitation, and a supportive environment [12]. Low socioeconomic

http://dx.doi.org/10.33096/ilkom.v18i1.3130.151-164

groups are more vulnerable to stunting, so intervention policies must be data-driven and reach the area's most in need [13]. However, mapping priority areas for stunting in Indonesia still faces limitations, particularly in considering spatial aspects and geodemographic factors in an integrated manner. As a result, interventions have not been fully evidence-based and may impact the effectiveness of stunting reduction programs.

As an acceleration measure, the government has integrated various stunting prevention programs into the National Medium-Term Development Plan and the National Strategy for Accelerating Stunting Reduction, which emphasize a multisectoral approach and data-driven interventions [14]. However, the main challenge in implementing these policies is the lack of spatial stunting maps that can comprehensively integrate social, economic, and environmental data. Therefore, a more adaptive mapping approach is needed, one of which is through the Fuzzy Geographically Weighted Clustering (FGWC) method optimized with the Flower Pollination Algorithm (FPA), to produce accurate regional groupings based on regional characteristics relevant to stunting issues.

Based on these gaps, this study addresses two central questions: how stunting vulnerability can be spatially mapped across Indonesia to better capture regional heterogeneity, and how multidimensional health, nutritional, socioeconomic, environmental, and demographic factors shape region-specific vulnerability patterns. By integrating FGWC with FPA, this research moves beyond conventional spatial analysis toward a geospatially optimized and geographically sensitive classification framework. Considering that stunting reflects structural inequalities with long-term implications for human capital and national development, identifying spatial typologies of vulnerability is crucial for designing precision-targeted interventions. Therefore, this study aims to develop a nationally comprehensive clustering model that provides a stronger analytical foundation for context-specific and evidence-based stunting reduction strategies in Indonesia.

Method

A. Related Research

Mapping stunting is an important aspect in efforts to accelerate the reduction of stunting prevalence, as it enables spatial understanding of high-risk areas based on social, economic, and environmental factors [13]. Stunting mapping efforts are generally carried out through conventional statistical approaches such as spatial regression and descriptive analysis based on administrative area aggregates [11]. Factors such as maternal education level [6], family income [15], sanitation [16], and access to clean water [17] are the dominant indicators analyzed in various studies. Research on stunting in Indonesia has begun to develop using various approaches. A study conducted by Otok et al. [18] combined the SEM-PLS method with FIMIX-PLS to identify factors affecting the nutritional status of toddlers in Southeast Sulawesi while addressing data heterogeneity between regions. Devi et al. [14] used a spatial approach with Spatial Error Model (SEM) to analyze the determinants of stunting in West Java Province. Azis and Aswi [7] applied a spatial approach based on Conditional Autoregressive (CAR) to capture local variations in the influence of stunting determinants.

However, most of the approaches used still rely on index or regression models, which have limitations in capturing the spatial complexity and heterogeneity of regions as a whole [19]. Index approaches tend to produce data aggregation that obscures local variations [20], and are less adaptive in classifying regions based on multidimensional characteristic patterns [21]. In addition, there have not been many studies that integrate spatial modeling methods with optimization algorithms to improve the accuracy of stunting risk mapping. As an alternative, the clustering approach began to be developed in stunting studies in Indonesia. Sari et al. [22] mapped the prevalence of stunting using the K-Mode algorithm to identify priority areas for intervention in Bangkalan. Meanwhile, another study by Yuhan et al. [23] used SEM-PLS and Fuzzy C-Means to detect clusters of areas with high stunting rates. Although promising, conventional clustering approaches have not considered spatial factors that are crucial in the distribution of stunting [24]. In addition, the use of optimization methods to improve the performance of classification models is still very limited.

Based on the above description, the novelty of this study can be explained through several aspects. First, this study uses a Fuzzy Geographically Weighted Clustering (FGWC) approach optimized using the Flower Pollination Algorithm (FPA) to map areas with stunting risk levels. This approach is expected to capture spatial complexity and data heterogeneity more accurately than conventional indexing and clustering methods. Second, this study takes into account relevant socioeconomic and biophysical indicators, such as housing quality, home ownership, and access to sanitation, which have not been widely integrated into previous stunting mapping studies. Thus, the mapping results not only contribute to the development of methodology but can also serve as a more comprehensive and applicable basis for the formulation of region-based intervention policies.

B. Dataset

This study uses six dimensions consisting of 21 variables, covering 514 districts in Indonesia, with the aim of mapping stunting geospatially and identifying priority areas for intervention. The dataset used is sourced from the Central Statistics Agency (BPS) and includes the latest data relevant to stunting analysis. Each variable was selected based on its ability to represent factors contributing to stunting, thereby providing a comprehensive picture of the conditions in each district/city. The indicators and variables used in this study are presented in **Table 1**.

Table 1. Dimensions and Variables of Stunting Mapping

Dimension	Variable	Description
Kesehatan	Immunization **(X_1)**	Percentage of children aged 12–23 months who received complete basic immunization
	Delivery assisted by health personnel **(X_2)**	Percentage of ever-married women aged 15–49 whose last delivery was assisted by trained health personnel in a health facility
	Modern family planning **(X_3)**	Proportion of women of reproductive age (15–49 years) or their partners who are sexually active and use modern contraceptive methods
	MCH Handbook **(X_4)**	Percentage of mothers who own and utilize the Maternal and Child Health Handbook (MCH)
	First pregnancy at ≥20 years old **(X_5)**	Percentage of women whose first pregnancy occurred at age ≥20 years
	Normal birth weight (>2.5 kg) **(X_6)**	Percentage of babies born with a birth weight ≥2.5 kg
Health	Exclusive breastfeeding **(X_7)**	Percentage of infants under 6 months who were exclusively breastfed
	Complementary feeding **(X_8)**	Percentage of children aged 6–23 months who received complementary feeding
	Average breastfeeding duration **(X_9)**	Average duration of breastfeeding among children under five (months)
Housing & Environment	Access to safe drinking water **(X_{10})**	Percentage of households with access to safe drinking water
	Access to improved sanitation **(X_{11})**	Percentage of households with access to improved and sustainable sanitation
	Rental housing **(X_{12})**	Percentage of households living in rental housing
Food	Protein consumption per capita **(X_{13})**	Average protein consumption per capita per day
	Food consumption pattern score **(X_{14})**	Food Consumption Pattern Score based on per capita energy intake
	Food security index **(X_{15})**	Regional food security index value
Social and Economic Protection	Utilization of health insurance **(X_{16})**	Percentage of population utilizing national or local health insurance
	Beneficiaries of KPS/KKS **(X_{17})**	Percentage of households receiving KPS/KKS (lowest 40% of the population)
	Beneficiaries of BPNT **(X_{18})**	Percentage of households receiving Non-Cash Food Assistance
	Beneficiaries of PKH **(X_{19})**	Percentage of households receiving the Family Hope Program
Demography	Average household size **(X_{20})**	Average number of household members per family
	Population growth rate **(X_{21})**	Annual population growth rate (%)

C. Data Preprocessing

Low-quality data can produce inaccurate and misleading analyses. Therefore, data preprocessing is an important step to ensure that data is ready to be processed using the tools and methods used. In this study, the data preprocessing process was carried out through several main stages. First, data cleaning, which is cleaning the dataset of errors, duplications, or missing values to make it more consistent and reliable. Second, data normalization, which standardizes the scale of variables so that differences in units or value ranges do not affect the analysis results, especially in clustering and geospatial mapping methods. Third, data integration, which combines data from various sources or tables into a single, complete dataset to facilitate cross-indicator and cross-variable analysis. Through these stages, the dataset used becomes cleaner, more consistent, and ready for analysis in geospatial research on stunting in Indonesia.

D. Fuzzy Geographically Weighted Clustering

Fuzzy Geographically Weighted Clustering (FGWC) is an extension of the Fuzzy C-Means algorithm that incorporates geographic context by considering both population size and the distance between regions when computing the membership value of each data point [25]. FGWC models the influence of one region on another as the product of population and inter-region distance, making the resulting clusters sensitive to spatial factors and affecting cluster centroids to generate “geographically aware” clusters. The computation of membership for each cluster in FGWC, which is updated in every iteration, is given by the following Equation (1):

$$\mu_i' = \alpha\mu_i + \beta \frac{1}{A} \Sigma_j^n \; w_{ij}\mu_j \tag{1}$$

α and β are scaling factors applied to the previous membership value and the weighted average membership of other data points, respectively. The specific values of α and β are are defined in Equation (2):

$$\alpha + \beta \; = \; 1 \tag{2}$$

The membership weight (w_{ij}) is calculated according to Equation (3):

$$w_{ij} = \frac{\left(m_i \, m_j\right)^b}{d_{ij}^a} \tag{3}$$

a and b are user-defined parameters. When the impact of population is considered equally important as the influence of distance, both a and b are set to 1. FGWC incorporates a geographic component into Geo-Demographic Analysis (GDA), producing clusters that are sensitive to environmental factors and influencing the positions of cluster centroids, thereby forming “geographically aware” clusters. By repeatedly applying geographic adjustments throughout the clustering process, FGWC not only determines the spatial distribution of clusters but also updates the values in the membership matrix.

E. Flower Pollination Algorithm

The Flower Pollination Algorithm (FPA) is a metaheuristic optimization method inspired by the pollination process of flowering plants, introduced by Xin in 2012 [26]. The goal of FPA is to emulate the “survival of the fittest” among flowering plants by selecting the best reproduction parameters, which correspond to the optimal solution of the objective function [27]. Over time, FPA has been extended to handle multi-objective optimization problems [28]. The pollination process can be simplified into four main rules:

1. Cross-pollination and biotic pollination are treated as global pollination, with pollen-carrying pollinators moving according to Levy flights (Rule 1).
2. Local pollination involves abiotic and self-pollination (Rule 2).
3. Pollinators such as insects influence flower persistence, represented as a reproduction probability proportional to the similarity between two flowers (Rule 3).
4. The switch between local and global pollination is governed by a transition probability $p \in [0,1]$, with a slight preference for local pollination (Rule 4).

to implement these rules in the algorithm, they are translated into mathematical update equations. During the global pollination phase, pollen gametes are dispersed by pollinators like insects, which can travel long distances. Rules 1 and 3, describing global pollination and flower persistence, can be expressed mathematically in Equation (4):

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(g_* - x_i^t) \tag{4}$$

Where x_i^{t+1} represents the pollen i or the solution vector x_i^t at iteration t, and g_* denotes the best solution identified so far among all solutions in the current iteration. The parameter γ acts as a scaling factor to control the step size. The term, $L(\lambda)$ specifies the step length based on Levy flights, reflecting the strength of pollination. Because insects can travel long distances with variable step lengths, Levy flights provide an efficient way to model this behavior. Specifically, $L > 0$ is sampled from a Lévy distribution.

$$L \sim \frac{\lambda\, \Gamma(\lambda)\, sin\,(\frac{\pi\lambda}{2})}{\pi} \frac{1}{\delta^{1+\lambda}}\ (\delta \gg \delta_0 > 0) \tag{5}$$

$\Gamma(\lambda)$ is the gamma function, and in Equation (5) it has a valid value when $\delta > 0$, In theory, the value of δ_0 = 0,1 [29]. Local pollination or self-pollination in FPA, applying rules 2 and 3, can be expressed as follows.

$$x_i^{t+1} = x_i^t + \in \left(x_j^t - x_k^t\right) \tag{6}$$

Where x_j^t and x_k^t represent pollen grains from different flowers of the same plant species, which models the persistence of flowers within a confined environment. In mathematical terms, if x_j^t and x_k^t belong to the same species or are selected from the same population, this corresponds to a local random walk when sampled from a uniform distribution over [0,1]. In this study, the centroid approach is applied to improve FGWC performance by substituting x with the centroid matrix v, consequently, The global optimum is defined in Equation (7) [30].

$$v_k^{t+1} = v_k^{t+1} + \gamma L(\lambda)\left(v_g - x_i^t\right) \tag{7}$$

Equation (8) is derived from Equation (6) [30].

$$v_k^{t+1} = v_k^{t+1} + \in L(\lambda)(v_r^t - v_k^t) \tag{8}$$

F. Cluster Validity Index

Cluster performance in fuzzy clustering can be assessed using Cluster Validity Indices (CVI), which evaluate the quality of clustering based on compactness, separation, and membership clarity. The Partition Coefficient (PC) measures the degree to which observations belong exclusively to a single cluster, with higher values indicating clearer and less overlapping clusters. Classification Entropy (CE) quantifies the uncertainty in cluster assignments, where lower values suggest better-defined clusters. The Partition Index (SC) evaluates the compactness of clusters, and lower SC values correspond to more homogeneous clusters. The Separation Index (S) measures the distance between clusters, with lower values indicating better separation. The IFV Index combines both compactness and separation to provide an overall validity measure, where higher values reflect well-formed clusters. The Xie-Beni Index (XBI) assesses the ratio of intra-cluster variance to inter-cluster distance, and lower XBI values indicate clusters that are compact and well-separated. Collectively, these indices help determine the optimal number of clusters and evaluate the stability and quality of clustering results in fuzzy clustering applications, including methods such as Fuzzy Geographically Weighted Clustering (FGWC).

Partition coefficient (PC)

Measures the degree to which observations belong exclusively to a single cluster. Higher PC values indicate clearer clusters with less overlap, as defined in Equation (9) [31].

$$PCI = \frac{1}{N}(\Sigma_{i=1}^{c} \Sigma_{j=1}^{N}\, \mu_{ij}^2) \tag{9}$$

Classification entropy (CE)

Measures the uncertainty or ambiguity of each observation’s membership across clusters. Lower CE values indicate better-defined clusters, as defined in **Equation (10)**.

$$CE = \frac{1}{N} \Sigma_{i=1}^{c} \Sigma_{j=1}^{N} \mu_{ij} \log \mu_{ij} \tag{10}$$

Partition Index (SC)

Evaluates the compactness of clusters. Lower SC values indicate more compact and homogeneous clusters, as defined in Equation (11).

$$SC = \Sigma_{j=1}^{c} \Sigma_{i=1}^{N} \left(w_{ij}\right)^{m} \left\|x_i - v_j\right\|^2 \tag{11}$$

***Separation Index* (SI)**

Measures how well clusters are separated. Lower S values indicate better separation between clusters, as defined in Equation (12).

$$SI = \frac{\Sigma_{i=1}^{c} \Sigma_{j=1}^{N} \left(\mu_{ij}\right)^2 ||x_j - v_i||^2}{N min_{i,k} ||x_j - v_i||^2} \tag{12}$$

***Xie and Beni index* (XBI)**

Computes the ratio of intra-cluster distance to inter-cluster distance. Lower XBI values indicate compact clusters that are clearly separated, reflecting better cluster quality, as defined in Equation (13) [32].

$$XBI = \frac{\Sigma_{i=1}^{c} \Sigma_{j=1}^{N} \left(\mu_{ij}\right)^m ||x_j - v_i||^2}{N min_{i,j} ||x_k - v_i||^2} \tag{13}$$

IFV Index

Combines cluster compactness and separation into a single measure. Higher IFV values indicate clusters that are both compact and well-separated, as defined in Equation (14) [33].

$$IFV = \frac{1}{c} \Sigma_{j=1}^{c} \left\{ \frac{1}{N} \Sigma_{k=1}^{N} \mu_{kj}^2 \left[log_2 c - \frac{1}{N} \Sigma_{k=1}^{N} log_2 \mu_{kj} \right]^2 \right\} \frac{SD_{max}}{\overline{\sigma_D}} \tag{14}$$

Algorithm 1 computational procedure of the proposed hybrid FGWC–FPA model, illustrating data preprocessing, centroid initialization, global–local pollination mechanism, and iterative optimization of the spatial fuzzy clustering objective function.

The selection of FGWC and FPA parameters was guided by empirical evaluation and prior studies in fuzzy clustering and metaheuristic optimization. The fuzziness parameter (m = 1.6) was selected to balance cluster overlap and membership discrimination, preventing excessive fuzziness while preserving gradual spatial transitions among regions. The spatial weighting coefficients (α = 0.7 and β = 0.3) prioritize local membership stability while retaining meaningful geographic influence within the clustering structure. In the FPA component, the switching probability (p = 0.7) slightly favors local pollination to improve convergence stability, whereas γ and λ regulate Lévy flight dynamics to maintain adequate global exploration. Collectively, these parameter settings ensure a balanced trade-off between exploration and exploitation, thereby enhancing optimization stability and clustering robustness.

Algorithm 1. Hybrid Optimization of FGWC using the Flower Pollination Algorithm (FPA)

```
Input: Dataset X, spatial distance matrix D, population matrix P, number of clusters C, fuzzifier
exponent m, weights α and β, spatial weighting constant a, spatial decay coefficient b, error
tolerance ε, maximum iteration maxIter, number of flowers $n_x$, switch probability p, step-size
factor γ, Lévy index λ, and shift δ.

Output: Optimized centroids $V_{opt}$, final membership matrix $\mu_{opt}$, minimum objective function value
$f_{opt}$, and cluster validity indices (PC, CE, SC, S, XB, IFV).

1. Initialize a set of flower populations V = {$v_1$, $v_2$, …, $v_{nx}$}.
2. For each flower $v_k$, compute the initial fitness $f_k$ using the FGWC objective function:
       $J_m = (V,K) = \sum_{i=1}^{n}\sum_{k=1}^{c} \frac{d^2(x_i,v_k)}{\sum_{r=1}^{c}\left(\frac{d(x_i,v_r)}{d(x_i,v_k)}\right)^{\frac{2}{m-1}}}$
3. Identify the current global best centroid g = argmin($f_k$).
4. Set iteration counter t = 0.
5. While (t < maxIter) and (convergence not reached):
   • t ← t + 1
   • For each flower $v_k$:
      • Generate random number r ∈ [0,1].
      • If (r < p): perform global pollination using Lévy flight:
            $v_k(t+1) = v_v(t) + \gamma \times L(\lambda) \times (g - v_k(t))$
      • Else: perform local pollination:
        select $v_i$ and $v_j$ randomly, then update centroid:
            $v_k(t+1) = v_k + \varepsilon \times (v_i - v_j)$
      • Update fuzzy memberships and spatial weighting as:
            $u_{ij} = \left[\sum_{r=1}^{c}\left(\frac{d(x_i,v_j)}{d(x_i,v_r)}\right)^{\frac{2}{m-1}}\right]^{-1}$
            $\mu_{ij}' = \alpha\mu_{ij} + \beta\sum_{p}\omega_{ip}\mu_{pj}$
      • Evaluate $J_m$(V, X) and update global best g if improved.
6. Return optimized centroids $V_{opt}$, membership matrix $\mu_{opt}$, objective value $f_{opt}$, and CVI.
```

The computational complexity of the proposed FGWC–FPA framework arises from the fuzzy geographically weighted clustering procedure and the metaheuristic optimization process. For a dataset with n regions, p variables, c clusters, and T FGWC iterations, a single FGWC execution requires approximately $O(npcT)$ operations due to membership and centroid updates across all regions and variables. When integrated with the Flower Pollination Algorithm using a population size N_p and G generations, the overall computational complexity becomes $O(N_pGnpc)$, as the FGWC objective function is evaluated for each pollen in every generation. Although the hybridization increases computational cost compared to standalone FGWC, the metaheuristic search enhances centroid optimization and mitigates convergence to local optima. Given the moderate dataset size (514 regions and 21 variables), the framework remains computationally feasible and demonstrates linear scalability with respect to the number of regions and variables, making it suitable for medium-scale spatial clustering applications.

Results and Discussion

The most optimal clustering process in this study was obtained through the application of Fuzzy Geographically Weighted Clustering (FGWC) optimized with the Flower Pollination Algorithm (FPA). The basic parameters of FGWC were set at m=1.6, α=0.7, β=0.3, a=1, b=1, and ε=1e-6, while the FPA parameters used were γ=1.2, λ=1.5, and p=0.7. The combination of these two approaches was chosen because it was able to accommodate the complexity of spatial data while improving the accuracy of the clustering results. FGWC allows each region to have membership levels in more than one cluster, thereby enabling a description of stunting conditions that are gradual in nature and not completely separate between districts. Optimization with FPA provides the additional advantage of more effective global search capabilities, so that the clustering solutions obtained are not trapped in local conditions alone. Stunting analysis was then conducted by grouping districts/cities in Indonesia based on multidimensional indicators covering health, nutrition, environment, food security, social protection, and demography. This multidimensional approach is important because stunting is not only influenced by health factors but is also closely related to socioeconomic conditions, food access, and the quality of the living environment. Thus, the clustering results not only provide a map of areas with varying stunting risks but also reveal the unique characteristics underlying the formation of each cluster. These results provide a solid basis for understanding the spatial variation of stunting in Indonesia and simultaneously provide an analytical foundation for developing more targeted intervention strategies according to the needs of each region.

Based on the results of cluster validity evaluation in **Table 2**, it can be seen that each index contributes differently in determining the optimal number of clusters. The Partition Coefficient (PC) value shows the highest result at 4 clusters (3.82194), indicating a better level of cluster membership certainty compared to other cluster numbers. The Separation Index (SC) also reaches the highest value at 4 clusters (9.14927), which shows that the separation between clusters is clearer and the heterogeneity between groups is stronger. Furthermore, the Index of Fuzzy Validity (IFV) and Xie-Beni Index (XB) values were also highest at 4 clusters (4.95045 and 4.09338, respectively), indicating a more stable cluster structure, with adequate distance between clusters and relatively low overlap between regions. The consistency of these four validity indicators reinforces the finding that four clusters are the most optimal number to represent the spatial variation of stunting in Indonesia. Thus, the discussion of the research results will focus on the characteristics and distribution of each cluster.

Table 2. Cluster Validity Index

Cluster	PC	CE	SC	S	IFV	XB
2	0.50214	**0.69099**	3.53326	115.5452	0.00869	2.20847
3	0.25000	1.01280	9.11126	**248.4274**	1.09559	4.03016
4	**3.82194**	1.38629	**9.14927**	687.9327	**4.95045**	**4.09338**

Table 3 shows that the average values of variables in each cluster differ significantly, reflecting the diversity of factors causing stunting across regions in Indonesia. Cluster 1 is characterized by major problems in the variables of rented housing and households receiving KPS/KKS, reflecting socioeconomic vulnerability as the dominant factor. Cluster 2 faces problems more related to the burden of social protection programs, as indicated by the high number of households receiving Non-Cash Food Assistance (BPNT) and the Family Hope Program (PKH), as well as the relatively large average number of household members. Cluster 3 presents more complex and multidimensional problems, covering aspects of maternal and child health (immunization, assisted childbirth, use of modern contraception, first pregnancy age ≥20 years), parenting and nutrition (exclusive breastfeeding, complementary feeding, per capita protein consumption), environmental conditions (access to drinking water and proper sanitation), to food security and demographic dynamics (expected food pattern score, utilization of health insurance, and population growth rate). Meanwhile, Cluster 4 has more focused problems, namely the low average duration of breastfeeding and the weak food security index. These variations in characteristics indicate that each cluster represents a different type of vulnerability, requiring intervention approaches tailored to the context of each region. The following discussion will elaborate further on the characteristics and distribution of regions in each cluster.

Table 3. Stunting Cluster Center

Cluster	**X_1**	**X_2**	**X_3**	**X_4**	**X_5**	**X_6**	**X_7**
1	58.19514	91.65646	69.34902	89.36268	57.83876	83.36868	87.23412
2	57.6037	91.54885	69.40201	89.15921	57.55889	83.18134	87.28276
3	**45.94127**	**76.2711**	**47.00161**	**73.84082**	**64.37132**	**62.79424**	**79.01902**
4	57.86475	91.64792	69.58176	89.30705	57.52476	83.36372	87.2856
Cluster	**X_8**	**X_9**	**X_{10}**	**X_{11}**	**X_{12}**	**X_{13}**	**X_{14}**
1	69.78681	10.45131	86.28096	80.74861	**5.140575**	61.48837	86.15408
2	69.47952	10.44069	85.75168	80.13716	5.002179	61.35477	85.98993
3	**60.27212**	10.44298	**73.16787**	**60.95629**	3.814868	**53.29837**	**76.80628**
4	69.65015	**10.07885**	86.16315	80.57501	5.058952	61.50098	86.1685
Cluster	**X_{15}**	**X_{16}**	**X_{17}**	**X_{18}**	**X_{19}**	**X_{20}**	**X_{21}**
1	74.59888	72.83526	**15.63369**	18.87985	16.7645	1.201624	1.415934
2	74.52784	72.3499	15.61166	**18.92981**	**16.85666**	**1.200762**	1.42947
3	80.40782	**58.37481**	10.60313	13.5856	15.22124	1.147488	**2.791576**
4	**74.53481**	72.6839	15.5835	18.86401	16.74662	1.201037	1.418089

These findings are further reinforced by the results of the Kruskal–Wallis test shown in **Table 4**, where all variables have p-values below the threshold of 0.05. Thus, the null hypothesis stating that there are no differences between clusters is rejected. These results confirm that the clustering process using FGWC optimized with FPA into four groups successfully distinguishes regions based on varying levels of social vulnerability. Furthermore, since all variables contribute to social vulnerability, clusters with higher average values for certain variables can be interpreted as regions facing more serious problems in those dimensions. This highlights the specific challenges faced by districts/cities in each cluster, thereby strengthening the justification for different intervention approaches between clusters.

Table 4. Results of the Kruskal–Wallis Test

Variable	Chi_Square	p_value	Variable	Chi_Square	p_value	Variable	Chi_Square	p_value
X_1	158.5601	3.75E-34	X_8	229.2900	1.97E-49	X_{15}	112.2421	3.61E-24
X_2	114.1394	1.41E-24	X_9	103.8260	2.34E-22	X_{16}	165.5268	1.18E-35
X_3	187.2210	2.43E-40	X_{10}	54.7172	7.89E-12	X_{17}	145.1902	2.87E-31
X4	32.1435	4.88E-07	X_{11}	30.9456	8.73E-07	X_{18}	109.7675	1.23E-23
X_5	63.1308	1.26E-13	X_{12}	35.1502	1.13E-07	X_{19}	114.2824	1.31E-24
X_6	60.3821	7.10E-14	X_{13}	44.0964	1.44E-09	X_{20}	119.5115	9.83E-26
X_7	196.0902	2.95E-42	X_{14}	24.0719	2.41E-05	X_{21}	27.4920	4.64E-06

The clustering results show four regional groups with different spatial patterns, as shown in **Figure 1**. Cluster 1, marked in light blue, covers 196 districts, spread across Sumatra, Kalimantan, Sulawesi, and parts of East Nusa Tenggara and Maluku. Cluster 2, marked in dark blue, consists of 102 districts predominantly in Central Java and East Java, as well as parts of central Sulawesi and several areas of Kalimantan. Cluster 3, marked in red and covering 56 districts, has the highest concentration in Papua, West Papua, and Maluku, with additional distribution in parts of Sumatra and East Nusa Tenggara. Meanwhile, Cluster 4, marked in green, covers 160 districts/cities, mainly in West Java, Bali, most of Kalimantan, Sulawesi, and West Nusa Tenggara. This diversity in numbers and spatial distribution shows that the pattern of stunting vulnerability is not homogeneous throughout Indonesia, but is influenced by different geographical, social, and economic factors between regions.

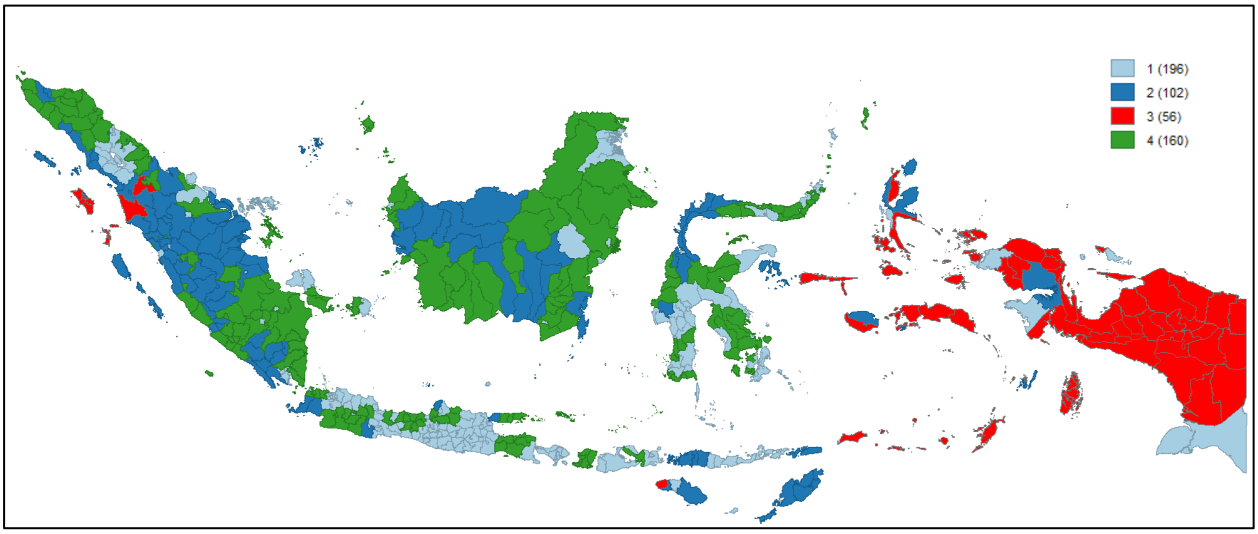

Figure 1. Geospatial Distribution of Stunting Risk Areas Identified Through FGWC-FPA.

Cluster 1, highlighted in light blue on the distribution map, shows a very large area in Indonesia. The areas included in this cluster are southern Sumatra, most of Central Java and East Java, Bali, West Nusa Tenggara, East Nusa Tenggara, and most of Sulawesi, especially the southern and northern parts. Several areas of Maluku and southern Papua are also included in this category. The even distribution across various regions makes Cluster 1 representative of the general stunting conditions experienced by most districts in Indonesia. Thus, this cluster can be viewed as a more general representation of national stunting characteristics compared to other clusters that may show more specific patterns.

From a socio-economic perspective, Cluster 1 is characterized by two main problems, namely the high proportion of households living in rented houses and the large number of KPS/KKS recipients. Living in a rented house can be seen as an indicator of limited asset ownership, which in turn is related to family economic stability. Meanwhile, the high number of KPS/KKS social assistance recipients indicates that most households in this cluster are classified as poor or vulnerable to poverty, and therefore remain highly dependent on government intervention to meet their basic needs. Although the stunting conditions in this cluster do not always reflect the most severe situations, socio-economic vulnerability remains a major challenge that cannot be ignored. These socioeconomic characteristics are closely related to the demographic conditions of the regions in this cluster. Most areas, such as Java, southern Sumatra, and several cities in Sulawesi, have relatively high levels of urbanization. The rapid urbanization process is often not matched by the availability of adequate and affordable housing, so many families end up living in rented houses. In addition, population density in these areas increases competition for economic resources, which increases households' vulnerability to poverty. The accumulation of these conditions is then reflected in the high number of social assistance recipients. Thus, the economic and demographic structure of the region plays an important role in shaping the socioeconomic profile of Cluster 1.

These findings are consistent with previous studies showing that socio-economic conditions, such as household income, asset ownership, and reliance on social protection programs, are strongly associated with stunting prevalence in Indonesia [34]. Rapid urbanization and high population density in regions like Java and southern Sumatra exacerbate these vulnerabilities by limiting access to adequate housing and economic opportunities, as also reported in earlier research [35]. The analysis of Cluster 1 confirms that stunting cannot be addressed solely through nutrition and health interventions. Socio-economic vulnerability, including dependence on social assistance and limited household assets, highlights the need for multidimensional intervention strategies. Approaches integrating social protection, housing access, and family economic empowerment, alongside health and nutrition programs, are supported by prior studies emphasizing the importance of comprehensive, context-specific policies to reduce stunting effectively and sustainably [36].

Cluster 2, highlighted in dark blue on the distribution map, shows a more limited distribution compared to Cluster 1. However, its distribution pattern shows a concentration in areas that still have high socio-economic vulnerability. Areas in this cluster are mostly found outside Java, covering several districts in Sumatra, Kalimantan, Sulawesi, and parts of eastern Indonesia. The relatively narrow but focused distribution in these pockets of vulnerability confirms that Cluster 2 represents areas with relatively more serious stunting conditions, requiring special attention in the formulation and implementation of government intervention programs. The main characteristics of Cluster 2 are marked by a high proportion of households receiving Non-Cash Food Assistance (BPNT), recipients of the Family Hope Program (PKH), and a large average number of household members. The high number of social assistance recipients indicates that households in this cluster are dominated by families with low levels of welfare who are still highly dependent on government support, both for basic food needs and children's needs. Meanwhile, the large average number of household members indicates a high burden of dependents, which in turn has implications for the limited allocation of resources for meeting children's nutritional needs. This condition puts children living in large and poor families at a higher risk of experiencing nutritional problems, including stunting [37].

The high dependence on social assistance programs and the large household size in this cluster are closely related to the economic structure and socio-cultural patterns of the local community. Most areas in Cluster 2 still rely on the informal sector or subsistence agriculture with low productivity, resulting in unstable household incomes. In addition, social norms that view having many children as an asset or status symbol are still quite strong, contributing to the high average number of household members. The combination of economic limitations, the burden of large families, and dependence on social assistance explains why Cluster 2 is more seriously vulnerable to stunting. Therefore, interventions in Cluster 2 need to be designed comprehensively, emphasizing three main aspects. First, increasing family economic independence through the development of productive businesses and improving community skills. Second, controlling the number of household members by strengthening family planning programs tailored to the local socio-cultural context. Third, strengthening local food security so that the availability of nutritious food does not solely depend on government social assistance.

Cluster 3 shows a concentrated distribution pattern in eastern Indonesia, particularly in almost all of Papua and West Papua provinces, as well as most districts in Maluku and East Nusa Tenggara. In addition to its dominance in the eastern region, this cluster also appears in the form of pockets of problems on several other islands, such as remote districts in Sulawesi and Kalimantan, as well as isolated points in western Sumatra. This distribution indicates that the characteristics of Cluster 3 are not limited to one large island, but are related to areas that are geographically difficult to reach or have significant limitations in public infrastructure. The socioeconomic and health characteristics of Cluster 3 are multidimensional, covering almost all determinants of stunting. In terms of maternal and child health, this cluster is characterized by low immunization coverage, births that are not fully assisted by health workers, low use of modern contraception, and limited use of the Maternal and Child Health Handbook (Book KIA). In terms of nutrition and child care practices, exclusive breastfeeding and complementary feeding are still far from optimal. In addition, indicators of access to basic services show serious weaknesses, such as the low proportion of households with access to safe drinking water and adequate sanitation. Food consumption patterns also do not support balanced nutrition, as seen in the low per capita protein consumption and food pattern scores. Low utilization of health insurance and a relatively high population growth rate further increase the burden on households and reduce families' capacity to meet their children's nutritional needs [38].

These conditions can be explained by a combination of structural and contextual factors. Many districts in Cluster 3 are located in remote areas, which often hinders access to health facilities, trained health workers, immunizations, and nutrition services. Limited basic infrastructure, including clean water, sanitation, and transportation, further exacerbates the situation. The relatively low level of education and health literacy among the community also has an impact on suboptimal breastfeeding and complementary feeding practices. From an economic perspective, limited market access and low purchasing power restrict the consumption of nutritious foods, especially animal protein. Meanwhile, demographic factors such as high birth rates and weaknesses in the coverage of government programs, such as the National Health Insurance (JKN) and nutrition programs, reduce the effectiveness of existing interventions. Considering the complexity of the problems, interventions in Cluster 3 must be integrated and cross-sectoral. The main priorities include strengthening basic health services through expanding immunization coverage and increasing the availability of trained birth attendants, family planning programs to control population growth, and specific and sensitive nutrition interventions in the form of support for breastfeeding and complementary feeding practices, food supplementation and fortification, and strengthening local food security. In addition, investment in basic infrastructure development, particularly clean water, sanitation, and regional accessibility, is a key element for nutrition and health interventions to be effective. This comprehensive approach is essential to reduce vulnerability in the most remote areas, while also reducing stunting disparities between regions in Indonesia. Cluster 4 has problems that are more focused on basic nutrition, particularly the average duration of breastfeeding and the food security index. This shows that although the regions included in this cluster do not experience multidimensional problems like cluster 3, they still face significant challenges in child care practices and the availability of nutritious food. Low average duration of breastfeeding has the potential to reduce optimal nutritional intake in early childhood, while a weak food security index reflects the vulnerability of households in accessing and consuming healthy and balanced food.

In terms of geographical distribution, Cluster 4 appears in various districts/cities in Sumatra, Java, Kalimantan, Sulawesi, and Nusa Tenggara, although it does not dominate nationally. This distribution pattern shows that the problems represented by Cluster 4 are not directly related to infrastructure limitations as in Cluster 3, but are more thematic in nature, related to consumption patterns, feeding culture, and people's purchasing power. The presence of Cluster 4 on several large islands confirms that food security and breastfeeding practices remain cross-regional challenges, both in rural and semi-urban areas. The main characteristics of Cluster 4 are marked by a low average duration of breastfeeding and a low food security index. The low duration of breastfeeding indicates that child feeding practices are not yet fully in line with health recommendations, which can ultimately have an impact on children's nutritional quality and growth. Meanwhile, weaknesses in food security reflect households' limitations in accessing and consuming sufficient, nutritious, and diverse food. The combination of these two factors makes Cluster 4 vulnerable to nutritional problems that increase the risk of stunting, even though the infrastructure and access to basic services in this region are relatively better than in Cluster 3.

Overall, Cluster 4 represents a group of regions that require specific interventions in the form of nutrition education and increased public awareness of the importance of exclusive breastfeeding and complementary feeding according to standards. In addition, strengthening the local food security system by increasing the availability of nutritious food, empowering families economically, and optimizing food assistance programs are strategic steps that need to be taken. If not handled appropriately, areas in Cluster 4 have the potential to shift towards more complex problems as seen in Cluster 3. Therefore, intervention strategies in Cluster 4 must be oriented towards sustainable promotional and preventive efforts so that problems can be controlled before they develop into multidimensional issues.

Conclusion

This study successfully mapped stunting vulnerability at the district level in Indonesia using a Fuzzy Geographically Weighted Clustering (FGWC) approach optimized with the Flower Pollination Algorithm (FPA). The analysis results show that stunting conditions in Indonesia are divided into four clusters with different characteristics. Cluster 1 represents the general condition of stunting related to limited home ownership assets and a high number of KPS/KKS recipients. Cluster 2 shows more serious vulnerability due to dependence on social assistance (BPNT and PKH) and large household size. Cluster 3 indicates complex multidimensional problems, especially in eastern Indonesia, including health, nutrition, sanitation, and access to basic services. Meanwhile, Cluster 4 shows more thematic issues, namely low duration of breastfeeding and weak food security. These findings confirm that stunting in Indonesia cannot be addressed with a single approach, but requires specific intervention strategies according to the characteristics of each cluster. Strengthening social protection and family economic empowerment is relevant for Clusters 1 and 2, while basic infrastructure development and improved access to health services are priorities in Cluster 3. Nutrition education and strengthening food security need to be focused on in Cluster 4. Thus, this evidence-based spatial approach provides a strong foundation for formulating more targeted and effective policies to accelerate stunting reduction in accordance with the needs of each region.

This study is subject to several limitations. First, the analysis relies on cross sectional data, which limits the ability to capture temporal dynamics and regional transitions in stunting vulnerability. Second, the spatial weighting structure assumes static geographic relationships and does not fully account for dynamic inter regional interactions or population mobility. Moreover, as a clustering based approach, the model identifies spatial patterns rather than causal relationships among determinants. Future research may incorporate longitudinal data, adaptive spatial weighting mechanisms, and predictive modeling frameworks to better capture temporal evolution and causal complexity.

Acknowledgement

The author gratefully acknowledges the financial support provided by the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia for funding this research under Contract Numbers 077/LL6/PL/AL.04/2025 and A.1/7/062010/LPPM/V/2025. This support enabled the successful implementation of all research stages, including data collection, processing, analysis, and reporting.

References

[1] F. Fajrini *et al.*, “Systematic Literature Review : Stunting pada Balita di Indonesia dan Faktor yang Mempengaruhinya,” *Kedokt. dan Kesehat.*, vol. 20, no. 1, pp. 55–73, 2024, doi: 10.24853/jkk.20.1.55-73.

[2] D. Nurpadilah and H. Wulandari, “Analisis Faktor Penyebab Stunting pada Anak Usia Dini,” *J. Ilm. Wahana Pendidik.*, vol. 10, no. 12, pp. 153–158, 2024, doi: 10.5281/zenodo.12512351.

[3] K. Rahmadhita, “Permasalahan Stunting dan Pencegahannya Stunting Problems and Prevention,” *J. Ilm. Kesehat. Sandi Husada*, vol. 11, no. 1, pp. 225–229, 2020, doi: 10.35816/jiskh.v10i2.253.

[4] S. J. W. Astuti, S. Suindyah Dwiningwarni, and S. Atmojo, “Modeling environmental interactions and collaborative interventions for childhood stunting: A case from Indonesia,” *Dialogues Heal.*, vol. 6, no. September 2024, p. 100206, 2025, doi: 10.1016/j.dialog.2025.100206.

[5] K. G. Dewey and K. Begum, “Long-term consequences of stunting in early life,” *Matern. Child Nutr.*, vol. 7, no. SUPPL. 3, pp. 5–18, 2011, doi: 10.1111/j.1740-8709.2011.00349.x.

[6] Hijrawati, A. N. Usman, S. Syarif, V. Hadju, S. As’ad, and Y. S. Baso, “Use of technology for monitoring the development of nutritional status 1000 hpk in stunting prevention in Indonesia,” *Gac. Sanit.*, vol. 35, pp. S231–S234, 2021, doi: 10.1016/j.gaceta.2021.10.028.

[7] A. A. Azis and A. Aswi, “Spatial Clustering of Stunting Cases in Indonesia: a Bayesian Approach,” *Commun. Math. Biol. Neurosci.*, vol. 2023, pp. 1–11, 2023, doi: 10.28919/cmbn/7898.

[8] A. Saleh, S. Syahrul, V. Hadju, I. Andriani, and I. Restika, “Role of Maternal in Preventing Stunting: a Systematic Review,” *Gac. Sanit.*, vol. 35, pp. S576–S582, 2021, doi: 10.1016/j.gaceta.2021.10.087.

[9] D. D. Jalata and B. G. Asefa, “Trends and Determinants of Dietary Diversity in Children Aged 6-59 Months

in Ethiopia: Analysis of 2005-2016 Demographic and Health Survey," *Curr. Dev. Nutr.*, vol. 6, no. 10, p. 6010008, 2022, doi: 10.1093/cdn/nzac135.

[10] A. D. Laksono, R. D. Wulandari, N. Amaliah, and R. W. Wisnuwardani, "Stunting among children under two years in Indonesia: Does maternal education matter?," *PLoS One*, vol. 17, no. 7 July, pp. 1–11, 2022, doi: 10.1371/journal.pone.0271509.

[11] N. Azzahra, E. Yuniarti, N. Syah, and I. Umar, "Bibliometric analysis of research stunting 2010-2023," *Multidiscip. Rev.*, vol. 8, no. 6, 2025, doi: 10.31893/multirev.2025160.

[12] H. Yuliansyah, Sulistyawati, and S. A. Mulasari, "Technological Innovation is Needed to Accelerate Stunting Reduction in Indonesia," *Commun. ACM*, vol. 65, no. 2, pp. 17–19, 2022, doi: 10.1145/3503779.

[13] J. Indra and K. Khoirunurrofik, "Understanding the role of village fund and administrative capacity in stunting reduction: Empirical evidence from Indonesia," *PLoS One*, vol. 17, no. 1 January, pp. 1–12, 2022, doi: 10.1371/journal.pone.0262743.

[14] Y. P. Devi *et al.*, "Spatial Analysis of Stunting Prevalence According to Family Data Collection Indicators in Indonesia," *Media Publ. Promosi Kesehat. Indones.*, vol. 8, no. 3, pp. 210–220, 2025, doi: 10.56338/mppki.v8i3.6931.

[15] F. Danso and M. A. Appiah, "Prevalence and associated factors influencing stunting and wasting among children of ages 1 to 5 years in Nkwanta South Municipality, Ghana," *Nutrition*, vol. 110, p. 111996, 2023, doi: 10.1016/j.nut.2023.111996.

[16] L. Cameron, C. Chase, S. Haque, G. Joseph, R. Pinto, and Q. Wang, "Childhood stunting and cognitive effects of water and sanitation in Indonesia," *Econ. Hum. Biol.*, vol. 40, no. May 2019, p. 100944, Jan. 2021, doi: 10.1016/j.ehb.2020.100944.

[17] D. Suciyanti, G. Wangge, U. Fahmida, and T. Supali, "Stunting Among Children in Rural Area of Indonesia: Five-Year Follow-Up Study," *Curr. Dev. Nutr.*, vol. 5, no. 1908, p. 187, 2021, doi: 10.1093/cdn/nzab035_095.

[18] B. W. Otok, Purhadi, R. Sriningsih, and D. S. Dila, "Segmentation of toddler nutritional status using REBUS and FIMIX partial least square in Southeast Sulawesi," *MethodsX*, vol. 12, no. December 2023, 2024, doi: 10.1016/j.mex.2023.102515.

[19] A. Ndagijimana *et al.*, "Childhood stunting is highly clustered in Northern Province of Rwanda: A spatial analysis of a population-based study," *Heliyon*, vol. 10, no. 2, 2024, doi: 10.1016/j.heliyon.2024.e24922.

[20] F. Amoako Johnson, "Spatiotemporal clustering and correlates of childhood stunting in Ghana: Analysis of the fixed and nonlinear associative effects of socio-demographic and socio-ecological factors," *PLoS One*, vol. 17, no. 2, pp. 1–22, 2022, doi: 10.1371/journal.pone.0263726.

[21] N. Hasdyna, R. K. Dinata, Rahmi, and T. I. Fajri, "Hybrid Machine Learning for Stunting Prevalence: A Novel Comprehensive Approach to Its Classification, Prediction, and Clustering Optimization in Aceh, Indonesia," *Informatics*, vol. 11, no. 4, 2024, doi: 10.3390/informatics11040089.

[22] A. N. Sari, D. H. Qurotu'ain, F. Harianto, and S. Z. Jannah, "Regional Mapping in Bangkalan District Based on Potential Indicators of Total Stunting Using K-Mode Cluster Algorithm," *Media Gizi Indones.*, vol. 17, no. 1SP, pp. 76–82, 2022, doi: 10.20473/mgi.v17i1sp.76-82.

[23] R. J. Yuhan, P. M. Kutanegarai, and S. R. Budiani, "Clustering Of Stunting Prevalence with Gender Equality in Households Index and Socio-Demographic Variables In Regency/Cities Of Bali, West Nusa Tenggara And East Nusa Tenggara Provinces," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1443, no. 1, 2025, doi: 10.1088/1755-1315/1443/1/012005.

[24] J. Schröders, S. Wall, H. Kusnanto, and N. Ng, "Millennium development goal four and child health inequities in Indonesia:A systematic review of the literature," *PLoS One*, vol. 10, no. 5, pp. 1–28, 2015, doi: 10.1371/journal.pone.0123629.

[25] G. Grekousis, "Local fuzzy geographically weighted clustering: a new method for geodemographic

segmentation," *Int. J. Geogr. Inf. Sci.*, vol. 35, no. 1, pp. 152–174, Jan. 2021, doi: 10.1080/13658816.2020.1808221.

[26] X.-S. Yang, "Flower Pollination Algorithm for Global Optimization," 2012, pp. 240–249. doi: 10.1007/978-3-642-32894-7_27.

[27] A. Kaur, S. K. Pal, and A. P. Singh, "Hybridization of Chaos and Flower Pollination Algorithm over K-Means for data clustering," *Appl. Soft Comput.*, vol. 97, no. xxxx, p. 105523, 2020, doi: 10.1016/j.asoc.2019.105523.

[28] X. S. Yang, M. Karamanoglu, and X. He, "Multi-objective flower algorithm for optimization," *Procedia Comput. Sci.*, vol. 18, pp. 861–868, 2013, doi: 10.1016/j.procs.2013.05.251.

[29] X. S. Yang, *Nature-Inspired Optimization Algorithms*. 2014. doi: 10.1016/B978-0-12-821986-7.00002-0.

[30] R. E. Caraka *et al.*, "Micro, small, and medium enterprises' business vulnerability cluster in indonesia: An analysis using optimized fuzzy geodemographic clustering," *Sustain.*, vol. 13, no. 14, 2021, doi: 10.3390/su13147807.

[31] J. c Bezdek, R. Ehrlich, and W. Full, "The Fuzzy c-Means clustering algorithm," *Remote sensing. Proc. IGARSS '88 Symp. Edinburgh, 1988. Vol. 3*, vol. 10, no. 2, pp. 1783–1784, 1988, doi: 10.1109/igarss.1988.569600.

[32] Xuanli Lisa Xie and Gerardo Beni, "A Validity Measure for Fuzzy Clustering," *IEEE transactions on pattern analysis and machine intelligence*, vol. 13, no. 8. pp. 841–847, 1991. doi: 10.1109/34.856.

[33] C. Hu, L. Meng, and W. Shi, "Fuzzy clustering validity for spatial data," *Geo-Spatial Inf. Sci.*, vol. 11, no. 3, pp. 191–196, 2008, doi: 10.1007/s11806-008-0094-8.

[34] A. Kustanto, O. Rachmat, and S. Setyadi, "The Prevalence of Stunting in Indonesia: An Examination of the Health, Socioeconomic Status, and Environmental Determinants," *J. Iran. Med. Counc.*, Nov. 2024, doi: 10.18502/jimc.v8i1.17062.

[35] A. D. Laksono *et al.*, "Determination of appropriate policy targets to reduce the prevalence of stunting in children under five years of age in urban-poor communities in Indonesia: a secondary data analysis of the 2022 Indonesian national nutritional status survey," *BMJ Open*, vol. 14, no. 9, p. e089531, Sep. 2024, doi: 10.1136/bmjopen-2024-089531.

[36] Widyaningsih, Mulyaningsih, Rahmawati, and Adhitya, "Determinants of socioeconomic and rural-urban disparities in stunting: evidence from Indonesia," *Rural Remote Health*, Mar. 2022, doi: 10.22605/RRH7082.

[37] D. Azriani *et al.*, "Risk factors associated with stunting incidence in under five children in Southeast Asia: a scoping review," *J. Heal. Popul. Nutr.*, vol. 43, no. 1, p. 174, Oct. 2024, doi: 10.1186/s41043-024-00656-7.

[38] D. Ayuningtyas, D. Hapsari, R. Rachmalina, V. Amir, R. Rachmawati, and D. Kusuma, "Geographic and Socioeconomic Disparity in Child Undernutrition across 514 Districts in Indonesia," *Nutrients*, vol. 14, no. 4, p. 843, Feb. 2022, doi: 10.3390/nu14040843.