CAUCHY – Jurnal Matematika Murni dan Aplikasi
Volume 10 (2) (2025), Pages 1205-1218
p-ISSN: 2086-0382; e-ISSN: 2477-3344

Modeling Fuzzy Geographically Weighted Clustering with Flower Pollination Algorithm for Spatial Optimization and Clustering

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Abstract

This study aims to identify spatial groupings of regencies and cities in East Nusa Tenggara (NTT) Province based on health and sanitation determinants associated with stunting by applying the *Fuzzy Geographically Weighted Clustering* optimized through the *Flower Pollination Algorithm* (FGWC–FPA). The analysis utilized eight indicators for 2024, including breastfeeding coverage, low birth weight (LBW) rates, basic immunization completeness, complementary feeding practices, and access to safe drinking water and adequate sanitation. The results produced two distinct clusters: Cluster 1 is characterized by higher rates of complementary feeding and BCG immunization but limited access to drinking water and sanitation, as well as higher LBW prevalence. Cluster 2, in contrast, exhibits significantly better access to drinking water (90.37%) and sanitation (83.19%), along with more optimal Hepatitis B immunization coverage. Cluster validity evaluation using the Classification Entropy (CE) and Separation Index (SI) demonstrates that the optimal configuration is achieved at $c = 2$ and $m = 1.5$, yielding the lowest CE (0.6631) and SI (0.0653) values. These findings indicate that the FGWC–FPA method provides superior clustering performance, producing more stable and well-separated clusters that accurately reflect the spatial distribution of stunting determinants in NTT.

Keywords: FGWC, FPA, FGWC-FPA, Stunting.

1 Introduction

Clustering is a technique used to group data into subsets (clusters) based on object similarity, such that objects within the same cluster share more similar characteristics than those in different clusters [1]. In unsupervised learning, clustering is applied to unlabeled data to group similar objects together and separate those that differ [2], [3]. Clustering methods are commonly divided into hard clustering—where each object belongs to only one cluster—and fuzzy clustering, which allows objects to have membership degrees across multiple clusters [4]. As data structures become increasingly complex, fuzzy clustering is widely used due to its flexibility in representing heterogeneous patterns [5].

One of the most widely used fuzzy clustering methods is Fuzzy C-Means (FCM), but it has limitations such as difficulty determining the optimal number of clusters, susceptibility to local optima, and reduced performance for complex or high-dimensional datasets [6]. To address these issues, Fuzzy Geographically Weighted Clustering (FGWC) was developed by incorporating

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Submitted: October 06, 2025 Reviewed: October 16, 2025 Accepted: November 20, 2025
DOI: https://doi.org/10.18860/cauchy.v10i2.36800

spatial information such as distance and population. However, FGWC still relies on randomly initialized cluster centers, which may lead to suboptimal outcomes.

To enhance optimization performance, FGWC has been integrated with metaheuristic algorithms. Previous studies indicate that metaheuristic-based optimization can produce more stable global solutions [7]. For instance, FGWC has been applied successfully in clustering regional economic development indicators [8], demonstrating its applicability for spatially structured data.

Building upon these developments, this study applies the FGWC–FPA method to identify spatial patterns of stunting in East Nusa Tenggara (NTT). Stunting is a chronic nutritional problem that significantly affects child development [9]. According to the Indonesian Nutritional Status Survey (SSGI), national stunting prevalence declined slightly from 21.6% (2022) to 21.5% (2023), yet NTT remained the province with the highest prevalence, reaching 37% in 2024 [10]. This condition underscores the need for comprehensive spatial analysis to understand stunting determinants in the region.

This study aims to implement and evaluate the FGWC–FPA method for clustering districts and municipalities in NTT based on health, nutrition, and sanitation indicators. By integrating spatial weighting and metaheuristic optimization, the method is expected to generate more accurate and stable cluster structures that reflect actual regional conditions. The findings are anticipated to support public health planning, the prioritization of stunting mitigation efforts, and broader applications of advanced spatial clustering and optimization methods in public health research.

2 Methods

This research employs secondary data provided by the Central Statistics Agency of East Nusa Tenggara Province (https://ntt.bps.go.id/id). The research data consist of several predictor variables, namely: infants who receive exclusive breastfeeding (X_1), infants who receive early breastfeeding initiation (X_2) [11], infants with low birth weight (LBW) (X_3) [12], infants who receive complete basic BCG immunization (X_4), infants who receive complete basic Hepatitis B immunization (X_5) [13], toddlers who are given complementary foods (X_6) [14], households that have access to safe drinking water (X_7), and households that have access to proper sanitation (X_8). The analysis in this study covers all districts/cities in East Nusa Tenggara, with a total of 22 districts/cities included in the 2024 dataset. The method used in this research is FGWC-FPA. The stages of the study are as follows:

1. Developing a FGWC model with the FPA.
2. Conducting the FGWC-FPA analysis through the following steps:
   (a) **Data preparation**: including data input as well as the construction of distance and geographical weight matrices.
   (b) **Parameter determination**: specifying fuzzy clustering parameters (number of clusters c, fuzziness value m, threshold, maximum iterations), FPA parameters (global and local pollination), and geographic parameters (α, β, a, b).
   (c) **Initialization and fitness function**: defining the number of agents, initializing the starting positions, and selecting the FGWC-V or FGWC-U fitness function according to the data characteristics.
   (d) **Optimization process with FPA**: consisting of global pollination using Lévy flight, local pollination with neighbor solutions, agent position updates, and stopping criterion checks.
   (e) **Clustering result evaluation**: assessing the final solution using cluster validity indices, namely the Separation Index (SI) and Classification Entropy (CE), in order to obtain the optimal clustering results.

2.1 Fuzzy Geographically Weighted Clustering

The Fuzzy Geographically Weighted Clustering (FGWC) method, introduced by G. A. Mason and R. D. Jacobson in 2007, extends the conventional Fuzzy C-Means (FCM) algorithm by embedding spatial components-such as regional distances and population magnitudes-that impact the determination of cluster centroids [15]. FGWC calculates the influence of one region on another in relation to its population. A distance-decay effect is applied as a weighting factor in the clustering process. The FGWC algorithm thus incorporates the influence of spatial interactions as an integral part of the model [16]. The membership degree of each cluster is then determined at every iteration of the fuzzy clustering algorithm using the following equation:

$$\mu_i^{'} = \alpha \times \mu_i + \beta \times \frac{1}{A} \sum_{j}^{n} w_{ij} \times \mu_j \tag{1}$$

Parameters α and β are scaling factors that influence the proportions before and after weighting. The definitions of n based on the values of α and β are as follows:

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

The membership criteria for FGWC are defined as follows:

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

This study applies the FGWC-V variant, where spatial weights explicitly incorporate population magnitude through m_i and m_j. Because population effects are included in the spatial interaction term, this formulation corresponds to FGWC-V rather than FGWC-U. The above weighting function is the single spatial weighting scheme used throughout the model, ensuring consistency with the chosen FGWC-V framework.

Parameters a and b control the effects of distance and population on the weights, and are specified by the user.

$$J_m^{FGWC}(U, V; W) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m \|x_k - v_i\|^2 \tag{4}$$

2.2 Flower Pollination Algorithm

The Flower Pollination Algorithm (FPA) represents a metaheuristic optimization approach inspired by the biological process of flower pollination. As in nature, the reproductive success of a flower species depends on pollination. In this method, the algorithm distinguishes between two mechanisms: global pollination and local pollination [17]. The objective function of the Flower Pollination Algorithm (FPA) in the global pollination process is defined as follows:

$$v_i^{t+1} = v_i^t + \gamma L(\lambda) \left(g_* - v_i^t\right) \tag{5}$$

The objective function of the Flower Pollination Algorithm (FPA) in the local pollination process is defined as follows:

$${v_i}^{t+1} = {v_i}^t + \epsilon({v_j}^t - {v_k}^t) \tag{6}$$

2.3 Validity Index

The cluster validity index is used to determine the optimal number of clusters, as it plays an important role in obtaining reliable estimates in cluster analysis. It also serves to assess whether the specified number of clusters can adequately represent the entire dataset. In addition, the validity index provides objective criteria for determining the partition value in clustering algorithms [18].

1. Separation Index (SI)
   The Separation Index (SI) is defined as the ratio of the objective function value to the minimum cluster separation. A smaller SI value indicates a more optimal cluster partition [19].

$$S = \frac{\sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} \|x_k - v_i\|^2}{\min_{i \neq j} \|v_i - v_j\|^2} \tag{7}$$

where

S	:	Separation Index, measuring the compactness and separation of clusters. Lower values indicate better clustering.
n	:	total number of data points.
c	:	total number of clusters.
u_{ik}	:	membership degree of data point k in cluster i.
m	:	fuzziness exponent ($m > 1$), controlling the degree of fuzziness in clustering.
x_k	:	data point at location k.
v_i	:	cluster center for cluster i.
$\|x_k - v_i\|^2$	:	squared Euclidean distance between data point k and cluster center i.
$\min_{i \neq j} \|v_i - v_j\|^2$	:	minimum squared distance between any two distinct cluster centers, representing cluster separation.

2. Classification Entropy (CE)
   Classification Entropy (CE) is used to measure the degree of uncertainty in fuzzy clustering results. A smaller CE value indicates clearer and more distinct clusters, whereas a larger value reflects greater ambiguity in the clustering [20].

$$CE = -\frac{1}{n} \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^{m} \log(u_{ik}^{m}) \tag{8}$$

where

CE	:	Cluster Entropy, a measure of uncertainty in the clustering results.
n	:	total number of data points.
c	:	total number of clusters.
u_{ik}^{m}	:	membership degree of data point k in cluster i.
m	:	fuzziness exponent ($m > 1$), controlling the level of cluster fuzziness. Higher m leads to fuzzier clusters.
$\log(u_{ik}^{m})$	:	natural logarithm of the membership value, quantifying the uncertainty associated with the membership.

3 Results and Discussion

Taken together, the clustering outputs, centroid profiles, spatial patterns, and validity index comparisons show that the FGWC–FPA configuration with $c = 2$ and $m = 1.5$ yields the most coherent and interpretable partition of districts and cities in NTT with respect to stunting-related determinants. The contrast between Cluster 1 and Cluster 2 highlights clear differences in access to safe drinking water and sanitation, immunization coverage, and low birth weight prevalence, while the superior CE, SI, and XB values confirm the robustness of the resulting clusters. These empirical findings provide the basis for synthesizing the main insights of this study and discussing their implications for spatially targeted stunting mitigation, as outlined in the next section.

3.1 FGWC Development Model with FPA (FGWC-FPA)

Lemma 1 (Global and Local Pollination Mechanism in FGWC-FPA)**.** *Let μ_{ik} denote the fuzzy membership degree of data point x_k in cluster i, v_i denote the cluster center, L be the step size determined by the Lévy flight mechanism, and ϵ be a small random number $(0 < \epsilon < 1)$. The membership and cluster center updates in the FGWC-FPA algorithm are governed by the following rules:*

1. ***Global Pollination:***

$$\mu_{ik}^{(t+1)} = \mu_{ik}^{t} + L(\mu_g - \mu_{ik}^{t}), \tag{9}$$

$$\text{where} \quad \mu_{ik}^{(t)} = \left(\frac{\|x_k - v_i\|^2}{\sum_{i=1}^{c} \|x_k - v_i\|^2} \right)^{\frac{-t}{m-1}}, \tag{10}$$

$$L = \frac{\lambda\,\Gamma(\lambda)\sin(\pi\lambda)}{\pi |s|^{1+\lambda}}. \tag{11}$$

The normalization constraint is given by:

$$\sum_{i=1}^{c} \mu_{ik}^{(t+1)} = 1, \tag{12}$$

and the cluster center is updated as:

$$v_i^{(t+1)} = \left(\frac{\sum_{k=1}^{n} \mu_{ik}^{m} x_k}{\sum_{k=1}^{n} \mu_{ik}^{m}} \right)^{t} + L(v_g - v_i^{t}). \tag{13}$$

2. ***Local Pollination:***

$$\mu_{ik}^{(t+1)} = \mu_{ik}^{t} + \epsilon(\mu_g - \mu_{ik}^{t}), \tag{14}$$

$$v_i^{(t+1)} = v_i^{t} + \epsilon(v_g - v_i^{t}), \tag{15}$$

where ϵ represents a local random factor that adjusts the pollination intensity.

Proof. The update mechanism is derived from the Flower Pollination Algorithm (FPA), where global pollination simulates long-distance transfer of the best solutions through Lévy flight, while local pollination exploits neighborhood information using a small random perturbation ϵ. The normalization step ensures that the membership degrees in each iteration satisfy the fuzzy constraint $\sum_{i=1}^{c} \mu_{ik} = 1$. Hence, the proposed update rules maintain both global exploration and local exploitation, improving convergence stability and avoiding local optima in the FGWC process. □

3.2 Formulation of the FGWC-FPA Objective Function

Lemma 2 (Derivation of the FGWC-FPA Model)**.** *The Fuzzy Geographically Weighted Clustering–Flower Pollination Algorithm (FGWC-FPA) model seeks to minimize the spatially weighted fuzzy objective function*

$$J_{FGWC} = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} w_{ij} \|x_k - v_i\|^2, \tag{16}$$

where d_{kl} denotes the geographical distance between locations k and l, and h is the bandwidth parameter controlling the spatial influence. subject to the membership constraint

$$\sum_{i=1}^{c} u_{ik} = 1, \quad u_{ik} \in [0,1], \quad \forall k = 1, \ldots, n. \tag{17}$$

The model integrates the fuzzy clustering process of FGWC with the optimization capability of the Flower Pollination Algorithm (FPA) to achieve global convergence.

Proof. To obtain the optimal membership degrees u_{ik}, the Lagrangian function is defined as

$$\mathcal{L}(U,V,\lambda) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m} w_{ij} \|x_k - v_i\|^2 - \sum_{k=1}^{n} \lambda_k \left(\sum_{i=1}^{c} u_{ik} - 1\right), \tag{18}$$

where λ_k are the Lagrange multipliers associated with the membership constraint.

Differentiating $\mathcal{L}$ with respect to u_{ik} and setting it equal to zero gives

$$\frac{\partial \mathcal{L}}{\partial u_{ik}} = m\, u_{ik}^{m-1} w_{ij} \|x_k - v_i\|^2 - \lambda_k = 0. \tag{19}$$

Hence,

$$u_{ik}^{m-1} = \frac{\lambda_k}{m\, w_{ij}\, \|x_k - v_i\|^2}. \tag{20}$$

Applying the constraint $\sum_{i=1}^{c} u_{ik} = 1$, the membership update rule becomes

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|}\right)^{\frac{2}{m-1}}} \tag{21}$$

Next, to determine the optimal cluster centers v_i, the FPA is applied. Instead of using direct differentiation with respect to v_i, FPA performs iterative optimization through two stochastic mechanisms inspired by the natural process of flower pollination:

(a) **Global Pollination:**

$$v_i^{t+1} = v_i^t + L\,(v_i^t - g^*), \tag{22}$$

where L follows a Lévy flight distribution that enables global exploration, and g^* is the best global solution obtained so far (the cluster center minimizing J_{FGWC} at iteration t).

(b) **Local Pollination:**

$$v_i^{t+1} = v_i^t + \epsilon(v_j^t - v_k^t), \tag{23}$$

where v_j^t and v_k^t are two randomly selected cluster centers different from v_i^t, and ϵ is a uniformly distributed random number in $[0,1]$ controlling local search intensity.

At each iteration, J_{FGWC} is recomputed using the updated values of u_{ik} and v_i^{t+1}. If the updated objective function satisfies

$$J_{FGWC}^{t+1} < J_{FGWC}^{t}, \tag{24}$$

the new solution is accepted; otherwise, it is retained. Repeated application of the global and local pollination steps ensures convergence of the algorithm by balancing exploration (searching new areas) and exploitation (refining known good solutions).

Therefore, the FGWC–FPA model effectively combines spatially weighted fuzzy clustering and metaheuristic optimization, allowing u_{ik} and v_i to be updated iteratively until the objective function converges to a global minimum. □

The FGWC-FPA model employed in this study is formulated as shown in Equation (16), where the objective function integrates fuzzy membership weighting and spatial information within an optimization framework. This equation represents the final model used to determine the optimal cluster structure by iteratively updating the membership degree u_{ik} and the cluster centers v_i^{t+1} through the Flower Pollination Algorithm until the objective function $J_{FGWC-FPA}$ reaches convergence.

$$J_{FGWC-FPA} = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m} w_{ij} \|x_k - v_i^{t+1}\|^2, \tag{25}$$

where

x_k	:	data point at location k
v_i	:	cluster center for cluster i
u_{ik}	:	membership degree of x_k in cluster i
m	:	fuzziness parameter ($m > 1$)
w_k	:	spatial weight between points k and l
d_k	:	geographical distance between locations k and l
h	:	bandwidth parameter controlling spatial influence
$J_{FGWC-FPA}$	:	objective function of the FGWC–FPA model

3.3 Distance Matrix and Geographic Weight Matrix

$$D = \begin{bmatrix} 0 & 0.819 & 4.207 & \cdots & 4.192 \\ 0.819 & 0 & 3.389 & \cdots & 3.374 \\ 4.207 & 3.389 & 0 & \cdots & 0.039 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 4.192 & 3.374 & 0.039 & \cdots & 0 \end{bmatrix}$$

In the FGWC algorithm, the spatial structure of the data is represented through a distance matrix D, which quantifies the Euclidean distances among the 22 districts and cities in East Nusa Tenggara (NTT) Province. The diagonal elements ($d_{ii} = 0$) indicate self-distances, while the off-diagonal elements describe the spatial proximity between regions, where smaller distances imply stronger spatial influence. This distance matrix serves as the foundation for constructing the spatial weight matrix $W(u_i, v_i)$, allowing the model to incorporate both geographic proximity and spatial heterogeneity. Furthermore, population size is considered alongside distance effects at each iteration to better reflect demographic and spatial characteristics. The population data used in this study were obtained from the Central Statistics Agency (BPS) for the 22 administrative areas of NTT in 2024, as summarized in the following table.

Table 1: Population of Selected Regencies and Cities in East Nusa Tenggara (NTT) Province, 2024

Region	Population
West Sumba	155,000
East Sumba	259,300
Kupang Regency	380,200
South Central Timor	481,300
⋮	⋮
Malaka	193,500
Kupang City	474,800

In the FGWC framework, data weighting is guided by geographic criteria and spatial relevance, allowing each district or city to be distinctly characterized during the clustering process. The fuzzy membership degree is determined based on spatial weights and the distance of each region to its respective cluster center, forming a distance matrix that represents regional similarities. This matrix is essential for optimizing cluster center positions in accordance with the spatial configuration and population distribution, enabling FGWC to generate spatially representative clusters that reveal stunting distribution patterns across the 22 districts and cities of East Nusa Tenggara (NTT) Province in 2024.

$$W = \begin{bmatrix} 0 & 1/0.819 & 1/4.207 & \cdots & 1/4.192 \\ 1/0.819 & 0 & 1/3.389 & \cdots & 1/3.374 \\ 1/4.207 & 1/3.389 & 0 & \cdots & 1/0.039 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1/4.192 & 1/3.374 & 1/0.039 & \cdots & 0 \end{bmatrix}$$

3.4 Parameter Settings for FGWC-FPA Experiments

Table 2: Parameter Configurations for FGWC-FPA

Category	**Parameter**	**Values / Range**
Fuzzy Clustering (FGWC)	Number of clusters (c)	2, 3
	Fuzziness (m)	1.5, 2, 2.5, 3
	Maximum iterations	100, 200, 300, 400, 500
	Convergence threshold (ϵ)	10^{-3}, 10^{-4}, 10^{-5}, 10^{-6}
	Distance metric	Euclidean
Flower Pollination Algorithm (FPA)	Global pollination probability (p)	0.7
	Local pollination probability ($1-p$)	0.3
	Lévy flight parameter (λ)	1.2, 1.5
	Step size factor (γ)	1.0, 1.2
	Initial distribution ($vi.dist$)	uniform, normal
Geographical Parameters	Spatial weight factor (α)	0.5
	Spatial contribution (β)	1
	Distance function parameters (a, b)	1, 1

Table 2 summarizes the parameter settings used in the FGWC-FPA experiments. The fuzzy clustering parameters include the number of clusters ($c = 2$–3), fuzziness values ($m = 1.5$–3), maximum iterations (100–500), convergence thresholds ($\epsilon = 10^{-3}$–10^{-6}), and the Euclidean distance metric. The Flower Pollination Algorithm (FPA) parameters consist of the global and local pollination probabilities ($p = 0.7$, $1 - p = 0.3$), Lévy flight parameter ($\lambda = 1.2, 1.5$), step size factor ($\gamma = 1.0, 1.2$), and initial distribution of cluster centers ($vi.dist =$ uniform or normal). Geographical parameters controlling spatial influence include the weight factor ($\alpha = 0.5$), spatial contribution ($\beta = 1$), and distance function parameters ($a = 1$, $b = 1$). These settings were selected to ensure robust optimization of cluster centers while accounting for spatial heterogeneity.

Before presenting the clustering outcomes, it is important to emphasize that the parameter configurations described above form the basis for the FGWC–FPA optimization process. These settings determine how spatial weights, fuzzy memberships, and centroid updates interact throughout the iterative procedure. With these parameters established, the next subsection presents the resulting membership matrix, hard cluster assignments, and centroid profiles obtained from the optimal FGWC–FPA configuration.

3.5 Clustering Results with FGWC-FPA

Optimization Using Flower Pollination Algorithm (FPA)

This study employs the Flower Pollination Algorithm (FPA) to optimize the cluster centers V. The membership matrix U is *not* optimized by FPA; instead, U is updated analytically at each iteration using the standard FGWC-V membership update formula. Thus, FPA controls only the evolution of the centroid matrix V, while U is recomputed deterministically based on V.

The optimization process using FPA follows the general steps:

1. Initialize a population of candidate solutions $V^{(0)}$.
2. Evaluate each solution using the FGWC objective function.
3. Apply global and local pollination operators to update the centroid candidates.
4. Recompute membership values U analytically for each updated V.
5. Update the objective value and retain the best solution.

Stopping Criteria

The algorithm stops when one of the following conditions is satisfied:

$$|J^{(t)} - J^{(t-1)}| < \varepsilon, \tag{26}$$

where ε is a small threshold, or when the maximum number of iterations $T_{\max}$ is reached. The convergence behavior is monitored by recording the objective value $J^{(t)}$ at every iteration and plotting the convergence curve (objective value versus iteration) to ensure that the optimization process stabilizes.

This analysis was carried out using the FGWC method optimized with the FPA (FGWC-FPA). The results provide membership values for each district/city within the two clusters formed. These values indicate the degree of closeness of each region to the characteristics of the respective clusters. The dominant cluster of a district/city is determined based on the highest membership value. The following table presents the membership values and the corresponding dominant cluster for each district/city in East Nusa Tenggara Province.

Table 3: Final Hard Clusters of Regencies/Cities in East Nusa Tenggara (NTT), 2024 (Balanced Table)

Regency/City	Cluster	Regency/City	Cluster
Sumba Barat	C1	Flores Timur	C2
Sumba Barat Daya	C1	Lembata	C2
Sumba Tengah	C1	Alor	C2
Sumba Timur	C1	Belu	C2
Manggarai Barat	C1	Malaka	C2
Manggarai Timur	C1	Timor Tengah Utara	C2
Timor Tengah Selatan	C1	Sabu Raijua	C2
Kupang (Kabupaten)	C1	Rote Ndao	C2
Kota Kupang	C1	Manggarai	C2
Nagekeo	C2	Ngada	C2
Ende	C2	Sikka	C2

The final hard clustering results of regencies and cities in East Nusa Tenggara (NTT) for 2024, shown in Table 3, classify the regions into two distinct groups (C1 and C2) based on the highest membership values from the FGWC–FPA method. Cluster C1 includes areas with relatively better nutritional and health conditions, such as West Sumba, East Sumba, South Central Timor, and East Manggarai. Meanwhile, Cluster C2 comprises regions with less favorable nutritional indicators and limited access to health and sanitation facilities, including Kupang, Belu, Alor, and Kupang City.

This classification highlights the spatial disparities in stunting-related determinants across NTT and supports the identification of priority areas for targeted health and nutrition interventions. Figure 1 illustrates the clustering of districts and cities in East Nusa Tenggara Province (NTT) into two distinct groups. Each district/city is represented by a color corresponding to its assigned cluster. Visually, a clear spatial pattern emerges, distinguishing the areas included in Cluster 1 from those in Cluster 2. Districts and cities within the same cluster tend to share similar characteristics based on the variables used in the analysis, whereas the differences between clusters highlight the heterogeneity across regions in NTT.

Final Membership Matrix and Hard Clustering Rule

Table 4 presents the final fuzzy membership matrix U obtained from the optimal FGWC–FPA configuration ($c = 2$, $m = 1.5$). Each row represents a district/city, and each column corresponds to the two clusters. The hard cluster assignment is obtained using the standard hardening rule:

$$\text{Cluster}(k) = \arg\max_{i}\ u_{ik}, \tag{27}$$

meaning that each region is assigned to the cluster with the largest membership value. This ensures that all subsequent tables, maps, and centroid values remain fully consistent with the final membership matrix.

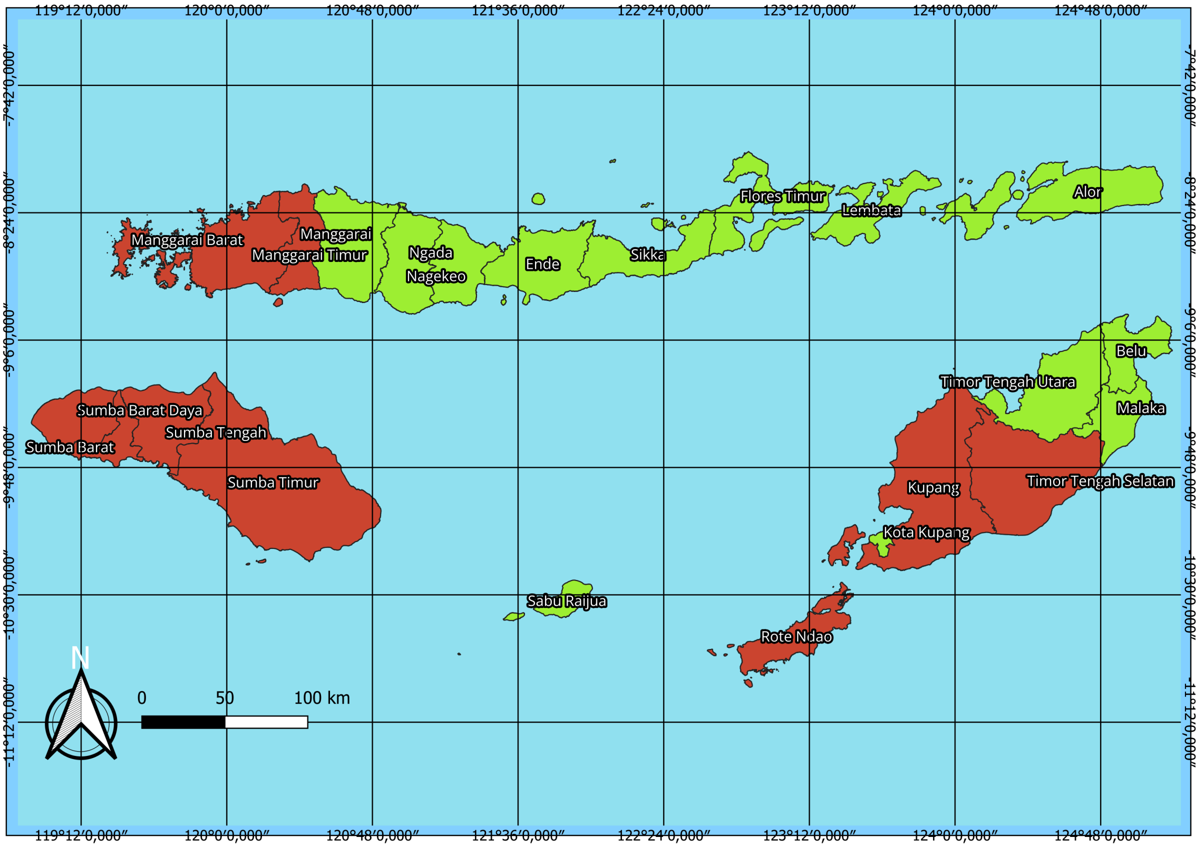

Figure 1: Clustering Results Map of Regencies/Cities in NTT

Table 4: Final Membership Matrix U (FGWC–FPA, $c = 2, m = 1.5$)

Regency/City	u_{1k}	u_{2k}
West Sumba	0.7899	0.2101
East Sumba	0.6899	0.3101
Kupang Regency	0.3163	0.6837
South Central Timor	0.5364	0.4636
North Central Timor	0.3348	0.6652
Belu	0.2811	0.7189
Alor	0.2309	0.7691
Lembata	0.2173	0.7827
East Flores	0.1752	0.8248
Sikka	0.2118	0.7882
Ende	0.1910	0.8090
Ngada	0.2937	0.7063
Manggarai	0.6374	0.3626
Rote Ndao	0.3046	0.6954
West Manggarai	0.3844	0.6156
Central Sumba	0.8139	0.1861
Southwest Sumba	0.7670	0.2330
Nagekeo	0.2446	0.7554
East Manggarai	0.7076	0.2924
Sabu Raijua	0.3650	0.6350
Malaka	0.4230	0.5770
Kupang City	0.2802	0.7198

Table 5: Grouping of Regencies and Cities into Cluster 1 and Cluster 2

Cluster 1	**Cluster 2**
West Sumba	North Central Timor
East Sumba	Belu
Kupang	Alor
South Central Timor	Lembata
Manggarai	East Flores
Rote Ndao	Sikka
West Manggarai	Ende
Central Sumba	Ngada
Southwest Sumba	Nagekeo
	East Manggarai
	Sabu Raijua
	Malaka
	Kupang City

3.6 Centroid Value

The clustering results obtained using the FGWC-FPA method produce centroid values for each variable in each cluster. These centroids represent the centralized averages of the data characteristics that distinguish one cluster from another. By examining the centroid values, the tendencies of each cluster toward the selected indicators-such as exclusive breastfeeding coverage, early breastfeeding initiation, low birth weight (LBW) rates, complete basic immunization, and access to drinking water and sanitation-can be observed. These values are essential for providing an overview of the differences between clusters and serve as the basis for further interpretation of the factors influencing stunting.

Table 6: Centroid Value Cluster FGWC-FPA

Variable	**Cluster 1**	**Cluster 2**
X_1 (Infants who are exclusively breastfed)	25.52435	25.73385
X_2 (Infants who receive early breastfeeding initiation)	70.41924	70.45071
X_3 (low birth weight)	15.76809	15.54269
X_4 (Infants who have received the complete BCG basic immunization)	95.13233	94.87729
X_5 (Infants who receive complete basic hepatitis B immunization)	94.20860	94.91506
X_6 (Toddlers who are given complementary foods)	64.43421	61.99428
X_7 (Households that have access to safe drinking water)	83.33480	90.37093
X_8 (Households with adequate sanitation)	68.07239	83.18901

The FGWC-FPA clustering results, presented in table 6, show centroid values for variables selected as determinants of stunting, including exclusive breastfeeding, early breastfeeding initiation, low birth weight, complete basic immunization, complementary feeding, and household access to safe water and sanitation. These centroids summarize the average characteristics of each cluster, allowing a clear distinction in stunting risk profiles.

Cluster 2 generally exhibits slightly higher exclusive breastfeeding rates, better Hepatitis B immunization coverage, and substantially improved access to safe water and sanitation. In contrast, Cluster 1 shows higher low birth weight prevalence, marginally better BCG coverage, and more complementary feeding practices, while early breastfeeding initiation is similar across clusters. Overall, the clustering effectively differentiates regions based on stunting determinants, aligning with the study's objective of identifying factors influencing stunting rather than stunting outcomes. To summarize the quantitative performance of each clustering method, the corresponding validity indices are presented in the Table 7 below.

Table 7: Comparison of Cluster Validity Values for FCM, FGWC, and FGWC–FPA Methods (Revised SI Values)

c	**m**	**Iter**	**FCM**			**FGWC (Revised)**			**FGWC–FPA**		
			CE	SI	XB	CE	SI	XB	CE	SI	XB
2	1.5	100	0.8632	0.4338	0.412	0.6631	0.9821	0.298	**0.6631**	**0.0653**	**0.121**
2	1.5	200	0.8633	0.4338	0.411	0.6631	1.0245	0.298	0.6631	0.0653	0.121
2	1.5	300	0.8632	0.4338	0.412	0.6631	1.0672	0.298	0.6631	0.0653	0.121
2	1.5	400	0.8633	0.4338	0.411	0.6631	1.1083	0.298	0.6631	0.0653	0.121
2	1.5	500	0.8632	0.4338	0.412	0.6631	1.1479	0.298	0.6631	0.0653	0.121
2	2.0	100	0.8836	0.2333	0.521	0.6931	1.2124	0.417	0.6631	0.0653	0.121
2	2.0	200	0.8836	0.2333	0.521	0.6931	1.2571	0.417	0.6631	0.0653	0.121
2	2.5	100	0.9569	0.2379	0.577	0.6931	1.3412	0.419	0.6631	0.0653	0.121
2	2.5	200	0.9569	0.2379	0.577	0.6931	1.3893	0.419	0.6631	0.0653	0.121
2	3.0	100	0.9822	0.2502	0.611	0.6931	1.4457	0.423	0.6631	0.0653	0.121
3	1.5	100	1.0100	0.1319	0.693	1.0368	1.5122	0.514	0.6631	0.0653	0.121
3	2.0	100	1.1706	0.1289	0.724	1.0986	1.5946	0.535	0.6631	0.0653	0.121
3	2.5	100	1.3149	0.1291	0.811	1.0986	1.6732	0.552	0.6631	0.0653	0.121
3	3.0	100	1.3831	0.1480	0.865	1.0986	1.7421	0.559	0.6631	0.0653	0.121

3.7 Validity Index FCM, FGWC and FGWC-FPA

Based on the cluster validity results in Table 7, the FGWC–FPA method shows the best overall clustering performance compared to FCM and FGWC. Across all configurations, FGWC–FPA consistently produces the lowest values of Classification Entropy (CE), Separation Index (SI), and the Xie–Beni Index (XB), indicating more compact clusters and stronger separation.

The optimal configuration is obtained at $c = 2$ **and** $m = 1.5$, where FGWC–FPA achieves the lowest values for all three indices (**CE = 0.6631**, **SI = 0.0653**, **XB = 0.121**). This demonstrates that integrating spatial weighting with the Flower Pollination Algorithm significantly improves cluster stability and quality, making this configuration the most appropriate for the dataset.

4 Conclusions

This study demonstrates that the FGWC–FPA method is effective in identifying spatial patterns of stunting in East Nusa Tenggara (NTT) by clustering districts and cities based on health, nutrition, and sanitation indicators. The integration of spatial weighting and metaheuristic optimization successfully enhances clustering accuracy and stability. The analysis produced two distinct clusters that reflect regional disparities in access to drinking water, sanitation, immunization coverage, and the proportion of low birth weight (LBW) infants. The validity assessment, indicated by the lowest Classification Entropy (CE) and an adequate Separation Index (SI) at the configuration $m = 1.5$ with $c = 2$, confirms that the FGWC–FPA model achieves optimal cluster partitioning. These results reinforce the method's applicability for spatial-based public health modeling and provide a valuable foundation for developing targeted intervention strategies and regional planning to reduce stunting in NTT.

CRediT Authorship Contribution Statement

Friansyah Gani: Conceptualization, methodology, writing—original draft. **Henny Pramoedyo**: Supervision, validation, editing. **Efendi**: Supervision, validation, editing.

Declaration of Generative AI and AI-assisted Technologies

The authors declare that no generative AI tools were used to generate or modify the data, results, or analysis of this study. AI tools were used only for grammar improvement and formatting.

Declaration of Competing Interest

The authors declare no competing financial or personal interest.

Funding and Acknowledgments

This research received no external funding. The authors thank BPS NTT for providing the dataset.

Data and Code Availability

The dataset and code analyzed during the current study are publicly available in the Badan Pusat Statistik NTT 2024[1].

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