Analysis of Stunting Spread in Mentawai Islands Regency Using K-Means Clustering Method

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Abstract. This research addresses the critical issue of child health and nutrition in the Mentawai Islands Regency, particularly stunting. Given the limited understanding among parents, the local Community Health Center (Puskesmas) has taken the initiative to conduct stunting mapping in the Mentawai Islands. The objective is to employ a decision support system utilizing the Clustering K-Means method, incorporating assessment criteria encompassing nutritional factors, poverty indicators, and educational aspects. This study aims to enhance parental comprehension, facilitate targeted healthcare interventions, and mitigate stunting prevalence. It leverages the K- Means clustering method to analyze and forecast future trends in stunting within the Mentawai Islands. Furthermore, it employs a Geographic Information System (GIS) to map the distribution of stunted children. As a result, it pinpoints priority zones for stunting intervention, visually represented through digital mapping. This study provides a digital map of priority areas for stunting intervention in the Mentawai Islands, aiding information technology professionals in effectively addressing stunting in children based on established priority levels.

Keywords: GIS; k-means; mapping; Mentawai Islands; stunting

1. Introduction

Infants are children aged 0-59 months, characterized by rapid growth and development and changes requiring higher quantities of high-quality nutrients [1]. The first five years are a critical period for a child, during which the brain cells and nervous system rapidly develop. Therefore, parents should make the most of this time by providing appropriate nutrition to ensure optimal growth and development [2].

The food consumed by toddlers must provide balanced nutrients. These balanced nutrients aid in the growth and development processes of the child. In addition to proper nutrition, immunization is crucial in enhancing a child's immunity and health [3].

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Health centers (Puskesmas) serve as community health service centers for local residents seeking medical treatment or health consultations [4]. They handle various community health issues, including childbirth, treatment, outpatient care, and baby and toddler healthcare services [5]. Puskesmas employs several staff members who attend to community health matters. One of their tasks is to ensure the health of all toddlers [6].

The identification of stunted toddlers is carried out to address nutritional problems in toddlers. Through this activity, parents will be motivated to pay closer attention to the nutritional needs of their children [7]. The challenge faced is that health workers still struggle to determine which toddlers are healthy and which are experiencing stunting, as numerous criteria must be met. This can lead to assessments for each toddler taking much time and being complex [8]. Determining healthy and stunted toddlers at Puskesmas could be more effective and efficient because the process still relies on forms as the assessment tool, which requires a lengthy data entry process and often leads to errors. Additionally, Puskesmas staff have difficulty determining healthy and stunted toddlers due to excessive criteria, which prolongs the process [9][10].

Therefore, a method is needed to efficiently make decisions regarding determining healthy and stunted toddlers with multiple criteria and requires fast processing. One solution is applying information technology in decision-making through implementing a Decision Support System (DSS) [11]. Applying a DSS in decision-making for a problem can be done swiftly. The DSS has several methods, including the K-Means clustering method. The basic concept of the K-Means clustering method is that the chosen best alternative is not only the closest to the positive ideal solution but also the farthest from the negative ideal solution [12][13].

This decision support system for determining healthy and stunted toddlers utilizes the K-Means clustering method. The K-Means clustering is a decision-making method influenced not only by beneficial factors but also by detrimental factors [14][15]. Many works use this concept in various Multiple Attribute Decision-Making (MADM) models to solve decision problems practically because of its simple and easy-to-understand concept, efficient computation, and ability to measure the performance of decision alternatives in a simple mathematical form [16][17].

Some previous studies are referenced to support this research. Ide Ilham and Deni Apriandi (2020), in the study entitled 'Decision Support System for Selecting Healthy Toddlers Using the Simple Additive Weighting (SAW) Method,' using four criteria: teeth, biodata, weight, and immunization. This research results in the presentation of assessments for all criteria and the display of healthy toddlers and those deemed unfit. From this research, the design of a decision support system for selecting healthy toddlers can assist committees in choosing healthy toddlers, generating activity reports, and recording score values [18].

Furthermore, the study by Septia Fajarika (2019) titled 'Decision Support System for Selecting Healthy Toddlers in the Sei Lapan Subdistrict Using the Multi-Attribute Utility Theory (MAUT) Method' is referenced. This study included eight criteria: teeth and mouth, hair, hands and nails, skin, hearing, vision, respiration, and limb function.

It is concluded that the criteria used in selecting healthy toddlers, as determined by the Puskesmas, are effective for implementation, and the MAUT method is very effective and accurate in implementing the selection of healthy toddlers because it involves several steps, all of which can be carried out effectively [19].

Another study using the Simple Additive Weighting (SAW) method by Yulia Juhan Sy and Widya Marna (2017) titled 'Decision Support System for Selecting Healthy Babies' is referenced. This study included four criteria: weight, skin color, baby's cry, and health. The result of this research is the ranking and weighting of healthy babies. The development of this decision support system application is expected to simplify, speed up, and accurately select healthy babies and design more appealing, practical, and informative report formats [20].

The difference between the research conducted by Ide Ilham and Deni Apriandi (2020) and Septia Fajrika (2019) with this research is that although all focus on the selection of healthy toddlers, the methods used are different [18][19]. Ide Ilham and Deni Apriandi (2020) used the Simple Additive Weighting (SAW) method, while Septia Fajrika (2019) used the Multi Attribute Utility Theory (MAUT) method. In contrast, this research focuses on using the K-Means clustering method in determining healthy toddlers and cases of stunting. The K-Means clustering method has advantages over the methods used in previous research. With the K-Means clustering method, the ideal solution for solving the problem can be identified, and the ranking of each alternative is determined based on this ideal solution. In contrast, the ideal solutions for the problem cannot be identified with ordinary weighting.

Based on the outlined issues, using the K-Means clustering method in this decision support system is expected to address the challenges in determining healthy toddlers and cases of stunting at Puskesmas based on established criteria. The output of this decision support system is a system for prioritizing stunting intervention for toddlers using the K-Means clustering method.

2. Method

This study employs the k-means method, a data analysis technique to group data into clusters or groupings based on similar characteristics. The research was conducted in the Mentawai Islands Regency, which consists of 10 districts spread across four large islands in the Mentawai Islands. The following illustration displays a map of the Mentawai Islands in Figure 1. This study employs the k-means method, a data analysis technique to group data into clusters or groupings based on similar characteristics. The research was conducted in the Mentawai Islands Regency, which consists of 10 districts spread across four large islands in the Mentawai Islands. The following illustration displays a map of the Mentawai Islands in Figure 1.

Fig. 1. Mentawai Islands map

The stages in the k-means clustering method can be seen in Figure 2.

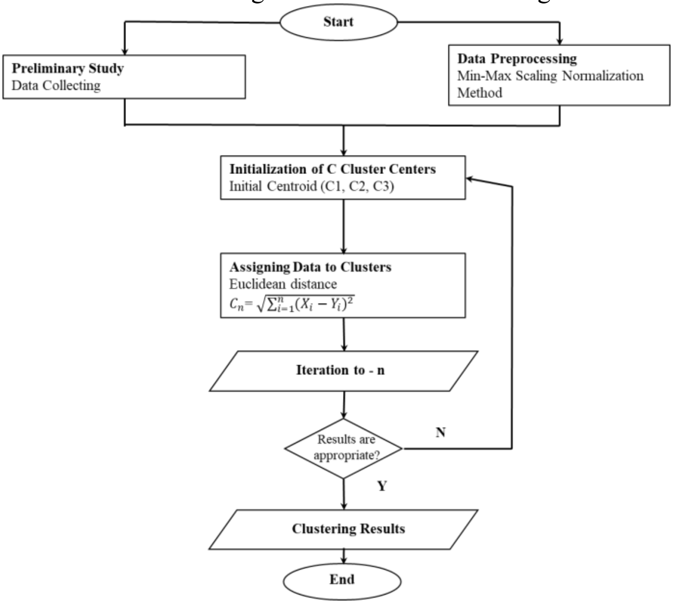

Fig. 2. Step of the K-Means method

The explanation of the stages of stunting distribution analysis using the k-means clustering method in Figure 2 includes:

1. Preliminary Study.
   Data was collected from the Mentawai Islands Regency Health Office, closely related to stunting.

2. Data Preprocessing.
   In this stage, the data undergoes the min-max scaling normalization method.
   $X_{normalization} = (X - X_{min}) / (X_{max} - X_{min})$ (1)

   where the X value in question is the original value while X_{min} and X_{max} are the minimum and maximum values for that attribute.
3. Initialization of C Cluster Centers or Initial Centroids.
   This process begins by creating several clusters (C); in this case, three clusters are created.
4. Assigning Data to Clusters.
   Each data point is then assigned to the nearest cluster based on Euclidean distance using the following formula:
   $C_n = \sqrt{\sum_{i=1}^{n}(X_i - Y_i)^2}$ (2)

   where X_i , Y_i = values of the i attribute.
   Recalculate Cluster Centers. This stage follows the Assign Data to Clusters step. After this process is completed, new centroids are created by taking the average of all data points within each cluster.
5. Iteration.
   Repeat steps 3 and 4 until a stopping condition is met. The stopping condition can be applied when no further changes in data grouping into clusters exist.
6. Clustering Results.

   After the iterations, the clustering results are obtained, which include some clusters with data points assigned to each cluster.

3. Result and Discussion

This research aims to provide priority information for areas with stunted toddlers in the Mentawai Islands using the K-Means clustering method to analyze and project future developments related to the Mentawai Islands. Additionally, it aims to map the distribution of stunted toddlers based on the projection results as part of a Geographic Information System (GIS). The research utilizes data obtained from the Mentawai Islands Regency Health Office, processed according to the research stages outlined in Figure 2.

1. Preliminary Study.
   The required data for clustering can be observed in Table 1.

Table 1. Stunting Distribution in The Mentawai Islands

No	District	Territorial Area (Km^2)	Slum Area (Ha)	Popu-lation	Poor Nutrition Toddlers	Health Ser-vices
1	Pagai Selatan	851.28	14.64	9,421	63	5
2	Sikakap	312.6	62.96	10,280	94	3

3	Pagai Utara	371.25	26.35	6,157	89	5
4	Sipora Selatan	348.33	47.24	10,022	104	6
5	Sipora Utara	272.4	38.48	12,528	81	8
6	Siberut Selatan	328	9.63	10,173	49	8
7	Siberut Barat Daya	1013.83	10.74	7,213	19	4
8	Siberut Tengah	589.75	14.74	7,251	68	3
9	Siberut Utara	782.68	12.9	8,387	74	5
10	Siberut Barat	1163.64	11.85	7,969	35	4

The testing was conducted in the ten districts within the Mentawai Islands Regency. Based on information obtained from the Mentawai Islands Regency Health Office, five pieces of data were acquired: area size, slum settlement area size, population, malnourished toddlers, and the total number of health services. These data will serve as reference points for the analysis of stunting distribution.

2. Data Preprocessing.
   The Min-Max Scaling method is used as a reference for normalizing the data in Table 1.
   Normalization of territorial area (km^2):

   Pagai Selatan = (851.28 - 272.4) / (1163.64 - 272.4)

   = 0.6495

   Sikakap = (312.6 - 272.4) / (1163.64 - 272.4)

   = 0.0451

   …

   Normalization of slum area (Ha):

   Pagai Selatan = (14.64 - 9.63) / (62.96 - 9.63)

   = 0.0939

   Sikakap = (62.96 - 9.63) / (62.96 - 9.63)

   = 1

   …

   Normalization of population:

   Pagai Selatan = (9421 - 6157) / (12528 - 6157)

   = 0.5123

Sikakap = (10280 - 6157) / (12528 - 6157)

= 0.6472

…

Normalization of poor nutrition toddlers:

Pagai Selatan = (63 - 19) / (104 - 19)

= 0.5123

Sikakap = (94 - 19) / (104 - 19)

= 0.6472

…

Normalization of ealth services

Pagai Selatan = (5 - 3) / (8 - 3)

= 0.4000

Sikakap = (3 - 3) / (8 - 3)

= 0

…

Table 2 below shows the normalized results using Min-Max Scaling.

Table 2. Normalization Results

No	District	Territorial Area (Km^2)	Slum Area (Ha)	Popu-lation	Poor Nutrition Toddlers	Health Ser-vices
1	Pagai Selatan	0.6495	0.0939	0.5123	0.5176	0.4
2	Sikakap	0.0451	1	0.6472	0.8824	0
3	Pagai Utara	0.1109	0.3135	0	0.8235	0.4
4	Sipora Selatan	0.0852	0.7052	0.6067	1	0.6
5	Sipora Utara	0	0.5410	1	0.7294	1
6	Siberut Selatan	0.0624	0	0.6304	0.3529	1
7	Siberut Barat Daya	0.8319	0.0208	0.1658	0	0.2
8	Siberut Tengah	0.3561	0.0958	0.1717	0.5765	0
9	Siberut Utara	0.5726	0.0613	0.3500	0.6471	0.4

10	Siberut Barat	1	0.0416	0.2844	0.1882	0.2

3. Initialization of C Cluster Centers or Initial Centroids.
   The reference data can be found in Table 3.

Table 3. Centroid-1

	District	**Territorial Area (Km^2)**	**Slum Area (Ha)**	**Popu-lation**	**Poor Nutrition Toddlers**	**Health Ser-vices**
K1	0.6495	0.0939	0.5123	0.5176	0.4	K1
K2	0.0852	0.7052	0.6067	1	0.6	K2
K3	0.8319	0.0208	0.1658	0	0.2	K3

4. Assigning Data to Clusters.
   Insert the Euclidean distance calculation to obtain the cluster data for each attribute.

$$C_{11} = \sqrt{(0.6495 - 0.6495)^2} + (0.0939 - 0.0939)^2 + (0.5123 - 0.5123)^2 + (0.5176 - 0.5176)^2 + (0.4 - 0.4)^2 = 0$$

$$C_{12} = \sqrt{(0.6495 - 0.0852)^2} + (0.0939 - 0.7052)^2 + (0.5123 - 0.6067)^2 + (0.5176 - 1)^2 + (0.4 - 0.6)^2 = 0.9868$$

$$C_{13} = \sqrt{(0.6495 - 0.8319)^2} + (0.0939 - 0.0208)^2 + (0.5123 - 0.1658)^2 + (0.5176 - 0)^2 + (0.4 - 0.2)^2 = 0.6831$$

$$C_{21} = \sqrt{(0.0451 - 0.6495)^2} + (1 - 0.0939)^2 + (0.6472 - 0.5123)^2 + (0.8824 - 0.5176)^2 + (0 - 0.4)^2 = 1.2237$$

$$C_{22} = \sqrt{(0.0451 - 0.0852)^2} + (1 - 0.7052)^2 +$$

$$(0.6472 - 0.6067)^2 + (0.8824 - 1)^2 +$$
$$(0 - 0.6)^2$$
$$= 0.6812$$

$$C_{23} = \sqrt{(0.0451 - 0.8319)^2} + (1 - 0.0208)^2 +$$
$$(0.6472 - 0.1658)^2 + (0.8824 - 0)^2 +$$
$$(0 - 0.2)^2$$
$$= 1.6212$$

……..

5. Iteration.
At this stage, the nearest cluster distance search results are displayed in Table 4, which can be seen below.

Table 4. First Iteration

District	Distance to C1	Distance to C2	Distance to C3	Ite-ration
Pagai Selatan	0.0000	0.9868	0.6831	1
Sikakap	1.2237	0.6812	1.6212	2
Pagai Utara	0.8333	0.7702	1.1624	2
Sipora Selatan	0.9868	0.0000	1.5429	2
Sipora Utara	1.1244	0.6498	1.6825	2
Siberut Selatan	0.8687	1.0378	1.2542	1
Siberut Barat Daya	0.6831	1.5429	0.0000	3
Siberut Tengah	0.6046	1.0832	0.7774	1
Siberut Utara	0.2238	0.9395	0.7494	1
Siberut Barat	0.5710	1.4833	0.2796	3

Then, recalculate the new cluster centroids based on the average attributes within each cluster and repeat the previous process.

<u>Cluster center: C1</u>
Territorial area: (0.6495+ 0.0624 + 0.3561 + 0.5726) / 4 = 0.4101
Slum area: (0.0939 + 0 + 0.0958 + 0.0613)/4=0.0628
Population: (0.5123 + 0.6304 + 0.1717 + 0.3500) / 4 =0.4161
Poor nutrition toddlers: (0.5176 + 0.3529 + 0.5765 + 0.6471) / 4 = 0.4161
Health services: (0.4 + 1 + 0 + 0.4) / 4 = 0.45

Cluster center: C2
Territorial area: (0.0451 + 0.1109 + 0.0852 + 0) / 4 = 0.0603
Slum area: (1 + 0.3135 + 0.7052 + 0.5410) / 4 = 0.6399
Population: (0.6472 + 0 + 0.6067 + 1)/4 = 0.5635
Poor nutrition toddlers: (0.8824 + 0.8235 + 1 + 0.7294)/4 = 0.8588
Health services: (0 + 0.4 + 0.6 + 1)/4 = 0.5

Cluster center: C3
Territorial area: (0.8319 + 1)/2 = 0.9160
Slum area: (0.0208 + 0.0416)/2 = 0.0312
Population: (0.1658 + 0.2844)/2 = 0.2251
Poor nutrition toddlers: (0 + 0.1882)/2 = 0.0941
Health services: (0.2 + 0.2)/2 = 0.2

Table 5. Centroid-2

	District	**Territorial Area (Km^2)**	**Slum Area (Ha)**	**Popu-lation**	**Poor Nutrition Toddlers**	**Health Ser-vices**
K1	0.4101	0.0628	0.4161	0.5235	0.4500	0.4101
K2	0.0603	0.6399	0.5635	0.8588	0.5000	0.0603
K3	0.9160	0.0312	0.2251	0.0941	0.2000	0.9160

Insert the Euclidean distance to get cluster data for each attribute.

$$C_{11} = \sqrt{(0.6495 - 0.4101)^2} + (0.0939 - 0.0628)^2 + (0.5123 - 0.4161)^2 + (0.5176 - 0.5235)^2 + (0.4 - 0.45)^2$$
$$= 0$$

$$C_{12} = \sqrt{(0.6495 - 0.0603)^2} + (0.0939 - 0.6399)^2 + (0.5123 - 0.5635)^2 + (0.5176 - 0.8588)^2 + (0.4 - 0.5)^2$$
$$= 0.9868$$

$$C_{13} = \sqrt{(0.6495 - 0.9160)^2} + (0.0939 - 0.0312)^2 + (0.5123 - 0.2251)^2 + (0.5176 - 0.0941)^2 + (0.4 - 0.2)^2$$
$$= 0.6831$$

$$C_{21} = \sqrt{(0.0451 - 0.4101)^2} + (1 - 0.0628)^2 + (0.6472 - 0.4161)^2 + (0.8824 - 0.5235)^2 + (0 - 0.45)^2$$

$$= 1.2237$$

$$C_{22} = \sqrt{(0.0451 - 0.0603)^2 + (1 - 0.6399)^2 + (0.6472 - 0.5635)^2 + (0.8824 - 0.8588)^2 + (0 - 0.5)^2}$$

$$= 0.6812$$

$$C_{23} = \sqrt{(0.0451 - 0.9160)^2 + (1 - 0.0312)^2 + (0.6472 - 0.2251)^2 + (0.8824 - 0.0941)^2 + (0 - 0.2)^2}$$

$$= 1.6212$$

……

The results of the nearest cluster distance search are displayed in Table 6, which can be seen below.

Table 6. Second Iteration

District	Distance to C1	Distance to C2	Distance to C3	Ite-ration
Pagai Selatan	0.2647	0.8799	0.6138	1
Sikakap	1.1816	0.6224	1.5926	2
Pagai Utara	0.6466	0.6617	1.1621	1
Sipora Selatan	0.8968	0.1915	1.5069	2
Sipora Utara	1.0405	0.6861	1.6562	1
Siberut Selatan	0.7088	0.9591	1.2652	1
Siberut Barat Daya	0.7609	1.4016	0.1398	3
Siberut Tengah	0.5187	0.9310	0.7702	1
Siberut Utara	0.2202	0.8352	0.6930	1
Siberut Barat	0.7353	1.3633	0.1398	3

Recalculate like the task before because there has been a change in clusters. So, a new cluster center calculation is performed based on the average attributes within that cluster, and the previous process is repeated.

Cluster center: C1

Territorial area: (0.6495 + 0.1109 + 0 + 0.0624 + 0.3561 +0.5726)/6 = 0.2919

Slum area: (0.0939 + 0.3135 + 0.5410 + 0 + 0.0958 + 0.0613)/6 = 0.1843

Population: (0.5123 + 0 + 1 + 0.6304 + 0.1717 + 0.3500)/6 = 0.4441

Poor nutrition toddlers: (0.5176 + 0.8235 + 0.7294 + 0.3529 + 0.5765 +

0.6471)/6 = 0.6078
Health services: 0.4 + 0.4 + 1 + 1 + 0 + 0.4)/6 = 0.5333

<u>Cluster center: C2</u>
Territorial area: (0.0451 + 0.0852)/2 = 0.0652
Slum area: (1 + 0.7052)/2 = 0.8526
Population: (0.6472 + 0.6067)/2 = 0.6269
Poor nutrition toddlers: (0.8824 + 1)/2 = 0.9412
Health services: (0 + 0.6)/2 = 0.3

<u>Cluster center: C3</u>
Territorial area: (0.8319 + 1)/2 = 0.9160
Slum area: (0.0208 + 0.0416)/2 = 0.0312
Population: (0.1658 + 0.2844)/2 = 0.2251
Poor nutrition toddlers: (0 + 0.1882)/2 = 0.0941
Health services: (0.2 + 0.2)/2 = 0.2

Table 7. Centroid-3

	District	**Territorial Area (Km^2)**	**Slum Area (Ha)**	**Popu-lation**	**Poor Nutrition Toddlers**	**Health Ser-vices**
K1	0.2919	0.1843	0.4441	0.6078	0.5333	0.2919
K2	0.0652	0.8526	0.6269	0.9412	0.3000	0.0652
K3	0.9160	0.0312	0.2251	0.0941	0.2000	0.9160

Insert the Euclidean distance to get cluster data for each attribute.

$$C_{11} = \sqrt{(0.6495 - 0.2919)^2} + (0.0939 - 0.1843)^2 + (0.5123 - 0.4441)^2 + (0.5176 - 0.6078)^2 + (0.4 - 0.5333)^2 = 0.4082$$

$$C_{12} = \sqrt{(0.6495 - 0.0652)^2} + (0.0939 - 0.8526)^2 + (0.5123 - 0.6269)^2 + (0.5176 - 0.9412)^2 + (0.4 - 0.3)^2 = 1.0581$$

$$C_{13} = \sqrt{(0.6495 - 0.9160)^2} + (0.0939 - 0.0312)^2 + (0.5123 - 0.2251)^2 + (0.5176 - 0.0941)^2 + (0.4 - 0.2)^2 = 0.6831$$

$$C_{21} = \sqrt{(0.0451 - 0.2919)^2 + (1 - 0.1843)^2 + (0.6472 - 0.4441)^2 + (0.8824 - 0.6078)^2 + (0 - 0.5333)^2}$$
$$= 1.0618$$

$$C_{22} = \sqrt{(0.0451 - 0.0652)^2 + (1 - 0.8526)^2 + (0.6472 - 0.6269)^2 + (0.8824 - 0.9412)^2 + (0 - 0.3)^2}$$
$$= 0.3406$$

$$C_{23} = \sqrt{(0.0451 - 0.9160)^2 + (1 - 0.0312)^2 + (0.6472 - 0.2251)^2 + (0.8824 - 0.0941)^2 + (0 - 0.2)^2}$$
$$= 1.6212$$

……..

The results of the nearest cluster distance search are displayed in Table 8, which can be seen below
can be seen below.

Table 8. Second Iteration

District	Distance to C1	Distance to C2	Distance to C3	Ite-ration
Pagai Selatan	0.4082	1.0581	0.6138	1
Sikakap	1.0618	0.3406	1.5926	2
Pagai Utara	0.5576	0.8424	1.1621	1
Sipora Selatan	0.7063	0.3406	1.5069	2
Sipora Utara	0.8684	0.8806	1.6562	1
Siberut Selatan	0.6357	1.2502	1.2652	1
Siberut Barat Daya	0.9361	1.5454	0.1398	3
Siberut Tengah	0.6095	1.0429	0.7702	1
Siberut Utara	0.3493	1.0280	0.6930	1
Siberut Barat	0.9135	1.4919	0.1398	3

6. Clustering Results.

There were no changes in clusters displayed in Table 6 and Table 8 from iteration 2nd and iteration 3rd, so the calculation process stops here. The results obtained from this calculation can be seen in Figure 3.

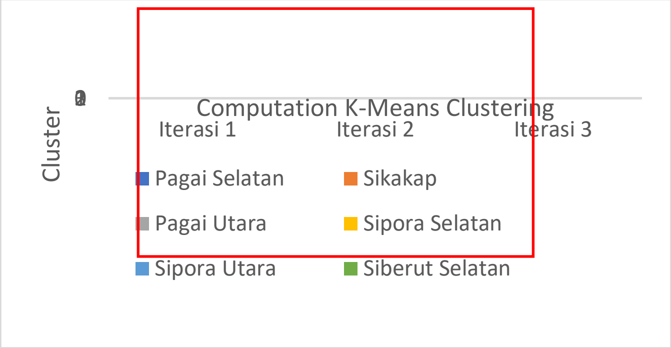

Fig. 3. The graph of K-Means clustering computation results

In Figure 3, there are three clusters: Cluster 1 consisting of Pagai Selatan, Pagai Utara, Sipora Utara, Siberut Selatan, Siberut Tengah, and Siberut Utara. Cluster 2 includes two districts: Sikakap and Sipora Utara. Meanwhile, Cluster 3 comprises Siberut Barat Daya and Siberut Barat, as seen in Figure 4.

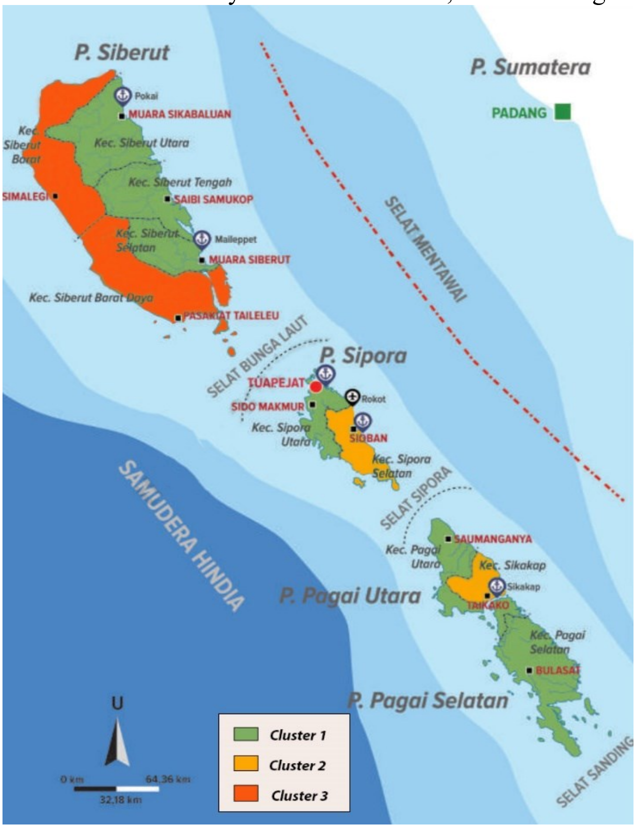

Fig 4. Map of Stunting Distribution Clusters in the Mentawai Islands

4. Conclusion

In this research, several conclusions were obtained based on the results of data processing using the K-Means Clustering method that was carried out. Firstly, analysis of the Distribution of Stunting Using the K-Means Clustering Method. This research was conducted in 10 sub-districts in the Mentawai Islands Regency. Based on information obtained from the Mentawai Islands Health Service, 5 data were obtained, namely area, slum area, population, malnourished children under five, and the number of health services that will be used as a reference in analyzing the distribution of stunting. Secondly, data preprocessing is done using the Min-Max Scaling method, which will be a reference for normalizing the data. Lastly, there are three clustering areas of stunting in the Mentawai Islands Regency after data processing using the K-Means Clustering method. The three clustering areas, namely Cluster 1 consisting of Pagai Selatan, Pagai Utara, Sipora Utara, Siberut Selatan, Siberut Tengah, and Siberut Utara. Cluster 2 includes two districts: Sikakap and Sipora Utara. Meanwhile, Cluster 3 comprises Siberut Barat Daya and Siberut Barat.

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