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Mitigation Priority Scale with Self-Organising Map in Viewing Flood Prone Area Distribution Pattern Mapping

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Abstract: Flooding is a prevalent natural calamity that causes detrimental effects. From 2019 to 2022, nearly all sub-districts spanning an area of 193,200 hectares experienced floods in the North Aceh region. Issues arising from insufficient information, particularly spatial data pertaining to the state of flood-prone areas and the subsequent damages that may be caused, which are crucial for guiding flood prevention measures. This study employed a Analytic Hierarchy Process (AHP) and self-organizing map (SOM) models to categorize areas based on the distribution patterns of flood-prone areas. The main objective was to assess the level of risk associated with flood disasters. The research approach involves collecting data at the office of the Regional Disaster Management Agency (BPBD) in flood-prone areas, followed by establishing the causes of flooding based on criteria such as Soil Structure, Soil Slope, and Land Use. The subsequent phase entails classification utilizing the self-organizing map (SOM) architectural model. District Lhoksukon has the following values: X1 = 1, X2 = 0.005865103, X3 = 0.274919614, X4 = 0.468069147. The value of W1 is 0.468069147. Cluster 1 consists of 21 sub-districts, cluster 2 consists of 3 sub-districts, and cluster 3 consists of 3 sub-districts. Cluster 3 exhibits moderate results and has a low susceptibility to flood distribution. Cluster 2 shows moderate susceptibility to flood distribution, whereas cluster 1 is highly susceptible to flood distribution. Essentially, the determination of mitigation priorities can be made by just examining the cluster pattern generated. Cluster 2 should be given the highest priority, followed by cluster 3, and lastly cluster 3.

Keywords: *Analytic Hierarchy Process, Cluster, Flooding, Mitigation, Self-Organizing Map.*

1. Introduction

Indonesia has experienced significant climate variability, Indonesia has experienced significant climate variability, including unpredictable and intense rainfall patterns. This unpredictability greatly enhances the likelihood of floods occurring [1], [2]. North Aceh Regency, being a location susceptible to flood disasters, encounters significant difficulties on an annual basis. The occurrence of floods in North Aceh has emerged as a prevalent issue, posing threats to infrastructure integrity, and causing substantial socio-economic consequences [3]. Therefore, it is crucial to augment readiness in challenging flood calamities. Efficient measures are required to minimize hazards and tackle the consequences produced by floods[4].

Various approaches can be made to implement methods that reduce the impact of flood catastrophes. These include raising public awareness[5], assessing the effectiveness of disaster management policies[6], and employing technology such early warning systems based on the Internet of Things (IoT) [7],[8]. In addition, flood detection can be performed utilizing machine learning techniques, among numerous others [9], [10].

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This research employ machine learning algorithms to cluster locations affected by floods as an initial step in the development of disaster mitigation responses. The impacted regions are categorized into distinct groups with differing levels of priority. The objective is to pinpoint the most susceptible regions and concentrate mitigation endeavors in those regions. Regions impacted by floods frequently encounter distinct obstacles and exhibit unique characteristics. Consequently, it becomes imperative to employ more accurate clustering techniques to verify that the suggested mitigation solutions are truly applicable and efficient.

The Self Organizing Map (SOM) is an unsupervised learning approach utilized in machine learning to cluster regions according to their similarity in attributes[11]. Conversely, the Analytical Hierarchy Process (AHP) is a hierarchical approach to decision-making that can be employed to establish priority scales for adopting mitigation strategies[12]. The Self Organizing Map (SOM) and Analytical Hierarchy Process (AHP) are two effective methodologies in this instance[13], [14].

There have been few studies that have used the combination of Self-Organizing Maps (SOM) and Analytic Hierarchy Process (AHP) to cluster locations affected by floods and assign priority scales for disaster mitigation[15] [16]. Hence, this study seeks to address this research deficiency by introducing a paradigm that combines these two approaches to produce more precise and pertinent clustering outcomes for flood risk reduction. Hence, this study is anticipated to provide a substantial input to the initiatives of mitigating the repercussions of floods in impacted regions[17].

A framework is promoted for the development of a method of screening on a smaller scale within a watershed. This tool is designed to assist in identifying priority areas for flood protection and implementing mitigation strategies in an urban area that is susceptible to flooding due to its situated landscape.

This study developed a screening technique to detect structures that are susceptible to risk by integrating easily accessible data on terrain, groundwater, surface water, tidal information for coastal towns, soils, open space, and rainfall data. The technique underwent testing in Broward County, Florida, and exhibited encouraging outcomes when compared to FEMA Flood maps and recurrent loss mapping.

2. Method

2.1 Data Collecting and Preprocessing

The study employs flood disaster data from North Aceh Regency for the period from 2020 to 2022. The obtained raw data underwent further processing to make data appropriate for deployment. The data used in this research includes the names of sub-districts, the average total number of villages, the number of houses, the number of persons, the number of public amenities, and the amount of flooded agricultural and plantation land over a period of 3 years. Prior to processing, the dataset completed an initial normalization operation with the subsequent equation:

$$r_{ij} = \frac{x_{ij}}{\max_i \ x_{ij}} \quad (1)$$

Where:

r_{ij} is the normalized value of the data point in the *i*-th row and *j*-th column after the normalization operation.

x_{ij} is The original value of the data point in the *i*-th row and *j*-th column before normalization.

$Max_i \ x_{ij}$ isThe maximum value among all data points in the *j*-th column.

The results generated by equation (1) were standardized and then combined with weights obtained by the Analytic Hierarchy Process (AHP). The Analytic Hierarchy Process offers a logical structure for decision making by assigning numerical values to criteria and alternative options and establishing connections between these components and the ultimate objective[21]. This study employs the Analytic Hierarchy Process to assign weights to features in data preprocessing. These weights are then used to assess the extent of flood impact in different regions, enabling the establishment of a prioritization scale for mitigation efforts. This process resulted in a new dataset that would be utilized as input for the Self-Organizing Map (SOM) algorithm, as a technique for clustering districts that share comparable characteristics[18],[19] , [20]. The ideal number of clusters is typically determined by picking the number of clusters that optimize the average silhouette score. The weights obtained from the Analytic Hierarchy Process (were determined through assessments conducted by knowledgeable entities involved in flood disaster management, specifically from the Regional Disaster Management Agency (BPBD).

2.2 Regional Ranking

The regional ranking is determined by assessing the magnitude of points assigned to each region. As the size of the point increases, the region is given a higher ranking. The calculation of points is performed using the subsequent equation:

$$Point = \sum w_i * f_i * W\_cluster \quad (2)$$

Where:

w_i is the feature weight.
F_i is the feature value.
W_cluster is the cluster weight.

3. Results And Discussion

The data on the impacts of floods in the North Aceh area, sourced from the Regional Development Planning Agency (BAPEDA) and the Regional Disaster Management Agency (BPBD), is shown in Table 1. The given data indicates the average intensity of floods that occurred from 2020 to 2022.

Tabel 1. Average Flood Impact in North Aceh Regency 2020 - 2022

District	Village	House	Person	Public	District
Baktiya	20	179	814	5	259
Baktiya Barat	26	46	2619	83	736
Banda Baro	21	0	0	1	74
Cot Girek	19	0	397	3	183
Dewantara	13	9	42	29	252
Geuredong Pase	13	0	0	2	229
Kuta Makmur	15	202	460	3	33
Langkahan	19	383	1210	4	95
Lapang	13	99	448	7	372
Lhoksukon	60	7524	35403	8	208

Matangkuli	40	1898	4510	11	256
Meurah Mulia	21	242	1380	2	62
Muara Batu	0	0	0	0	0
Nibong	12	0	0	3	160
Nisam	17	0	0	3	62
Nisam Antara	0	0	0	0	0
Paya Bakong	8	0	0	4	87
Pirak Timu	40	1755	5227	39	265
Samudera	29	369	1039	8	320
Sawang	10	6	27	3	91
Seunuddon	20	21	79	1	1835
Simpang Keuramat	18	69	312	1	45
Syamtalira Aron	34	916	2767	28	168
Syamtalira Bayu	10	5	147	4	200
Tanah Jambo Aye	13	8	41	3	369
Tanah Luas	37	514	4158	38	273
Tanah Pasir	22	83	817	8	263
Baktiya	20	179	814	5	259

Feature Priority Scale Assessment

The feature priority scale is determined through the assessment carried out by competent entities from BPBD. Table 2 displays the outcomes of the feature priority analysis.

Table 2. Feature Priority Comparison

	F1	F2	F3	F4	F5
F1	1	2/4	2/5	2/3	2/1
F2	4/2	1	4/5	4/3	4/1
F3	5/2	5/4	1	5/3	5/1
F4	3/2	3/4	3/5	1	3/1
F5	1/2	1/4	1/5	1/3	1
	F1	**F2**	**F3**	**F4**	**F5**
F1	1	0.5	0.4	0.67	2
F2	2	1	0.8	1.33	4
F3	2.5	1.25	1	1.67	5
F4	1.5	0.75	0.6	1	3
F5	0.5	0.25	0.2	0.33	1

F1 represents the notion of a Village, F2 represents a House, F3 represents Life, F4 represents Public Facilities, and F5 represents Land. By employing the comparison data presented in table 2, this identify the feature weights. The eigenvalues are multiplied by a factor of 100 to provide an integer value, which serves as the final weight.

3.1 Formation of a New Dataset

A new dataset was created by performing an initial normalization of the original dataset using equation (1).

The initial normalization results are multiplied by the feature weights, thus forming a new dataset as shown in table 3.

Table 3. New Dataset

District	F1	F2	F3	F4	F5
Baktiya	4.59	0.67	0.69	1.25	0.99
Baktiya Barat	5.97	0.17	2.22	20.75	2.81
Banda Baro	4.82	0.00	0.00	0.25	0.28
Cot Girek	4.36	0.00	0.34	0.75	0.70
Dewantara	2.98	0.03	0.04	7.25	0.96
Geuredong Pase	2.98	0.00	0.00	0.50	0.87
Kuta Makmur	3.44	0.75	0.39	0.75	0.13
Langkahan	4.36	1.43	1.03	1.00	0.36
Lapang	2.98	0.37	0.38	1.75	1.42
Lhoksukon	13.77	28.00	30.00	2.00	0.79
Matangkuli	9.18	7.06	3.82	2.75	0.98
Meurah Mulia	4.82	0.90	1.17	0.50	0.24
Muara Batu	0.00	0.00	0.00	0.00	0.00
Nibong	2.75	0.00	0.00	0.75	0.61
Nisam	3.90	0.00	0.00	0.75	0.24
Nisam Antara	0.00	0.00	0.00	0.00	0.00
Paya Bakong	1.84	0.00	0.00	1.00	0.33
Pirak Timu	9.18	6.53	4.43	9.75	1.01
Samudera	6.66	1.37	0.88	2.00	1.22
Sawang	2.30	0.02	0.02	0.75	0.35
Seunuddon	4.59	0.08	0.07	0.25	7.00
Simpang Keuramat	4.13	0.26	0.26	0.25	0.17
Syamtalira Aron	7.80	3.41	2.34	7.00	0.64
Syamtalira Bayu	2.30	0.02	0.12	1.00	0.76
Tanah Jambo Aye	2.98	0.03	0.03	0.75	1.41
Tanah Luas	8.49	1.91	3.52	9.50	1.04
Tanah Pasir	5.05	0.31	0.69	2.00	1.00

3.2 Clustering results

The results of clustering of flood affected areas using the SOM algorithm are shown in table 4.

Table 4. Clustering results

District	Cluster
Baktiya	1
Baktiya Barat	1
Banda Baro	1
Cot Girek	1
Dewantara	1
Geuredong Pase	1
Kuta Makmur	1
Langkahan	1
Lapang	1
Lhoksukon	2
Matangkuli	2
Meurah Mulia	2
Muara Batu	3
Nibong	3
Nisam	3
Nisam Antara	2
Paya Bakong	2
Pirak Timu	2
Samudera	3
Sawang	3
Seunuddon	3
Simpang Keuramat	2
Syamtalira Aron	2
Syamtalira Bayu	2
Tanah Jambo Aye	3
Tanah Luas	3
Tanah Pasir	3

Cluster 1 consists of 21 sub-districts, cluster 2 consists of 3 sub-districts, and cluster 3 consists of 3 sub-districts. The spatial map of the flood impact clustering results is shown in Figure 1. Green indicates cluster 1, brown indicates cluster 2, and red indicates cluster 3.

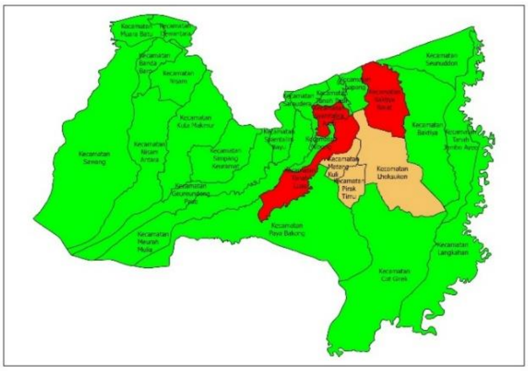

Fig 1. Clustering map of flood impact areas

3.3 Clustering Result Analysis

Cluster analysis is carried out by looking at the similarity of characteristics in each cluster formed. The image below shows the stages carried out in analyzing clusters.

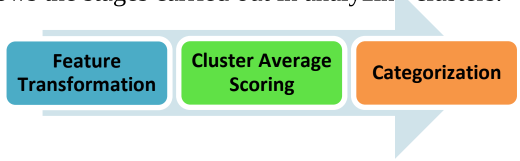

Fig 2. Stages of cluster analysis

Feature transformation is carried out by changing the data in table 1. The transformation results are grouped based on each cluster. Based on the scoring data results, cluster characteristics were obtained as shown in table 5.

Table 5. Categorization

District	Village	House	Person	Public Facility	Land
1	Low	Low	Low	Low	Low
2	High	High	High	Medium	Medium
3	Medium	Medium	High	High	Medium

3.4 Mitigation Priority Scale Assessment

The evaluation of the level of priority for mitigation is conducted through multiple steps. The flood impact data in table 4 was utilized using equation 2, resulting in the data shown in table 6. Specifically: w1 = 14, w2 = 28, w3 = 30, w4 = 21, w5 = 7. The cluster weight values are determined as follows: wC1 = 1, wC2 = 3, and wC3 = 2. The outcomes derived from this procedure are displayed in table 6.

Table 6. Mitigation Priority scale

District	F1	F2	F3	F4	F5	Point	Global Rank
Baktiya	13.72	28.00	30.00	2.10	0.77	223.77	1
Baktiya Barat	9.24	6.44	4.50	9.66	0.98	92.46	2
Banda Baro	9.24	7.00	3.90	2.73	0.98	71.55	3
Cot Girek	6.02	0.28	2.10	20.79	2.80	63.98	4
Dewantara	8.54	1.96	3.60	9.45	1.05	49.20	5
Geuredong Pase	7.84	3.36	2.40	6.93	0.63	42.32	6

Kuta Makmur	6.72	1.40	0.90	2.10	1.19	12.31	7
Langkahan	4.62	0.00	0.00	0.21	7.00	11.83	8
Lapang	2.94	0.00	0.00	7.35	0.98	11.27	9
Lhoksukon	5.04	0.28	0.60	2.10	0.98	9.00	10
Matangkuli	4.34	1.40	0.90	1.05	0.35	8.04	11
Meurah Mulia	4.62	0.56	0.60	1.26	0.98	8.02	12
Muara Batu	4.76	0.84	1.20	0.42	0.21	7.43	13
Nibong	2.94	0.28	0.30	1.68	1.40	6.60	14
Nisam	4.34	0.00	0.30	0.84	0.70	6.18	15
Nisam Antara	3.50	0.84	0.30	0.84	0.14	5.62	16

The practical application of the Self-Organizing Map (SOM) technique for clustering flood-affected areas yields three unique clusters, each consisting of: Cluster 1 comprises the following members: Samudera, Seunuddon, Dewantara, Tanah Pasir, Stepan, Baktiya, Meurah Mulia, Lapang, Cot Girek, Kuta Makmur, Banda Baro, Tanah Jambo Aye, Simpang Keuramat, Nisam, Nibong, Geuredong Pase, Syamtalira Bayu, Sawang, Paya Bakong, Muara Batu, and Nisam Antara. Cluster 2 comprises the following constituents: Lhoksukon, Pirak Timu, and Matangkuli. Cluster 3 comprises the following constituents: West Baktiya, Tanah Luas, and Syamtalira Aron.

Cluster 1 is a cluster with minimal flood impact on all features. Cluster 2 has significant flood impacts on village features, dwellings, and people, whereas public facilities and land features have mild flood impacts. Cluster 3 exhibits a moderate level of flood impact on village features, buildings, and land, whereas human features and public facilities have a high level of impact.

Essentially, the determination of mitigation priorities can be made by just examining the cluster pattern generated. Cluster 2 should be given the highest priority, followed by cluster 3, and lastly cluster 3. Nevertheless, this approach remains insufficient for making informed decisions. Conducting a comprehensive examination of the current conditions in each location is necessary in order to establish the priority sequence for managing flood catastrophes in each respective area.

3.5 Discussion

This study used the Self-Organizing Map (SOM) method to group flood-affected areas, with the objective of giving priority to mitigation measures in the North Aceh region. The study gathers flood catastrophe data from North Aceh Regency and utilises neural network techniques to classify affected areas into various clusters with varying levels of importance. The SOM models is employed to categorise areas according to the distribution patterns of flood-prone locations. The evaluation of the prioritisation scale for mitigation encompasses the process of normalising data on the impact of floods, the application of weight values, and the calculation of cluster weight values. The study utilises the Analytic Hierarchy Process to allocate weights to features in data preprocessing. This allows for the creation of a prioritisation scale for mitigation activities, which is determined by the allotted points for each region. The results of the feature priority analysis are considered while determining the feature priority scale. The study findings suggest that the SOM approach yields favourable clustering outcomes, characterised by distinct features within each cluster. The cluster analysis results correspond to the creation of a prioritisation scale for flood disaster mitigation in each sub-district. Nevertheless, the hierarchy of importance is contingent upon the specific circumstances of the flood consequences in each sub-district. The study's model can serve as an initial approach for officials to design flood prevention strategies in the North Aceh district.

4. CONCLUSION

The utilisation of the SOM algorithm for clustering flood-affected regions yields positive cluster results, as shown from the findings of cluster analysis, which demonstrate that the generated clusters possess unique characteristics which set regions apart from one another. Establishing the priority scale for flood disaster mitigation in each sub-district area aligns with the cluster findings. However, the prioritisation is contingent upon the specific conditions of the flood's effects in each sub-district.

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Author contributions

Wahyu Fuadi: Conceptualization, Methodology, Software, Field study. **Ilham Sahputra:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Dedi Fariadi:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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