

# Implementation Self Organizing Map for Cluster Flood Disaster Risk

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**Keywords:** Cluster, Flood Disaster, SOM.

**Abstract:** Floods have devastating effects on human, economic, and environmental life. The flood risk can't be avoided completely so it must be managed. Flood disaster management does not seek to eliminate the danger of flooding, but to cope with it. Thus, this study aims to (1) classify the provinces in Indonesia based on the results of flood risk analysis; (2) Identify flood risk characteristics in each group; and (3) Analyze the flood risk level of each province in Indonesia. The research method used in this research is the method of Self Organizing Map (SOM) by using software R. This research conducted cluster class based on flood risk variables, i.e. province, number of incidents, a victim, houses and damages. The results showed the grouping divided into 6 clusters with members of each cluster are; cluster 1 (central of java and east java), cluster 2 (west java), cluster 3 (Aceh, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, Bangka Belitung, Kepulauan Riau, DKI Jakarta, Bali, Nusa Tenggara Barat, East Kalimantan, North Sulawesi and Papua), cluster 4 (Banten, West Papua), cluster 5 (South Kalimantan), and cluster 6 (central).

## 1 INTRODUCTION

Indonesia is one country that has disaster-prone areas, one of the disasters that often befall Indonesia is flooded. Floods have an impact that can be bad for human life. Flood disaster can affect the disruption of the economy and the environment (UNISDR, 2015). Negative impacts caused by floods are important for anticipatory steps. To take anticipatory steps requires knowledge of the hazards of their impact (Zischg, et al., 2018). There have been several previous studies on the analysis of the negative impacts of floods. Studies show that the impact of flooding is not only on aspects of buildings and materials. However, the effect on the prevalence of increased psychological illnesses after the flood disaster (Zhong, et al. 2018).

To explore the linearity of relationships using spatial analysis and temporal variants of the impact of floods. The results show that most and most affected are nonlinearly properties especially those close to the river (Rajapaksa, Zhu, & Lee, 2017). Hydrographic construction design for the study of climate change impacts, informative hydrograph development in flood disaster impact studies (Brunner, Sikoska, & Seibert, 2018). Factor analysis that influences flood by using weighted overlay technique approach, research result can give information about danger

zone of food for early (Azmeri, Hadihardja, & Vadia, 2016)

Several previous studies have conducted various analysis approaches to the impact of floods. In this study we propose anticipatory steps in obtaining flood information in the territory of Indonesia. This research can provide knowledge by conducting flood risk level analysis at every province in Indonesia. In order for prevention and mitigation measures to be carried out properly, effectively and efficiently.

The method proposed in this research is the Self Organizing Map method (SOM) and the aid of computation method using R programming language to support the faster analysis process done. The self-organizing map is a statistical data analysis method of the branch of unsupervised learning, whose goal is to determine the properties of input data without explicit feedback from a teacher (Martin & Obermayer, 2009). The SOM algorithm creates mappings which transform high-dimensional data space into low-dimensional space in such a way that the topological relations of the input patterns are preserved (Kölküer & Green, 2007). Some previous studies used the self-organizing map method. The use of SOM integrated with image processing to model the detection of damaged gaps in bridges (Chen, et.al, 2017). SOM implementation can be used to model traffic

disruption patterns (Steiger, et.al., 2016). SOM implementation can effectively help better rescue planning in the aftermath of a disaster. The built model is used to produce a risk map of survival. Some problems can be modeled and, in the map, using the SOM approach. The SOM method adopted in this study to cluster can provide clustering of areas most affected by floods. This study aims to provide early knowledge about the potential for flood disasters in the territory of Indonesia.

## 2 RELATED WORK

### 2.1 Self Organizing Map

Kohonen Self Organizing Maps is a network found by Teuvo Kohonen is one of the most widely used networks. Named "self-organizing" because this method does not require a special surveillance and SOM approaches through unsupervised competitive experiments. The word "maps" it self because this method using the map in weighting input data. Each node in this network works to present each data input, therefore this network can also be called "Self-Organizing Feature Maps", the concept of "features" becomes an important and valuable thing, specifically the topology relationship between the inputted data will be maintained and original when mapped in the SOM network (Guthikonda, 2005).

In perspective, SOM can be seen not only as a tool but as a toolbox that contains the features of numbers and can be more interesting in different situations. SOM Kohonen network has three topology types, namely linear array, rectangular, and hexagonal. Linear array topology shows cluster units arranged linearly

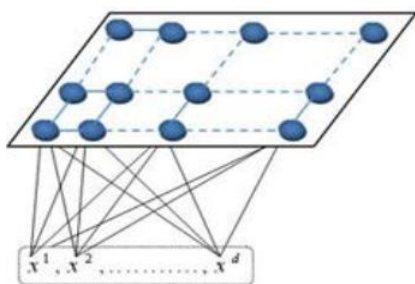


Figure 1: Kohonen Topological Map.

Source: Yusob, B., et al., (2013)

### 2.2 Cluster Validation

Cluster validation is a procedure that evaluates the results of quantitative and objective cluster analysis. Index Dunn is one part of the cluster validity such as the Davies-Bouldin index or the Silhouette index in this case Dunn index is an internal evaluation scheme where the result is an internal evaluation scheme.

$$Dunn = \frac{d_{min}}{d_{max}} \tag{1}$$

$d_{min}$  = smallest distance between observations on different clusters

$d_{max}$  = largest distance in each data cluster

## 3 RESULTS AND DISCUSSION

Based on the objective of this research is to group the provinces in Indonesia and identify the characteristics based on flood disaster risk in 2008-2018 by using Self Organizing Maps method. The Kohonen network is used to divide input patterns into clusters. Suppose the input is a vector consisting of n components to be grouped within a maximum of group m. SOM network requires a training progress to minimize the average distance of an object to the nearest.

In figure 2 below is below is the number of progress training that shows the number of iterations against the average distance to the nearest unit. Progress or iteration training is used to find out how much it takes for the cluster to be optimal, the more iterations are carried out, the smaller the distance of cluster units and the results of grouping will be better. After passing an iteration of approximately 4000 shows that the progress of the training begins to stabilize with the average cluster unit distance below 0.05 and the researcher uses 10,000 iterations to do this grouping. To help researchers determine which clusters produced in SOM can be done using the Cluster Amount of Squares (WCSS). The Cluster Sum of Squares (WCSS) is able to help groups desired by researchers.

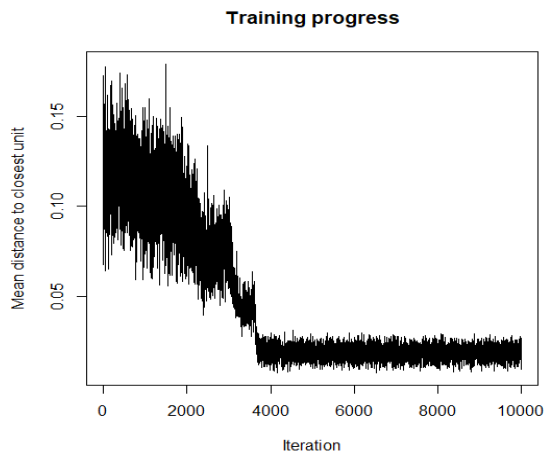


Figure 2: Training Process.

Figure 3. Seen at the time of forming one cluster, curve still shows steepness and increasingly sloping according to cluster increase. In essence the number of clusters that are formed when the number of members who joined fewer and fewer. To prove whether the number of clusters selected is correct or has not been used cluster validity test, the following is the output of programs R on the test of cluster validity:

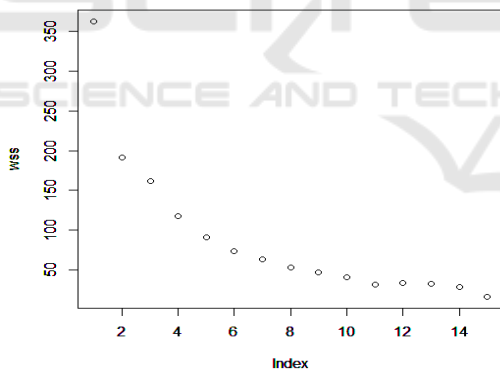


Figure 3: Within Cluster Sum of Squares.

Figure 4 cluster validation can be known if the cluster to be formed is 4 clusters up to 8 cluster then the best cluster is 6 clusters, as shown in the picture above optimal scores shows there are two methods that choose the 6 most reverse clusters are Dunn and Silhouette, while connectivity shows that 4 clusters are the best number of clusters, because there are 2 that say that 6 clusters are the best result, the researcher will use 6 clusters for flood disaster grouping in Indonesia by province using 6 clusters. After the number of clusters is determined then the next process is to make fan diagram.

Validation Measures:

	4	5	6	7	8
som Connectivity	20.3607	24.8508	30.2599	36.5393	37.1913
Dunn	0.1986	0.1644	0.2378	0.2332	0.1516
Silhouette	0.3160	0.3411	0.3563	0.2899	0.3101

Optimal Scores:

	Score	Method	clusters
Connectivity	20.3607	som	4
Dunn	0.2378	som	6
Silhouette	0.3563	som	6

Figure 4: Cluster Validity Test.

The results of the provincial grouping using SOM are as shown in table 1 below.

Table 1: Number and Grouping Members.

Group	Number of Member	Members of the group
1	2	Central Java, East Java
2	1	West Java
3	27	Aceh, North Sumatera, West Sumatera, Riau, Jambi, South Sumatera, Bengkulu, Lampung, Bangka Belitung Islands, Riau Islands, DKI Jakarta, Yogyakarta, Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, East Kalimantan, North Sulawesi, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku, Papua
4	2	Banten, West Papua
5	1	South Kalimantan
6	1	Central Kalimantan

The mapping results from the grouping analysis using Self Organizing Maps are shown in Figure 5.



Figure 5: Mapping Using SOM Algorithm.

SOM grouping table and SOM mapping visually and see the table of group average, cluster 1 consisting of Central Java and East Java has the largest number of occurrences. Successively 929 and 963 incidents with the number of house damage (heavily damaged, medium, light, submerged) also have a high value. This group corresponds to the one associated with the blue circle in Self Organizing Maps.

West Java in an orange circle is cluster 2 in Self Organizing Maps output has a high number of occurrences with damage of house (damaged heavy, medium, light, submerged) which is most numerous than a group. Victims (died, injured, suffered) are high while the number of injured is very large that is 37195 inhabitants, higher than other groups. The green circle is associated with 27 provinces: Aceh, North Sumatera, West Sumatera, Riau, Jambi, South

Sumatera, Bengkulu, Lampung, Bangka Belitung Islands, Riau Islands, Jakarta, Yogyakarta, Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, East Kalimantan, North Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku, Papua are incorporated in cluster 3 has an average.

The number of occurrences with the category of damage to the house (heavily damaged, medium, light, submerged) is very small, so it has a low average value too. On average the number of victims (died and missing, injured, suffered and displaced) and also broke facilities (health, worship, education). Banten and West Papua are associated in a red circle on Self Organizing Maps, which is cluster 4, where this cluster has the lowest number of events compared to other clusters.

Table 2: Cluster Profile.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Number of events	946	786	126.96	85.5	184	116
People Died and Missing	112	148	28.93	250	44	2
Injuries	14731.5	37195	532.96	8351	381	860
Suffered and displaced	996364.5	2013938	257086.8	319338.5	4860178	398342
Heavy Damage House	1791	4839	759.22	966	262	0
Houses Damaged Medium	1954	2455	130.3	81	8	0
Light Damaged House	6928	9232	2776.81	179.5	275	3349
House Submerged	393278	647737	51033.3	48395	235426	58527
Health facility	0.5	1	0.78	0	0	48
Worship Facilities	13	115	4.44	0	13	131
Educational Facilities	29.5	44	10.63	1	15	158

The low number of damages to houses (severely damaged, medium, light, submerged) and poor facilities (health, worship, education) are still needed for education or training on disaster mitigation due to the average. The highest number of deaths and disappearances compared to other clusters, while the number of victims (injured, suffered and displaced) has a moderate average. In cluster 5, South Kalimantan is associated with a purple circle, for this cluster has the lowest number of events, and the low number of damage to the house (damaged, medium, light) is accompanied by low facility damage (health, worship, education), but the number of houses soaked in water is so high that the number of displaced persons also has the highest number among other clusters. Finally, central Borneo is associated in a brown circle with a low number of incidents, and a

low number of (low, medium, light, submerged) damage to homes, and low casualties (dead and missing, injured, suffered and displaced) also, in this case need improvements in terms of facilities (health, worship, education) because it has the highest damage value compared with other clusters.

#### 4 CONCLUSIONS

The number of groups formed as many as 6 groups, is the number determined by researchers with the approach using Within Cluster Sum of Squares. The use of Self Organizing Maps algorithm resulted in a grouping with a group of 27 provinces, two groups of 2 provinces and three groups of 1 province each. Groups 1 and 4 each consist of Central Java, East Java and Banten, West Papua. Groups of 2.5.6 and 4

each consist of West Java, Central Kalimantan, and South Kalimantan. Group 3 consists of Aceh, North Sumatera, West Sumatera, Riau, Jambi, South Sumatera, Bengkulu, Lampung, Kep. Bangka Belitung, Kep. Riau, DKI Jakarta, In Yogyakarta, Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, East Kalimantan, North Sulawesi, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku, Papua.

Zhong, S., Yang, L., Toloo, S., Tong, S., Sun, X., Crompton, D., et al. 2018. The Long Term Physical and Psychological Health Impacts of Flooding: A Systematic Mapping. *Science of The Total Environment*, 165-194.

Zischg, A. P., Hofer, P., Mosimann, M., Röthlisbergerab, V., Ramirez, J., Keiler, M., et al. 2018. Flood Risk (d) Evolution: Disentangling Key Driver of Flood Risk Change with a Retro Model Experiment. *Science of The Total Environment*, 195-207.

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## REFERENCES

- Azmeri, Hadihardja, I., & Vadia, R. 2016. Identification of Flash Flood Hazard Zones in Mountainous Small Watershed of Aceh Besar Regency Aceh Province Indonesia. *The Egyptian Journal of Remote Sensing and Space Science*, Vol 19(1), 143-160.
- Brunner, M. I., Sikoska, A., & Seibert, J. 2018. Bivariate Analysis of Flood in Climate Impact Assessments. *Science of The Total Environment*, 1392-1403.
- Chen, J. H., Su, M. C., Cao, R., Hsu, S. C., & Lu, J. C. 2017. A Self Organizing Map Optimization Based Image Recognition and Processing Model for Bridge Crack Inspection. *Automation in Construction*, Vol 73, 58-66.
- Guthikonda, S. M. 2005. Self-Organizing Maps. In Kohonen, & Teuvo, *Self-Organizing Maps* (p. 10). US: Springer.
- Köküer, M., & Green, R. 2007. Towards Automatic Risk Analysis for Hereditary Non-Polyposis Colorectal Cancer Based on Pedigree Data. *Outcome Prediction in Cancer*, 319-337.
- Martin, R., & Obermayer, K. 2009. Self-Organizing Maps. *Encyclopedia of Neuroscience*, 551-560. Academic Press.
- Rajapaksa, D., Zhu, M., & Lee, B. 2017. The Impact of Flood Dynamics on Property Values. *Land Use Policy*, Vol 69, 317-325.
- Steiger, E., Resch, B., Albuquerque, J. P., & Zipf, A. 2016. Mining and Correlating Traffic Events from Human Sensor Observations with Official Transport Data Using Self Organizing Maps. *Transportation Research Part C: Emerging Technologies*, 73, 91-104.
- UNISDR. 2015. *Making Development Sustainable: The Future of Disaster Risk Management*. United Nations: Geneva.
- Yusob, B., et al. 2013. Spiking Self-Organizing Maps for Classification Problem. *Technology Came*, Vol 11, 57-64.