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Modelling of Flood Hazard Early Warning Group Decision Support System

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Abstract

Early warning of flood hazards needs to be carried out comprehensively to avoid a higher risk of disaster. Every decision on early warning of a flood hazard is carried out in part by one party, namely the government or water resource managers. This research aims to provide a collaborative decision-making model for early warning of flood hazards through a Group Decision Support System Model (GDSS), especially in Indonesia. The novelty of this research is that the GDSS model involves more than one decision-maker and multi-criteria decision-making for early warning of flood hazards in the downstream Kali Sadar River, Mojokerto Regency, East Java Province, Indonesia. The GDSS model was developed using a hybrid method, namely the Analytical Network Process (ANP) and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). There was more than one decision result; voting was carried out using the BORDA method to produce the decision. The test results of GDSS were obtained using a Spearman rank correlation coefficient of 0.8425 and matrix confusion, an accuracy value of 86.7%, a precision value of 86.7%, a recall value of 86.7%, and an f-measure of 86.7%. Based on the test results, good results were obtained from the GDSS model.

Keywords: ANP; Early Warning; Flood Hazard; Group Decision Support System; VIKOR.

1. Introduction

Indonesia is a country that has many areas with a high risk of natural disasters, including floods, extreme weather, earthquakes, and tsunamis. According to the 2019 World Risk Index, Indonesia is ranked 37th out of 180 countries most vulnerable to disasters [1]. The 2022 World Risk Report released by Bündnis Entwicklung Hilft and IFHV of the Ruhr-University Bochum shows that Indonesia is the third most disaster-prone country in the world [2]. Indonesia ranks third in the world as the country most vulnerable and most frequently hit by flood disasters, after India and China [2]. According to a report by the National Disaster Management Agency, there were 3,531 natural disaster events in Indonesia throughout 2022. The most frequent disasters in 2022 were floods, namely 1,524 incidents. This number is equivalent to 43.1% of the total national disaster events [3]. Based on this data, Indonesia is a country prone to natural disasters, especially floods.

Management problems often occur starting with data information, dissemination of data information, and decision-making related to early warning of flood hazards. Decision-making was based on existing data related to these criteria as well as in water resource management [4]. This is due to differences in preferences in making decisions from the

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government and water resource managers. Data and information on flood warnings need to pay attention to the following criteria: rainfall, river discharge, water level, embankment conditions, and drainage condition data [5].

Flood warnings certainly involve several decision-making parties (DM), so a flood warning group decision support system is needed [6]. Group decision support systems can accommodate the need for joint decision-making. Several opinions about preferences from several decision makers (DMs) are processed with the help of a group decision support system, and these DMs must be present together [7, 8]. Group decision support systems can also overcome inconsistencies that may occur in decision-making [9, 10]. The MCDM method is divided into two categories, namely Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM) [11, 12]. Usually used to assess or select a limited number of alternatives. MODM is used to solve problems in continuous space (such as problems in mathematical programming) [11]. Several studies related to multi-criteria decision-making have been carried out, such as reducing disaster risks such as flood hazards. Multicriteria decision-making was a technological advancement and innovation in data collection before and after a disaster occurred [13]. Multi-criteria analysis has also been used in Brazil in the flood warning mechanism [14]. Flood warnings certainly involve several decision-makers (DMs), so a flood warning group decision support system is needed [6]. Group decision support systems can accommodate the need for joint decision making.

Based on a comparative study of MADM methods, the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method offers a compromise solution for decision making and the best alternative is selected based on the breadth of the solution needs [15, 16]. The VIKOR method is one of the MADM methods used in decision-making to determine alternative rankings. The VIKOR method requires weight values to produce alternative rankings. Analytic Network Process (ANP) or Analytic Hierarchy Process (AHP) can provide weight values for the VIKOR method [17]. The ANP value is closer to existing reality than AHP, so ANP is more widely used because it provides weight to the feedback analysis [18]. If the alternative rankings produced by the GDSS have different alternative rankings, voting will be carried out. One voting method is Borda Count [19].

This research has been carried out by providing a new solution model related to collaboration in flood warning decision-making through a group decision support system (GDSS) model for flood warnings. The novel solution model uses multi-criteria decision-making (MCDM) with case data on the Kali Sadar River, Mojokerto Regency, East Java Province, Indonesia. The hybrid method that has been implemented uses the analytic network process (ANP) as a form of criteria importance analysis in producing weight values as input to the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method. The VIKOR method will provide preferences for flood hazard conditions based on the preference scorer. There are two parties giving preference values who contribute to decision-making, so it is necessary to vote on the values produced using the VIKOR method. Voting uses the Borda method to provide a higher objectivity value than manually. Testing of the preference results for the GDSS of the flood warning has been carried out using the spearman rank correlation and matrix confusion methods.

2. Material and Methods

2.1. Scope of Study

The research that has been carried out has the aim of creating a group decision support system (GDSS) model for early warning of flood hazards. The group decision support system that has been carried out in this research involves two decision-making parties, namely the government and river water resource managers. The government in question is a regional government such as the Regional Disaster Management Agency (Badan Penanggulangan Bencana Daerah-BPBD). The river water resource manager in question is Perum Jasa Tirta. Flood warning guidelines use contingency guidelines from the government and flood alert guidelines from water resource managers. The determination of flood alert status is determined by the head of government based on the flood alert status issued by a group decision-making system involving decision maker 1 from the government (DM-1) and decision maker 2 (DM-2) from the water source manager through incoming data, as shown in Figure 1.

Event data (cases) have five (5) incident data criteria, namely rainfall, water level, drainage conditions, and embankment conditions. The incident data criteria in multi-criteria decision making are called multi-criteria decision making (MCDM), as shown in Table 1. The incident (case) data model used is based on the Kali Sadar River data model, Mojokerto City, East Java Province, Indonesia, 2002–2017. The location of Kali Sadar River, Mojokerto Regency, East Java Province in Indonesia is shown in Figure 2, -7.527745895738239, 112.61724854770911 (latitude and longitude). The Kali Sadar River is 27,750 meters long, with a watershed area of 88,749 Km^2, and upstream elevation +900 meters, and downstream elevation +20 meters from sea level.

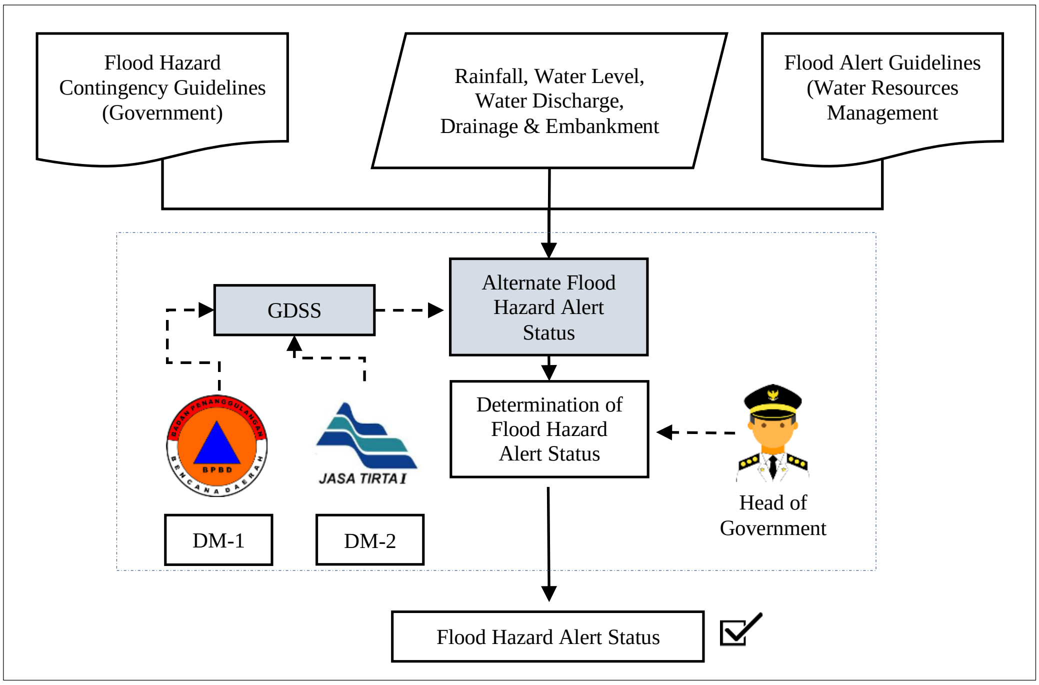

Figure 1. Block Diagram of the GDSS Model for Determining Flood Hazard Status

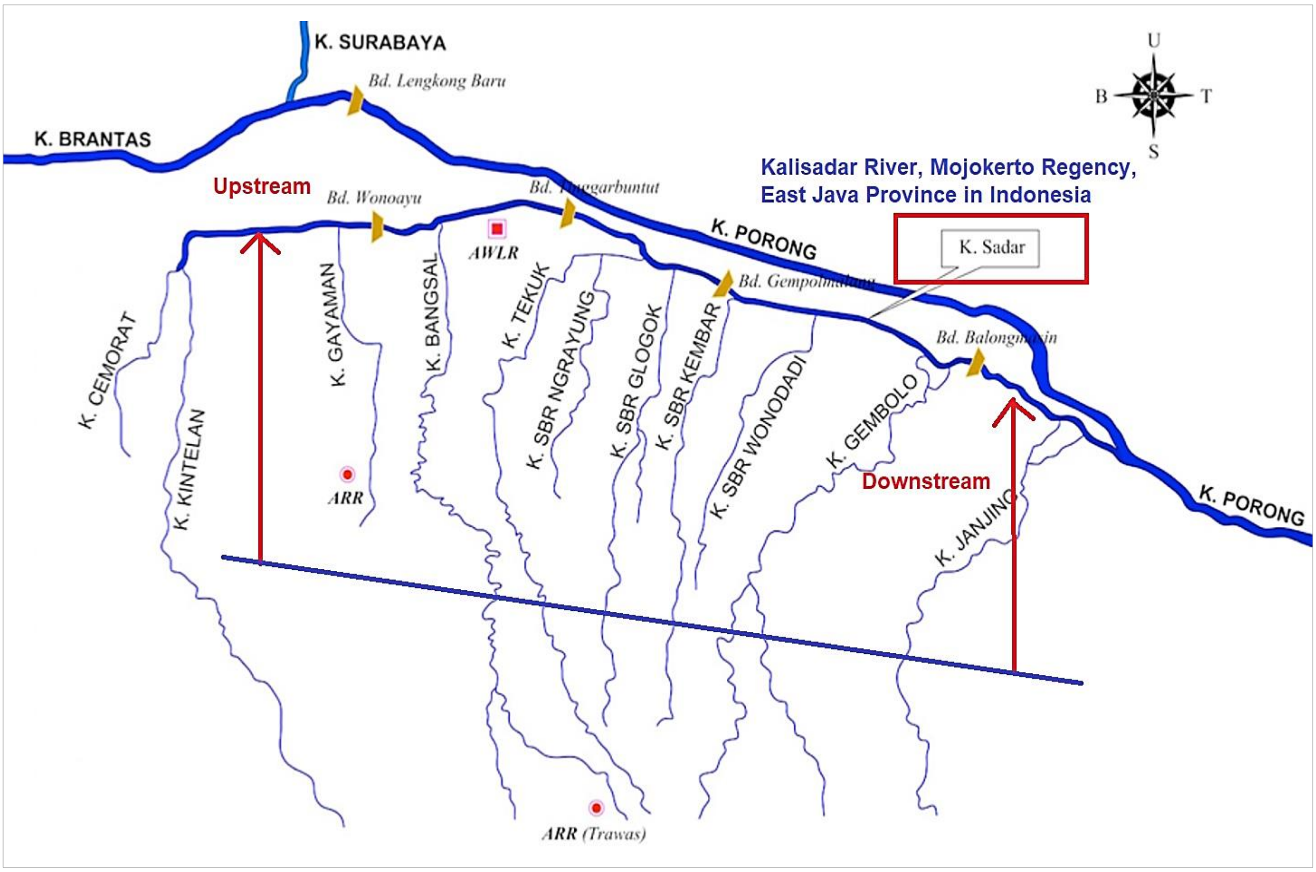

Figure 2. The location of Kali Sadar River, Mojokerto Regency, East Java Province in Indonesia (-7.527745895738239, 112.61724854770911)

The MCDM that is being built has a preferred status for early warning of flood hazard starting from the lowest level, low (L), moderate (M), Considerable (C), and High (H) based on the water resources management guidebook. Each flood hazard early warning preference status has a range of values for each criterion from different event data as shown in Table 2. Hereafter, the criteria from event data (cases) are called criteria.

Table 1. Event Data Model and Flood Warning Status for the Kali Sadar River

Event data (n)	Rainfall-RF	Water Discharge-WD	Water Level-WL	Embankment-E	Drainage-D	Alert Status
1	0	581	393	Good	Good	Moderate
2	12	278	311	Good	Good	Low
3	97	923	517	Heavily damaged	Heavily damaged	High
4	17	811	393	Moderate damage	Moderate damage	Considerable
5	13	687	390	Moderate damage	Heavily damaged	Moderate
6	0	21	39	Good	Good	Low
7	0	123	84	Good	Good	Low
8	0	816	415	Good	Moderate damage	Considerable
9	85	879	465	Heavily damaged	Heavily damaged	High
10	61	841	494	Good	Moderate damage	Considerable
11	0	3	10	Good	Good	Low
12	0	4	10	Good	Good	Low
13	0	2	12	Good	Good	Low
14	0	2	12	Good	Good	Low
15	0	2	12	Good	Good	Low

Table 2. Preference table of the relationship between criteria and preference status for early flood warnings

Criteria	Preference Status of Flood Warning			
	Low	Moderate	Considerable	High
	Preference Value			
	1	2	3	4
Rainfall-C1	RF =0	0 < RF <= 10	10 < RF <= 20	RF > 20
Water Discharge-C2	WD < 401,38	401,38 <= WD < 807,92	807,92 <= WD < 818,45	WD => 818,45
Water Level-C3	WL < 389,5	389,5 <= WL <= 39,6	391,6 <= WL <= 393,1	WL > 393,1
Embankment -C4	Good	Moderate damage	Moderate damage	Heavily damaged
Drainase-C5	Good	Moderate damage	Moderate damage	Heavily damaged

3. Research Methodology

The GDSS group decision support system model for flood warnings has several criteria, namely rainfall, river discharge, water level, embankment conditions and drainage condition data. The research stages that have been carried out on the GDSS for flood warnings are shown in Figure 3.

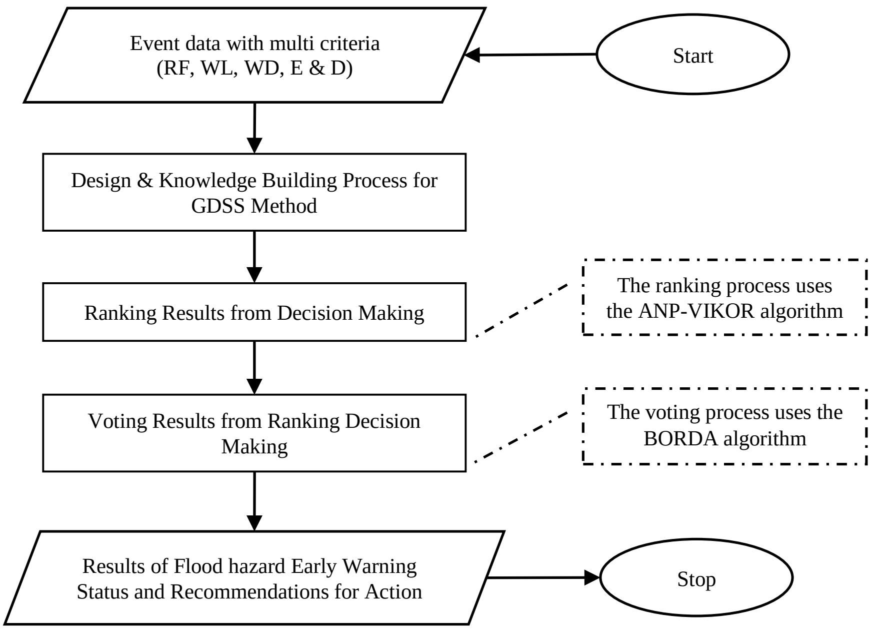

Figure 3. Block Diagram of Methodology

Multi-criteria event data as input for the Flood Hazard Warning Group Decision Support System (GDSS). The results of decision-making ranking (Decision Making-DM) through the process of comparing criteria and weight values produced by ANP become input for the VIKOR ranking method. VIKOR will provide preferences for flood hazard conditions based on the preference rating provider. There are two parties giving preference values who contribute to decision-making, so it is necessary to vote on the values produced using the VIKOR method. The preference value giver is the decision maker (DM), namely DM1 and DM1. Voting uses the BORDA method/algorithm to provide a higher objectivity value than manually. The architectural model of the GDSS Flood Warning is shown in Figure 4.

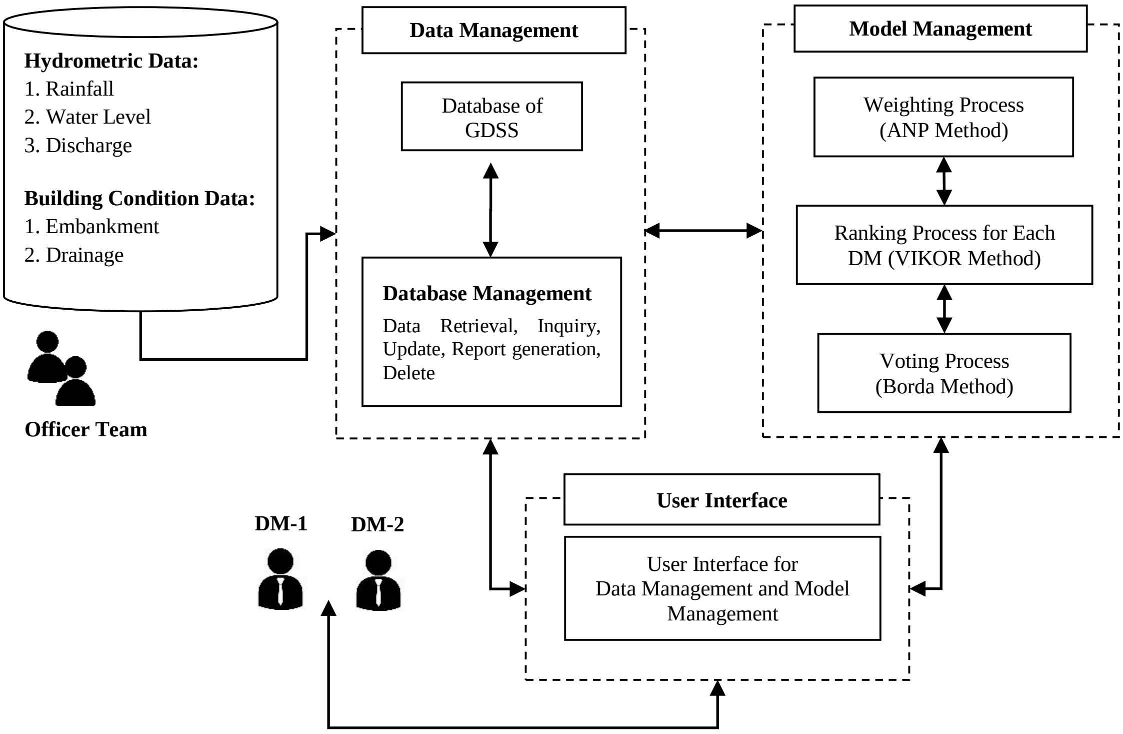

Figure 4. GDSS Architectural Model of Flood Warning

4. Results and Discussion

Based on Figures 2 and 3, the stages of the computational process model for the flood warning decision support system are as follows:

- The ANP algorithm computing process used is used to determine (generate) the final weight of each criterion. The weights of these criteria become input to the VIKOR algorithm computing process.
- The VIKOR algorithm computing process is used to rank alternative flood statuses. The stages of the ANP-VIKOR algorithm computing process are shown in Figure 5.
- The BORDA algorithm computing process will be used to vote on the results of each decision maker (Decision Maker/DM) from the results; ranking process. If the results of the ranking process are the same between DM-1 and DM-2 then there is no need for a voting process and if vice versa then voting is carried out as shown in Figure 5.
- The results of the BORDA algorithm computing process were carried out using Spearman correlation and confusion matrix testing.

ANP-VIKOR Algorithm Computing Process:

The data used for GDSS flood hazard warnings is shown in Table 2. The event data model is fifteen (15) data with five flood hazard level statuses from lowest to highest, namely alert, alert 3, alert 2, and alert 1. The event data model is a number 15 data are alternatives from 1 group of event sequences, either DM-1 or DM-2. Each incident data has criteria, namely, rainfall, discharge, water level, embankment conditions, and drainage conditions. Table 2 is rearranged into Table 3, where the incident data is an alternative solution to GDSS.

Table 3 is the event data model for GDSS input. The GDSS output results will later be tested using the Spearman Rank Correlation and *Confusion* Matrix. The 15 data becomes input to GDSS and later becomes an alternative output for flood hazard status conditions. The suitability of the model input data and output data will be compared to see whether the GDSS model provides good results.

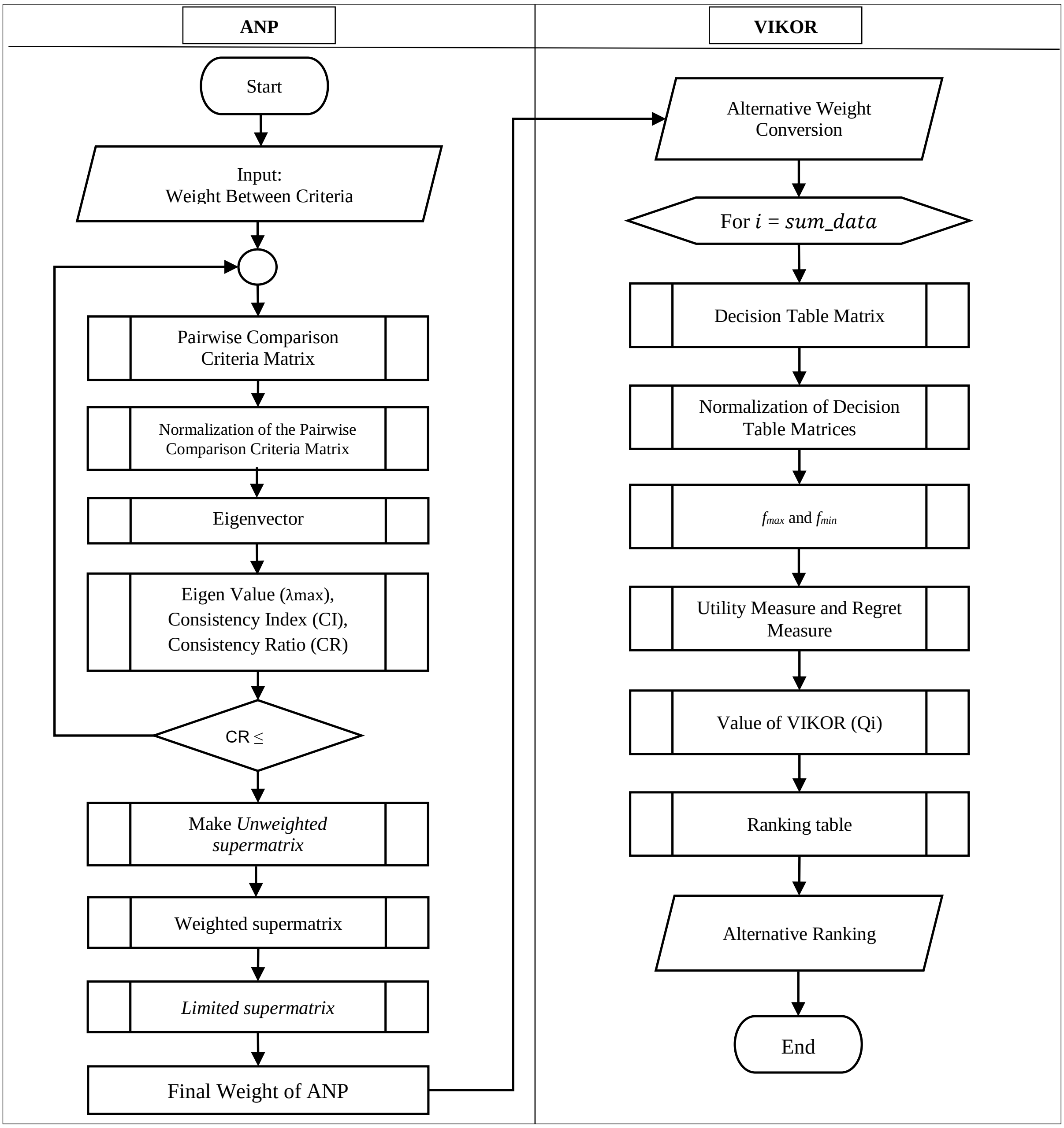

Figure 5. ANP-VIKOR algorithm computing process

Table 3. Alternative Data from The GDSS Flood Warnings

Alternative (n)	Rainfall-RF	Water Discharge-WD	Water Level-WL	Embankment-E	Drainage-D	Alert Status
1	0	581	393	Good	Good	Moderate
2	12	278	311	Good	Good	Low
3	97	923	517	Heavily damaged	Heavily damaged	High
4	17	811	393	Moderate damage	Moderate damage	Considerable
5	13	687	390	Moderate damage	Heavily damaged	Moderate
6	0	21	39	Good	Good	Low
7	0	123	84	Good	Good	Low
8	0	816	415	Good	Moderate damage	Considerable
9	85	879	465	Heavily damaged	Heavily damaged	High
10	61	841	494	Good	Moderate damage	Considerable
11	0	3	10	Good	Good	Low
12	0	4	10	Good	Good	Low
13	0	2	12	Good	Good	Low
14	0	2	12	Good	Good	Low
15	0	2	12	Good	Good	Low

The criteria weight table is shown in Table 4. For example, Rainfall (RF)-C1 has a criteria weight of 1 for a value of RF = 0, and then a criteria weight of 3 for a value of 0 < RF <= 10, a criteria weight of 5 for a value of 10 < RF <= 20, and a criteria weight of 20 for a value of RF > 20. Each criterion has a weight, which is called the criteria weight. Criterion weight is the score given to each decision criterion so that it can describe high or low importance. Based on the weight value of the criteria, it has meaning; criteria that have a higher weight than the others are more important [20].

Table 4. Criteria weight based on preference values

Criteria	Preference Value			
	1	2	3	4
Rainfall-C1	RF =0	0 < RF <= 10	10 < RF <= 20	RF > 20
Criterion Weight of C1	***1***	***3***	***5***	***7***
Water Discharge-C2	WD < 401,38	401,38 <= WD < 807,92	807,92 <= WD < 818,45	WD => 818,45
Criterion Weight of C2	***1***	***3***	***5***	***7***
Water Level-C3	WL < 389,5	389,5 <= WL <= 39,6	391,6 <= WL <= 393,1	WL > 393,1
Criterion Weight of C3	***1***	***3***	***5***	***7***
Embankment -C4	Good	Moderate damage	Moderate damage	Heavily damaged
Criterion Weight of C4	***1***	***3***	***5***	***7***
Drainase-C5	Good	Moderate damage	Moderate damage	Heavily damaged
Criterion Weight of C5	***1***	***3***	***5***	***7***

From Table 3, it is converted based on the criteria weight values referring to Table 4, and the results of the conversion are shown in Table 5, namely the criteria weights for each alternative. Table 5 is converted into a Pairwise Comparison Criteria Matrix, which becomes input for the ANP method, and then the output of the ANP method becomes input for the VIKOR method.

Table 5. Criteria Weight for Each Alternative

No	Alternative	C1	C2	C3	C4	C5
1	A1	1	3	5	1	1
2	A2	5	1	1	1	1
3	A3	7	7	7	7	7
4	A4	5	5	5	5	5
5	A5	3	3	3	3	5
6	A6	1	1	1	1	1
7	A7	1	1	1	1	1
8	A8	1	5	7	1	3
9	A9	7	7	7	7	7
10	A10	7	7	7	1	3
11	A11	1	1	1	1	1
12	A12	1	1	1	1	1
13	A13	1	1	1	1	1
14	A14	1	1	1	1	1
15	A15	1	1	1	1	1

The VIKOR value is Qi calculated using Equation 1 [21, 22]:

$$Q_i = v\left(\frac{(S_j - S^-)}{S^* - S^-}\right) + (1 - v)\left(\frac{(R_j - R^-)}{R^* - R^-}\right) \tag{1}$$

where v , the value used is 0.5 (*by consensus*), S^* is max S_j, S- is min S_j, R^* is max R_j, R- is min, R_j; $i = 1 \,..\, m$ (For this case m = number of alternatives = 15), S_j ; $i = 1$, v is introduced as weight of the strategy of "the majority of criteria" (or "the maximum group utility"), here suppose that v = 0.5 [23].

The results of VIKOR, Qi calculations are shown in Tables 6 and 7.

Table 6. Calculation results of Qi from DM-1

DM-1	
Alternative	**Qi**
A1	0.8851030691
A2	0.9603405669
A3	0
A4	0.258848239
A5	0.5809049244
A6	1
A7	1
A8	0.7645037857
A9	0
A10	0.6741207857
A11	1
A12	1
A13	1
A14	1
A15	1

With the same calculations and weights for DM-2, the VIKOR Q_i calculation results for DM-2 can be seen in Table 7 as follows:

Table 7. Calculation results of Qi from DM-2

DM2	
Alternative	**Qi**
A1	0.9167585926
A2	0.8787104249
A3	0
A4	0.2630780229
A5	0.5699094072
A6	1
A7	1
A8	0.80273195
A9	0
A10	0.4804933598
A11	1
A12	1
A13	1
A14	1
A15	1

BORDA Algorithm Computing Process:

At the ranking stage, this can be done by sorting from smallest to largest value [24-26]. The following shows the ranking results for DM-1 and DM-2 which can be seen in Table 8.

Table 8. Ranking Results

DM1		DM2		Ranking
Alternative (1)	**Qi**	**Alternative (2)**	**Qi**	
A3	0	A3	0	1
A9	0	A9	0	2
A4	0.258848239	A4	0.2630780229	3
A5	0.5809049244	A10	0.4804933598	4
A10	0.6741207857	A5	0.5699094072	5
A8	0.7645037857	A8	0,80273195	6
A1	0.8851030691	A2	0.8787104249	7
A2	0.9603405669	A1	0.9167585926	8
A6	1	A6	1	9
A7	1	A7	1	10
A11	1	A11	1	11
A12	1	A12	1	12
A13	1	A13	1	13
A14	1	A14	1	14
A15	1	A15	1	15

In BORDA's calculations, initially determining the list of candidates in this study had candidates A1, A2, A2, A3, A4, A5, A6, A7, A8, A9, A10, A11, A2, A13, A14, and A15. Calculates a score for each candidate based on the ranking given by each voter. Candidates ranked first will get the highest score, while candidates ranked lowest will get the lowest score. For example, if there are 5 candidates, then the candidate who is ranked 1st will get a score of 5, while the candidate who is ranked 5th will get a score of 1. Add up the scores for each candidate. Select the candidate with the highest score as the winner [27, 28]. The following is the voting calculation from the two decision-makers. The number of candidates available is 15, so the highest number of points a candidate can get is 14 (15-1). The calculation to find the BORDA value can be seen in Table 9, and the results of the BORDA ranking can be seen in Table 10.

Table 9. BORDA Calculation Results

Alternative	Rank															Rank	Weight
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**		
A1							1	1								15	0.0714
A2							1	1								15	0.0714
A3	2															28	0.1333
A4			2													24	0.1143
A5				1	1											21	0.1000
A6									2							12	0.0571
A7										2						10	0.0476
A8						2										18	0.0857
A9		2														26	0.1238
A10				1	1											21	0.1000
A11											2					8	0.0381
A12												2				6	0.0286
A13													2			4	0.0190
A14														2		2	0.0095
A15															2	0	0.0000
Weight	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0	210	

Table 10. BORDA Ranking Results

Alternative	Weight	Real Condition
A3	0.1333	High
A9	0.1238	High
A4	0.1143	Considerable
A5	0.1000	Moderate
A10	0.1000	Considerable
A8	0.0857	Considerable
A2	0.0714	Low
A1	0.0714	Moderate
A6	0.0571	Low
A7	0.0476	Low
A11	0.0381	Low
A12	0.0286	Low
A13	0.0190	Low
A14	0.0095	Low
A15	0.0000	Low

From Table 9, for the alternative case example A1, it is ranked 7 and 8, so it is written with the number 1 in rank 7 and rank 8: (1×8) + (1×7) = 15 and 15/210 = 0.0714 for A1. Meanwhile, A3 has the highest value, namely (2×14) / 210 = 28/210 = 0.1333 (Same calculation for the others).

Alternative Weights start from 14 = (15-1) to 0 = (1-1)

Spearman Correlation Testing

Spearman correlation testing is carried out by looking for the correlation value of Borda's voting results with the actual ranking results, with Equation 2 below. The calculation results are shown in Table 11:

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \tag{2}$$

where r_s is Spearman correlation coefficient, d_i^2 is difference in ranking between the first and second variables at the i-th observation, and n is number of observations.

Table 11. Spearman correlation test results

Alternative	BORDA Rating	Actual Results Ranking	*di*	*di*^{2}
A1	9	9	0	0
A2	15	15	0	0
A3	10	10	0	0
A4	11	11	0	0
A5	2	2	0	0
A6	14	14	0	0
A7	1	8	-7	49
A8	8	1	7	49
A9	12	12	0	0
A10	13	13	0	0
A11	3	3	0	0
A12	4	4	0	0
A13	5	5	0	0
A14	6	6	0	0
A15	7	7	0	0
Summary				**98**

The guideline values in determining the level of correlation strength of variables calculated based on spearman rank correlation are [29-31]:

0.00 – 0.25: very low relationship;

0.26 – 0.50: sufficient relationship;

0.51 – 0.75: strong relationship;

0.76 – 0.99: very strong relationship;

1: perfect relationship.

$$r_s = 1 - \frac{6*98}{15(15^2-1)} = 0.825$$

The Spearman correlation test has a score of 82.5%. Spearman rank is used to test the relationship between two variables or degrees, namely alternative results with five (5) data criteria, namely rainfall, river flow, water level, drainage conditions, and embankment condition data. The results of the Spearman rank correlation test were 0.825, which shows that there is a very strong correlation between the BORDA ranking results and the test data. The comparison results of the voting results and the actual ranking results are shown in Table 12. The difference in ranking results in the BORDA results shows the order A2, A1, and the actual ranking results are A1, A2.

Table 12. Comparison of BORDA ranking results and actual ranking

BORDA Results	Actual Ranking Results
Alternative	**Alternative**
A3	A3
A9	A9
A4	A4
A5	A5
A10	A10
A8	A8
A2	**A1**
A1	**A2**
A6	A6
A7	A7
A11	A11
A12	A12
A13	A13
A14	A14
A15	A15

Confusion Matrix Testing:

Confusion Matrix is used to test the accuracy value of the GDSS for Flood Hazard model with performance measurements including accuracy, recall, and precision as shown in Figure 6 [32, 33].

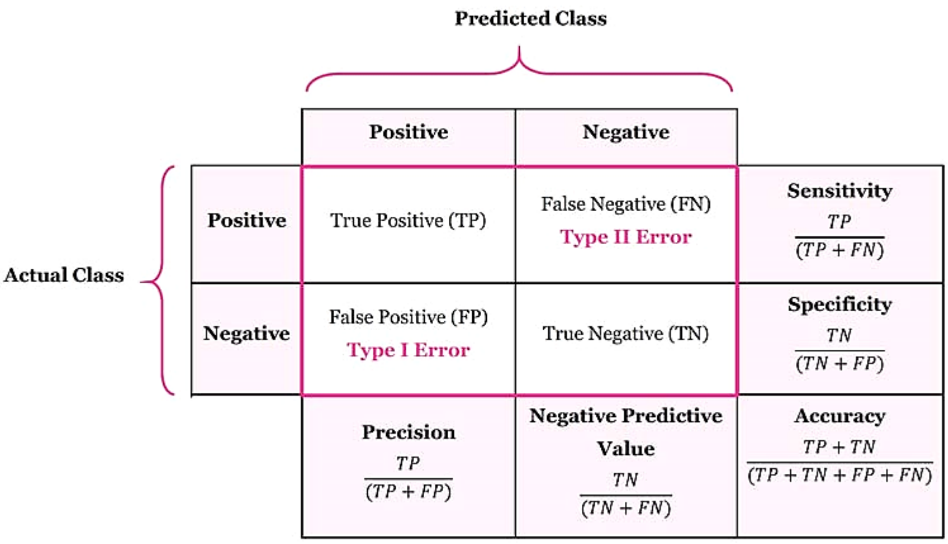

Figure 6. Confusion matrix

From Figure 7 and Table 12, the true positive value is 13 and the true negative value is 2, so to get the accuracy value, it can be calculated by referring to the equation in Figure 6. The results of the Confusion Matrix accuracy calculation are shown in Table 13.

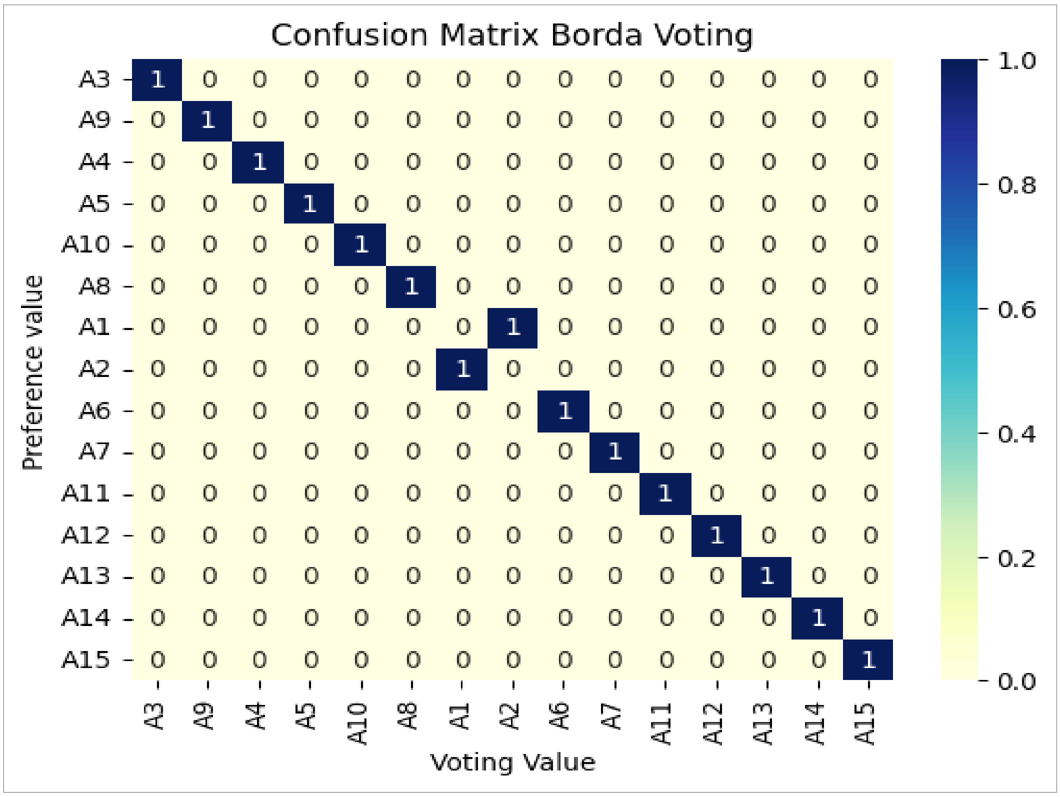

Figure 7. Mapping Results of BORDA Results with Confusion Matrix

Table 13. Mapping Results of BORDA Results with Confusion Matrix

Alternative	Precision	Recall	F1-score	Accuracy
A3	1	1	1	
A9	1	1	1	
A4	1	1	1	
A5	1	1	1	
A10	1	1	1	
A8	1	1	1	
A1	**0**	**0**	**0**	
A2	**0**	**0**	**0**	$\text{Accuracy} = \frac{13}{15} \times 100 = 86.7\%$
A6	1	1	1	
A7	1	1	1	
A11	1	1	1	
A12	1	1	1	
A13	1	1	1	
A14	1	1	1	
A15	1	1	1	

$$Precision = \frac{13}{15} \times 100 = 86.7\%$$

$$Recall = \frac{13}{15} \times 100 = 86.7\%$$

$$F1 - Score = \frac{13}{15} \times 100 = 86.7\%$$

From the results of the confusion matrix calculation, the accuracy, precision, recall and F1-score values were 86.7%. otherwise.

5. Conclusion

Determination of criteria, alternatives, and preferences based on flood warning management guidelines to support the creation of a flood warning GDSS model. Criteria weights are given according to their importance, where one criterion is more important than the others. The test results of GDSS were obtained using a Spearman rank correlation coefficient of 0.8425 and matrix confusion, an accuracy value of 86.7%, a precision value of 86.7%, a recall value of 86.7%, and an f-measure of 86.7%. Based on the test results, good results were obtained from the GDSS model. This research provides a strong foundation for future advances in flood early warning systems tailored to the conditions of each river or river basin and opens up research opportunities in the field of hydroinformatics.

6. Declarations

6.1. Author Contributions

Conceptualization, A.A.S. and L.M.L.; methodology, A.A.S.; software, A.A.S.; validation, A.A.S.; formal analysis, A.A.S.; investigation, A.A.S.; resources, A.A.S. and L.M.L.; data curation, A.A.S.; writing—original draft preparation, A.A.S., L.M.L., and E.S.; writing—review and editing, E.S. and M.S.; visualization, E.S. and M.S. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Conflicts of Interest

The authors declare no conflict of interest.

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