Performance fuzzy analytical hierarchy process to identify drought areas for disaster mitigation

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ABSTRACT

Drought causes crop failure in the agricultural sector and a limited supply of clean water. Land damage due to drought in Lamongan has reached ±12,000 ha in the last decade. The lack of information regarding drought disaster mitigation resulted in quite large losses in several agricultural sectors. The purpose of this study is to develop a decision support system (DSS) that can provide information regarding the identification of drought-prone areas. The fuzzy analytical hierarchy process (FAHP) method is implemented with four criteria: rainfall intensity, slope, soil type, and distance to the river. FAHP is good for processing the weighting of several criteria and categories to produce good choices. Results, the tests carried out there were 20 sub-districts prone to drought, with an accuracy rate of the FAHP method of 85%. The average value of respondent satisfaction averaged 97.2%. DSS application can provide the status of areas prone to drought. For future studies, the temperature and evapotranspiration parameters can be added, to provide better results.

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1. INTRODUCTION

Drought is a climatic phenomenon that endangers tropical countries every year by the impacts of global warming which causes extreme climate [1] changes from year to year [2], [3]. Drought is one of the most complex and poorly understood disasters that has the greatest impact on humans and usually affects large areas [4]. Drought causes great damage to the environment, economy, and society [5]. Drought is a crucial factor in the availability of water reserves required for farming and other human needs. On the other hand, some drought-prone areas highly depend on rainfall frequency [6]. Drought may cause limited water resources [6] which bring social and economic effects [7], agricultural crop failure [8]–[12], and an increase in food costs [7].

Lamongan is one of the drought-prone regencies in Indonesia. Drought in Lamongan has caused limited clean water. Land damage in Lamongan due to drought has reached ±12,000 ha in the last decade [8]. In 2018, 78 villages experienced clean water crisis and drought. Furthermore, drought has resulted in harvest failure. The most common problem is the lack of information about drought disaster mitigation which results in a big loss in the agricultural sector [13]. Information on the distribution of drought-prone areas can be used as input for conducting risk assessments and disaster risk-oriented water resource management. Drought necessitates drought risk management, which is characterized by an early warning and drought mitigation system.

Previous studies used to identify drought disasters include research conducted by Aghelpour *et al.* [14] monitored agricultural drought using an adaptive neuro-fuzzy inference system combined with a bio-inspired optimization algorithm. Research by Zhang *et al.* [15] predicts drought with monthly rainfall variables and soil moisture data from the global land data assimilation system, version 2 (GLDAS-2.0) is used to calculate meteorological and agricultural drought indicators. Research Zhou *et al.* [16] performs high spatial resolution drought monitoring time series is essential for effective agricultural management with moderate resolution imaging spectroradiometer (MODIS) has been applied for regional drought monitoring. Research by Poornima and Pushpalatha [5] uses a recurrent neural network to predict drought indices that handle real-time nonlinear data. Research by Adede *et al.* [4] adopts an artificial neural network (ANN) approach for drought monitoring. Research by Hao *et al.* [17] a drought assessment model using the R software.

Decision support system (DSS) is a system that can assist in making decisions within an organization or company [18], [19]. DSS enables a more efficient decision-making process [20]. It is made to support the solution of a problem. The advantage of a DSS is the ability to solve complex problems both in terms of hardware and software so that the DSS can produce a decision quickly and has a reliable level of accuracy. DSS has many types including multicriteria decision-making. Problems related to flood disaster management are resolved by making multi-criteria decisions. This is because the results of multicriteria decision-making are systematic and suitable for overcoming complex problems [21]. Several kinds of multicriteria decision-making are the analytic hierarchy process [22], multi-attribute utility theory [21], a technique for order preference by similarity to an ideal solution [19], and the fuzzy analytical hierarchy process (FAHP) [23]–[25]. FAHP method is well-known for its ability to process the weighting of several criteria and categories to generate some good alternatives.

This research aimed to produce DSS in the form of Web which could provide information on drought-prone areas online in Lamongan. This paper is structured as follows: section 1 explains the introduction, section 2 describes the research method, section 3 presents the results and discussion, and section 4 presents the conclusions of the study.

2. RESEARCH METHOD

In system development, in this research, the system is built on a web-based. The reason for choosing web-base is because many users are more comfortable using it and users can access it anywhere and anytime [19]. In this research, the system is built on a web-based using the FAHP method is explained in Figure 1.

The process begins by collecting parameter data in sub-districts in Lamongan which are sampled based on data on rainfall intensity, slope, soil type, and distance to the river. The data that is processed is data that comes from the regional disaster management agency (BPBD) of Lamongan Regency. The next process is to design the system by applying the FAHP method to the system. The application of FAHP method is implemented as a method in the process of identifying drought-prone areas. After getting the design method, the next step is to build the system. In this study, the DSS application was developed using the PHP and MySQL programming languages for database storage. At the system testing stage, a trial-error process is carried out to evaluate the system. In this step, the researcher conducted a validation test. Validation testing was carried out to determine the results of FAHP manual calculations and the results of the prediction system. System testing and maintenance were conducted by trial and error processes to evaluate the system. In this step, the researchers studied users' impressions and intentions when using the system [20].

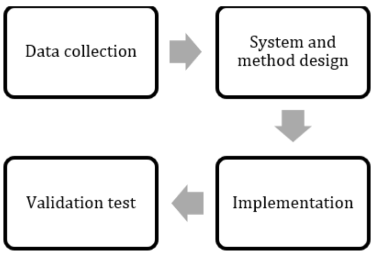

Figure 1. System development

2.1. Studi area

This paper uses data in sub-districts in Lamongan as a study case. Data on sub-districts in the Lamongan district will be used as an alternative in determining drought-prone areas. In general, drought disasters are caused by several factors, including rainfall intensity, slope, soil type, and distance to the river to determine drought-prone areas. The following is the Lamongan Regency environmental index for 2020-2022 shown in Table 1.

Table 1. Environmental Index Lamongan Regency

Element	Unit	2020	2021	2022
Land quality index	%	58.91	38.84	39.76
Water quality index	%	68.18	59.52	58.39
Air quality index	%	84.27	84.04	84.50
Environmental quality index	%	72.67	64.92	64.70

Source: environmental services

2.2. Algorithm fuzzy analytical hierarchy process

FAHP is developed from the analytical hierarchy process (AHP) method, which is considered better for describing vague decisions [26]–[28]. A triangular fuzzy number (TFN) is a special class of fuzzy numbers whose membership is determined by three real numbers and stated as low, middle, and upper. A comparison table from the AHP linguistic scale value to the fuzzy number scale is shown in Table 2.

FAHP method is developed from the AHP method, which is considered better for describing vague decisions. Drought-prone areas calculation using the FAHP method is explained in Figure 1. Steps in the FAHP method calculation process are shown in Algorithm 1.

Algorithm 1. FAHP

Step 1: defining problems about drought-prone areas and parameters that are used in this research in the form of a hierarchy structure.

Step 2: create a comparison matrix for all criteria and then calculate the consistency ratio value from the comparison matrix with the provision of CR≤0.1.

Step 3: change weighting results from scale AHP to scale TFN.

Step 4: determining the fuzzy value of the synthetic extent S_i with (1) to (3).

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} \quad (1)$$

Where:

$$\sum_{j=i}^{m} \mathrm{M}_{\mathrm{gi}}^{\mathrm{j}} = \left(\sum_{j=1}^{m} l_j , \sum_{j=1}^{m} m_j , \sum_{j=1}^{m} u_j\right) \quad (2)$$

Notes:

M: TFN numbers, m: total criteria, j: column, i: row, g: parameter (low, medium, upper).

While:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i-1}^{n} u_i}, \frac{1}{\sum_{i-1}^{n} m_i}, \frac{1}{\sum_{i-1}^{n} l_i}\right) \quad (3)$$

Step 5: determining vector value (V) and defuzzification ordinate value (d'). If the possibility between fuzzy number comparison $M_1 = (l_1, m_1, u_1)$ and $M_2 = l_{2,} m_2, u_2$ and the possibility $M_2 \geq M_1$, comparison of convex fuzzy number possibility can be used (4).

$$V = (M_2 \geq M_1) = \begin{cases} 1, if\ m_2 \geq m_1 \\ 0, if\ l_1 \geq u_2 \\ \dfrac{l_1 - u_2\ for\ other\ condition}{(m_2 - u_2) - (m_1 - l_1)} \end{cases} \quad (4)$$

Step 6: so that it is obtained weighted vector as (5).

$$W = \left(d(A_1), d(A_2), \dots d(A_n)\right)^T \quad (5)$$

Step 7: the next step is the normalization of the fuzzy weighted vector value (W) with (6).

$$d(A_n) = \frac{d\prime(A_n)}{\sum_{i=1}^{n} d\prime(A_n)} \quad (6)$$

Table 2. Comparison scale

Description scale	Scale	
	AHP	TFN
Both elements are equally importance	1	1, 1, 3
One element is slightly more important than another element	3	1, 3, 5
One element is more important than another element	5	3, 5, 7
A powerful element is more important than another element	7	5, 7, 9
One element is more essential than another element	9	7, 9, 9

2.3. Decision support system

Interactive-based DSS can be used to decide on an organization [29]. DSS utilizes unstructured data and models to solve problems so that it can provide various alternatives for information and interpretation [30]. DSS has been synergized by a knowledge management system and has developed to make decisions. There are four steps in DSS which include: intelligence, design, choice, and implementation. DSS provides several benefits including obtaining fast and reliable decision results so it does not waste much time and can solve complex as well as unstructured problems.

3. RESULTS AND DISCUSSION

In this research, we determined four criteria which were written as C1 to C4. These criteria will later be calculated using the FAHP method to determine drought-prone areas. An explanation of the four criteria can be seen in Table 3. The use of the FAHP method is suitable for finding better solutions to multi-criteria decision-making (MCDM) problems.

The following is the FAHP algorithm that will be used in this study. Step 1 is defining problems in the form of a hierarchy structure. Preparing comparison matrix for all criteria. Step 2 is calculating the consistency ratio value from the comparison matrix with the provision of CR≤0.1 is shown in Table 4. From the calculation, it was obtained λ maximum of 16.1 w. CI was 0.02. IR was 0.89 and the ratio consistency value of 0.0093. Thus, it can be declared that the matrix was consistent. Step 3 changes the weighted results of pairwise comparisons into the TFN scale.

Step 4 determining fuzzy value of synthetic extent S_i as in (2). The results of the sum of each TFN number and the results of the inverse of the total number and fuzzy synthetic extent S_i value shown in Table 5. Step 5 after S_i value was obtained, and the following step was to compare the level of possibility between the fuzzy synthetic extend value and its minimum value. If the possibility of fuzzy number comparison $M_1 = (l_1, m_1, u_1)$ and $M_2 = \ l_{2,}\ m_2, u_2$ and the possibility $M_2 \geq \ M_1$, comparison of convex fuzzy number possibility can be used (3). Step 6 is determining the normalization of fuzzy weighted vector value (w) with (4). The result of the weighted vector fuzzy value is shown in Table 6.

After obtaining the vector values for each criterion, the next step was to perform FAHP calculations in each subdistrict in Lamongan Regency to display drought-prone areas based on the largest to smallest weight ranking. The following is a list of drought-prone subdistricts in Lamongan which were determined from the highest weight value to the lowest value as in Table 7.

Table 3. The DSS criteria

Criteria code	Criteria
C1	Rainfall intensity
C2	Land slope
C3	Types of soil
C4	Distance to the river

Table 4. Matrix ratio consistency

Criteria	Total	Priority	Results
C1	5.20	0.55	5.75
C2	4.30	0.23	4.53
C3	2.30	0.14	2.44
C4	3.30	0.08	3.38
Total			16.1
CR			0.0093

Table 5. Inverse and synthetic extent value

Inverse criteria				Fuzzy syntetic extent $\boldsymbol{S_i}$ value			
Criteria	Low	Middle	Upper	Criteria	Low	Middle	Upper
C1	12.0	18.0	22.0	C1	0.2449	0.4823	0.8833
C2	7.12	11.1	15.1	C2	0.1451	0.2977	0.6080
C3	4.30	6.50	9.30	C3	0.0886	0.1751	0.3747
C4	1.50	1.70	2.50	C4	0.0297	0.0449	0.1017
Total	24.9	37.3	49.0				
Invers	0.0401	0.0268	0.0204				

Table 6. Weighted vector

Code	Criteria	$d(A_n)$
C1	Rainfall intensity	0.4902
C2	Land slope	0.3235
C3	Types of soil	0.1422
C4	Distance to the river	0.0441

Table 7. Drought-prone areas result

Latitude	Longitude	District	Value
-7.227947	112.131099	Modo	0.354
-7.305105	112.202635	Ngimbang	0.353
-7.355219	112.113214	Sukorame	0.346
-7.308781	112.131099	Bluluk	0.302
-7.180323	112.274168	Sugio	0.300
-7.175469	112.369541	Kembangbahu	0.285
-7.110216	112.464908	Deket	0.280
-7.080565	112.379972	Turi	0.248
-7.136392	112.345699	Sukodadi	0.198
-6.971933	112.290561	Laren	0.150
-7.11667	112.41667	Lamongan	0.148
-7.188449	112.411265	Tikung	0.146
-7.277529	112.345699	Mantup	0.130
-7.190734	112.464908	Sarirejo	0.128
-7.183951	112.202635	Kedungpring	0.121
-7.067586	112.512589	Glagah	0.117
-7.1033128	112.2026347	Babat	0.108
-7.312134	112.262246	Sambeng	0.088
-6.901013	112.226479	Brondong	0.080
-7.029803	112.464908	Karangbinangun	0.060

Accuracy testing is used to determine the ability of the system to make decisions, and whether the results are accurate or not. Table 8 shows a comparison of rank DSS calculation and expert assessment with a sample of 20 data. Based on the table, the accuracy of the prediction is calculated by ranking order. The results showed that 85% accuracy was obtained by adding up the results of the correct and incorrect decisions from the system. Calculation testing used the highest weight ranking as a drought-prone area.

After the procedure for testing the functionality of the system was carried out, testing the application of the information system to the user was also conducted. This was done by distributing a questionnaire containing five questions to 10 respondents. Based on the results of the respondents' assessment, the average value of respondent satisfaction averaged 97.2% for the existence of a DSS for the identification of drought-prone areas in the Lamongan Regency. In this study, we used the FAHP method with its good ability to process the weighting of several criteria and categories to produce several good choices. There are many problems related to disaster management that can be solved by multi-criteria decision-making. The multi-criteria decision-making method is known for its ability to process the weighting of several criteria and categories to produce several good choices which allow for the incorporation of multiple criteria into a decision [31] based on the preferences and behavior of the decision-makers.

The results showed that several sub-districts were prone to drought, such as Modo, Ngimbang, Sukorame, Bluluk, Sugio, Kembangbahu, Sukodadi, Lamongan, Tikung, Mantup, Sarirejo, Kedungpring, Glagah, Tripe, Sambeng, Brondong, and Karangbinangun. Accuracy testing is used to determine the ability of the system to make decisions, and whether the results are accurate or not. Table 7 shows a comparison of rank DSS calculation and expert assessment with a sample of 20 data. Based on the table, the accuracy of the prediction is calculated by ranking order. The results showed that 85% accuracy was obtained by adding up the results of the correct and incorrect decisions from the system. Calculation testing used the highest weight ranking as a drought-prone area.

Drought is getting worse with the impact of global warming which causes very extreme climate changes from year to year. The impact of drought includes limited water resources which have an economic and social impact [11], crop failure increased food costs [2]. Drought threatens crop failure and increases food costs, so it is necessary to reduce the risk of drought. Information regarding the distribution of drought-prone areas can be used as input for conducting risk assessments and conducting disaster risk-oriented management of water resources. One of the efforts in flood disaster management is to use a DSS that can map drought-prone areas with the help of the FAHP method. Food security is highly dependent on the agricultural sector in the country. Our findings show that the rapid dissemination of information to the public to be more aware of drought in the agricultural sector is urgently needed. This DSS is expected to be able to assist policy making in related organizations as an early warning system for drought.

Table 8. Comparison expert assessment and DSS

Latitude	Longitude	No	District	Expert assessment	FAHP assessment	Result
-7.227947	112.131099	1	Modo	Drought-prone area	Drought-prone area	Correct
-7.305105	112.202635	2	Ngimbang	Drought-prone area	Drought-prone area	Correct
-7.355219	112.113214	3	Sukorame	Drought-prone area	Drought-prone area	Correct
-7.308781	112.131099	4	Bluluk	Drought-prone area	Drought-prone area	Correct
-7.180323	112.274168	5	Sugio	Drought-prone area	Drought-prone area	Correct
-7.175469	112.369541	6	Kembangbahu	Drought-prone area	Drought-prone area	Correct
-7.110216	112.464908	7	Deket	Not drought prone	Drought-prone area	False
-7.080565	112.379972	8	Turi	Not drought prone	Drought-prone area	False
-7.136392	112.345699	9	Sukodadi	Drought-prone area	Drought-prone area	Correct
-6.971933	112.290561	10	Laren	Not drought prone	Drought-prone area	False
-7.11667	112.41667	11	Lamongan	Drought-prone area	Drought-prone area	Correct
-7.188449	112.411265	12	Tikung	Drought-prone area	Drought-prone area	Correct
-7.277529	112.345699	13	Mantup	Drought-prone area	Drought-prone area	Correct
-7.190734	112.464908	14	Sarirejo	Drought-prone area	Drought-prone area	Correct
-7.183951	112.202635	15	Kedungpring	Drought-prone area	Drought-prone area	Correct
-7.067586	112.512589	16	Glagah	Drought-prone area	Drought-prone area	Correct
-7.103312	112.2026347	17	Babat	Drought-prone area	Drought-prone area	Correct
-7.312134	112.262246	18	Sambeng	Drought-prone area	Drought-prone area	Correct
-6.901013	112.226479	19	Brondong	Drought-prone area	Drought-prone area	Correct
-7.029803	112.464908	20	Karangbinangun	Drought-prone area	Drought-prone area	Correct

4. CONCLUSION

The purpose of this research is to produce a DSS that can provide information regarding the online identification of drought-prone areas in each region in the Lamongan Regency. It can be concluded that the DSS application can provide the best decision solutions and accurate results with the criteria determined by stakeholders. Calculations are made by considering 4 parameters, namely including rainfall intensity, slope, soil type, and distance to the river. The application will display the final calculation data sorted by the highest weight rating with an accuracy rate of 85%. This ranking makes it easier for stakeholders to see the distribution of data on drought-prone areas. In addition, respondents' satisfaction with the system averaged 97.2% in DSS for identifying drought-prone areas in Indonesia. In future studies, the temperature and evapotranspiration parameters can be added, to provide better results.

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REFERENCES

[1] P. K. Das, S. K. Mohinuddin, S. K. Midya, D. K. Das, R. Sharma, and S. Bandyopadhyay, "Can multiscalar meteorological drought indices detect soil moisture droughts? A study of Indian regions," *Hydrological Sciences Journal*, vol. 66, no. 9, pp. 1475–1487, 2021, doi: 10.1080/02626667.2021.1942475.

[2] M. R. Aprillya, E. Suryani, and A. Dzulkarnain, "The analysis of quality of paddy harvest yield to support food security: A system thinking approach (case study: East Java)," *Procedia Computer Science*, vol. 161, pp. 919–926, 2019, doi: 10.1016/j.procs.2019.11.200.

[3] M. R. Aprillya and E. Suryani, "Simulation of system dynamics for improving the quality of paddy production in supporting food security," *Journal of Information Systems Engineering and Business Intelligence*, vol. 9, no. 1, pp. 38–46, 2023, doi: 10.20473/jisebi.9.1.38-46.

[4] C. Adede, R. Oboko, P. W. Wagacha, and C. Atzberger, "A mixed model approach to vegetation condition prediction using artificial neural networks (ANN): case of Kenya's operational drought monitoring," *Remote Sensing*, vol. 11, no. 9, 2019, doi: 10.3390/rs11091099.

[5] S. Poornima and M. Pushpalatha, "Drought prediction based on SPI and SPEI with varying timescales using LSTM recurrent neural network," *Soft Computing*, vol. 23, no. 18, pp. 8399–8412, 2019, doi: 10.1007/s00500-019-04120-1.

[6] A. Dai, "Drought under global warming: a review," *WIREs Climate Change*, vol. 2, no. 1, pp. 45–65, 2011, doi: 10.1002/wcc.81.

[7] V. Blauhut, L. Gudmundsson, and K. Stahl, "Towards pan-European drought risk maps: quantifying the link between drought indices and reported drought impacts," *Environmental Research Letters*, vol. 10, no. 1, pp. 1–11, 2015, doi: 10.1088/1748-9326/10/1/014008.

[8] F. I. Nurrahman and A. Pamungkas, "Adaptations to drought in Lamongan municipality," *Procedia - Social and Behavioral Sciences*, vol. 135, pp. 90–95, 2014, doi: 10.1016/j.sbspro.2014.07.330.

[9] V. Sahana, A. Mondal, and P. Sreekumar, "Drought vulnerability and risk assessment in India: Sensitivity analysis and comparison of aggregation techniques," *Journal of Environmental Management*, vol. 299, 2021, doi: 10.1016/j.jenvman.2021.113689.

[10] J. H. Stagge, I. Kohn, L. M. Tallaksen, and K. Stahl, "Modeling drought impact occurrence based on meteorological drought indices in Europe," *Journal of Hydrology*, vol. 530, pp. 37–50, 2015, doi: 10.1016/j.jhydrol.2015.09.039.

[11] A. Dzulkarnain, E. Suryani, and M. R. Aprillya, "Analysis of flood identification and mitigation for disaster preparedness: a system thinking approach," *Procedia Computer Science*, vol. 161, pp. 927–934, 2019, doi: 10.1016/j.procs.2019.11.201.

[12] S. F. Ana W, “System dynamics modelling for increasing of paddy production with land suitability level to support food security,” *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 1, pp. 233–240, 2020, doi: 10.30534/ijatcse/2020/35912020.

[13] M. R. Aprillya, E. Suryani, and A. Dzulkarnain, “System dynamics simulation model to increase paddy production for food security,” *Journal of Information Systems Engineering and Business Intelligence*, vol. 5, no. 1, pp. 67-75, 2019, doi: 10.20473/jisebi.5.1.67-75.

[14] P. Aghelpour, H. Bahrami-Pichaghchi, and O. Kisi, “Comparison of three different bio-inspired algorithms to improve ability of neuro fuzzy approach in prediction of agricultural drought, based on three different indexes,” *Computers and Electronics in Agriculture*, vol. 170, 2020, doi: 10.1016/j.compag.2020.105279.

[15] Y. Zhang, Z. Hao, S. Feng, X. Zhang, Y. Xu, and F. Hao, “Agricultural drought prediction in China based on drought propagation and large-scale drivers,” *Agricultural Water Management*, vol. 255, 2021, doi: 10.1016/j.agwat.2021.107028.

[16] X. Zhou, P. Wang, K. Tansey, S. Zhang, H. Li, and L. Wang, “Developing a fused vegetation temperature condition index for drought monitoring at field scales using Sentinel-2 and MODIS imagery,” *Computers and Electronics in Agriculture*, vol. 168, no. 17, 2020, doi: 10.1016/j.compag.2019.105144.

[17] Z. Hao, F. Hao, V. P. Singh, W. Ouyang, and H. Cheng, “An integrated package for drought monitoring, prediction and analysis to aid drought modeling and assessment,” *Environmental Modelling and Software*, vol. 91, pp. 199–209, 2017, doi: 10.1016/j.envsoft.2017.02.008.

[18] M. I. Bachtiar, H. Suyono, M. Fauzan, and E. Purnomo, “75 method comparison in the decision support system of a scholarship selection,” vol. 11, no. 2, pp. 75–82, 2021.

[19] A. Jauhari and F. A. Mufarroha, “Smart mobile application for decision support systems on determination of resident in dormitory,” *Jurnal Ilmiah Kursor*, vol. 10, no. 3, pp. 135–144, 2020, doi: 10.21107/kursor.v10i3.236.

[20] M. R. Aprillya and U. Chasanah, “Geographic information system multi attribute utility theory for flood mitigation in agricultural sector,” *Matrik: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer*, vol. 22, no. 1, pp. 117–128, 2022, doi: 10.30812/matrik.v22i1.1511.

[21] L. B. L. da Silva, J. S. Humberto, M. H. Alencar, R. J. P. Ferreira, and A. T. de Almeida, “GIS-based multidimensional decision model for enhancing flood risk prioritization in urban areas,” *International Journal of Disaster Risk Reduction*, vol. 48, 2020, doi: 10.1016/j.ijdrr.2020.101582.

[22] C. H. Primasari, R. Wardoyo, and A. K. Sari, “Integrated AHP, Profile Matching, and TOPSIS for selecting type of goats based on environmental and financial criteria,” *International Journal of Advances in Intelligent Informatics*, vol. 4, no. 1, pp. 28-39, Mar. 2018, doi: 10.26555/ijain.v4i1.105.

[23] P. C. Shete, Z. N. Ansari, and R. Kant, “A pythagorean fuzzy AHP approach and its application to evaluate the enablers of sustainable supply chain innovation,” *Sustainable Production and Consumption*, vol. 23, pp. 77–93, 2020, doi: 10.1016/j.spc.2020.05.001.

[24] E. Ilbahar, A. Karaşan, S. Cebi, and C. Kahraman, “A novel approach to risk assessment for occupational health and safety using pythagorean fuzzy AHP and fuzzy inference system,” *Safety Science*, vol. 103, pp. 124–136, 2018, doi: 10.1016/j.ssci.2017.10.025.

[25] Y. Xiao, S. Yi, and Z. Tang, “Integrated flood hazard assessment based on spatial ordered weighted averaging method considering spatial heterogeneity of risk preference,” *Science of the Total Environment*, vol. 599–600, pp. 1034–1046, 2017, doi: 10.1016/j.scitotenv.2017.04.218.

[26] T. W. Githinji, E. W. Dindi, Z. N. Kuria, and D. O. Olago, “Application of analytical hierarchy process and integrated fuzzy-analytical hierarchy process for mapping potential groundwater recharge zone using GIS in the arid areas of Ewaso Ng’iro – Lagh Dera Basin, Kenya,” *HydroResearch*, vol. 5, pp. 22–34, 2022, doi: 10.1016/j.hydres.2021.11.001.

[27] A. H. Afolayan, B. A. Ojokoh, and A. O. Adetunmbi, “Performance analysis of fuzzy analytic hierarchy process multi-criteria decision support models for contractor selection,” *Scientific African*, vol. 9, pp. 1–23, 2020, doi: 10.1016/j.sciaf.2020.e00471.

[28] T. L. Saaty, “Decision making — the analytic hierarchy and network processes (AHP/ANP),” *Journal of Systems Science and Systems Engineering*, vol. 13, no. 1, pp. 1–35, 2004, doi: 10.1007/s11518-006-0151-5.

[29] B. A. Alyoubi, “Decision support system and knowledge-based strategic management,” *Procedia Computer Science*, vol. 65, pp. 278–284, 2015, doi: 10.1016/j.procs.2015.09.079.

[30] S. Sundari, Karmila, M. N. Fadli, D. Hartama, A. P. Windarto, and A. Wanto, “Decision support system on selection of lecturer research grant proposals using preferences selection index,” *Journal of Physics: Conference Series*, vol. 1255, no. 1, pp. 1–8, 2019, doi: 10.1088/1742-6596/1255/1/012006.

[31] Y. Dong, D. M. Frangopol, and S. Sabatino, “Optimizing bridge network retrofit planning based on cost-benefit evaluation and multi-attribute utility associated with sustainability,” *Earthquake Spectra*, vol. 31, no. 4, pp. 2255–2280, Nov. 2015, doi: 10.1193/012214EQS015M.

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