Journal of Intelligent Decision Support System (IDSS) 7 (2) (2024), pp. 102-112

Published by: Institute of Computer Science (IOCS)

Journal of Intelligent Decision Support System (IDSS)

Journal homepage: www.idss.iocspublisher.org

Application of sma method and ahp to predict the level of tidal flood vulnerability in Tegal City

Bangkit Indarmawan Nugroho[1], Muhammad Farkhan[2], Sawaviyya Anandianskha[3], Gunawan Gunawan[4]

[1,3]*Information System, STMIK YMI TEGAL, Tegal City, Indonesia*
[2,4]*Informatics Engineering, STMIK YMI TEGAL, Tegal City, Indonesia*

Article Info

Article history:

Received May 30, 2024
Revised Jun 04, 2024
Accepted Jun 09, 2024

Keywords:

Analytic Hierarchy Process;
Disaster Mitigation;
Flood Vulnerability;
Simple Moving Average;
Tidal Flooding.

ABSTRACT

This study examines the application of the Simple Moving Average (SMA) and Analytic Hierarchy Process (AHP) methods to predict tidal flood vulnerability in Tegal City. The objective is to develop a more accurate prediction method for tidal flood vulnerability. The methods used are a combination of SMA and AHP. The results indicate that this combination is effective in producing more accurate predictions compared to conventional methods. Villages such as Muarareja, Tegalsari, Mintaragen, and Panggung have been identified as highly vulnerable and require more intensive mitigation. The implications highlight the importance of a multi-method approach to understanding complex phenomena like flood vulnerability. For future research, it is recommended to integrate real-time weather data and consider socio-economic factors to enhance accuracy and relevance in disaster mitigation. The findings are expected to assist in better urban planning and resource allocation, as well as improve community resilience against tidal flood disasters.

Corresponding Author:

Muhammad Farkhan,
Informatics Engineering,
STMIK YMI TEGAL,
#1 Pendidikan Street, Tegal City, Central Java, 52142, Indonesia.
Email: muh.farkhan10@gmail.com

Introduction

Rob flooding is a flood that occurs due to tides that overflow inland (Buchori et al., 2021). Tegal City is one of the cities prone to tidal flooding because of its location along the north coast of Central Java. Additionally, Tegal City has specific conditions that make it vulnerable to tidal floods, such as low topography, the presence of many rivers that flow into the sea, and rapid coastal development often without adequate drainage infrastructure (Rahman et al., 2021). The combination of these factors makes Tegal City highly vulnerable to tidal floods, especially during the rainy season and periods of high tides. Tidal floods can cause enormous losses, both in economic and social terms (Dedekorkut-Howes et al., 2020). Therefore, efforts are needed to predict the level of tidal flood vulnerability in Tegal City in order to reduce the adverse impacts caused (Rudiarto & Pamungkas, 2020).

The problem faced is the difficulty of accurately predicting the level of tidal flood vulnerability (Park & Lee, 2020). Existing prediction methods are still not able to provide satisfactory results, so a better approach is needed to increase the level of prediction accuracy (Boukerche & Wang, 2020). The inability to make accurate predictions can cause difficulties in making decisions related to disaster mitigation (Merz et al., 2020). This can have an impact on the safety of citizens and considerable material losses (Valsamos et al., 2021).

This problem can be overcome by applying the simple moving average (SMA) method and analytic hierarchy process (AHP) in predicting the level of tidal flood vulnerability (Liu et al., 2020; Rusdiana et al., 2020). The Simple Moving Average (SMA) method is used to analyze historical data such as rainfall, while the Analytic Hierarchy Process (AHP) method is used to determine the weights of each criterion that affects tidal flood vulnerability. The AHP criteria in this study include land elevation, soil type, distance from the coast, distance from rivers, land cover, and slope. This method can help in generating more accurate predictions based on historical data and relevant criteria (Ali et al., 2021). The proposed innovation is a combination of simple moving average (SMA) and analytic hierarchy process (AHP) methods in predicting the level of tidal flood vulnerability (Coffey & Claudio, 2021; Knoth et al., 2021). The uniqueness of this approach lies in the integration of both methods, where SMA provides a strong quantitative analysis basis for historical data, while AHP provides a robust qualitative framework for integrating various environmental criteria. This makes the approach more flexible and adaptive to changes in environmental conditions and available data compared to other prediction methods that rely on only one type of analysis (Pereira et al., 2021).

This research aims to develop a more accurate method for predicting tidal flood vulnerability in Tegal City (Sutrisno et al., 2020). By improving prediction methods, it will assist the government and relevant parties in making informed decisions for tidal flood disaster mitigation (Ciampa et al., 2021; Enríquez et al., 2022). Current methods, including statistical and mathematical models (Antwi-Agyakwa et al., 2023), often fail to provide accurate prediction (Tredennick et al., 2021). his study employs the Simple Moving Average (SMA) and Analytic Hierarchy Process (AHP) to analyze tidal flood vulnerability in Tegal City, aiming to produce predictive models that mitigate flood impacts and advance science and technology (Fitriyani et al., 2020; Li et al., 2021). It is hoped that this research can produce predictive models that can help in reducing the adverse effects caused by tidal floods and have a positive impact on the development of science and technology (Wu, 2021).

Several related studies have been conducted in an effort to predict the level of tidal flood vulnerability. Research (Hughes et al., 2022) using the Random Forest Classification method to predict tidal flooding in coastal areas. This study found that this method was able to provide quite good results in predicting the level of tidal flood vulnerability. Next research (Sitorus et al., 2023) proposes the use of neural network methods to predict the level of tidal flood vulnerability. This study found that this method was able to provide more accurate results compared to traditional statistical methods. Although several studies have been conducted in an attempt to predict the vulnerability rate of tidal flooding, there is still room for further development. The state of the art of this study is the use of a combination of SMA and AHP methods in tidal flood prediction, which has not been widely applied in coastal areas such as Tegal City, so this study aims to fill the literature gap by combining simple moving average methods and analytic hierarchy processes in predicting the level of tidal flood vulnerability in Tegal City.

Method

Research Design

This research uses a quantitative approach with a combination design of experimental methods, quantitative analysis, and model validation. This research design includes several stages namely data collection, data pre-processing, algorithm implementation and model evaluation.

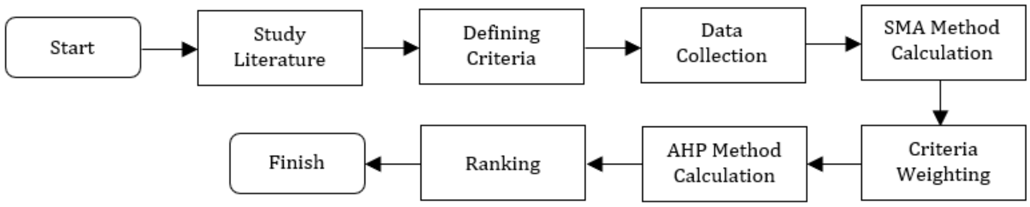

Figure 1. Research flow

The research flow in Figure 1 shows the steps in research that begins with literature study, namely studying and understanding theories related to SMA and AHP methods from national and international journals. Then determine the criteria for tidal flood vulnerability based on related journals. Furthermore, collecting data consisting of historical rainfall data in Tegal City obtained from the BMKG of Tegal City, criteria for tidal flood vulnerability obtained from related journals. Next, perform calculations using the SMA method. Then weighting the criteria that have been determined, these criteria include land height, soil type, distance from the coast, distance from rivers, land cover and slope. Next, perform calculations using the AHP method from criteria that have been given weights. Finally, ranking each village that has a high, medium and low level of tidal flood vulnerability.

Data Collection

The required data includes information on the historical rainfall of Tegal City in 2017–2022 obtained from the Meteorology, Climatology and Geophysics Agency (BMKG) of Tegal City. In addition, there are distance data from the coast and distance from the river obtained from measurements through Google Maps. Data on land elevation, soil type, land cover, and slope obtained from the Central Statistics Agency (BPS) of Tegal City in its publication. Map prone to flooding in Tegal City based on the 2019 RPJMD from BPBD Tegal City.

Data Pre-processing

The data pre-processing phase includes data cleansing by removing incomplete or invalid data, data normalization to standardize data values to be at the same scale, and grouping data by year and geographic location for more focused analysis.

Algorithm Implementation

The simple moving average (SMA) algorithm is used for historical data analysis, while the analytic hierarchy process (AHP) algorithm is used to determine the weight of each criterion that affects the vulnerability of tidal floods. The Simple Moving Average method in this study was used to predict the historical data of rainfall in Tegal City with a certain period. The SMA method has a formula such as equation (1).

$$F_{t+1} = \frac{(Y_t + Y_{t+1} + Y_{t+2} + \cdots + Y_{t+n+2})}{n} \tag{1}$$

Where F_{t+1} is the forecast value for the next period, Y_t is the actual value in a certain period, n is the limit sum of the moving averages. The AHP method is used to integrate factors that affect the level of tidal flood vulnerability. AHP criteria in this study were determined from a literature study of scientific journals, these criteria include land elevation, soil type, distance from the beach, distance from rivers, land cover and slope.

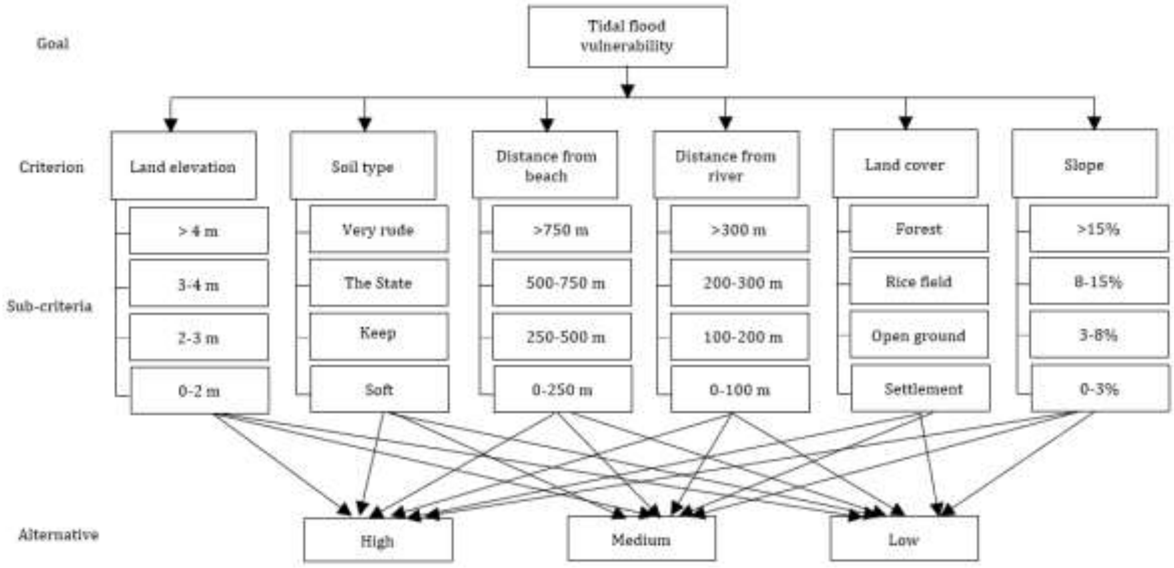

Figure 2. AHP hierarchical structure

Figure 2 shows the hierarchical structure of AHP the level of tidal flood vulnerability consisting of goals or desired goals, criteria for achieving goals and alternatives as a result of decision recommendations from goals.

Table 1. Weighting of each criterion (Wirayudaa et al., 2020)

No	Criterion	Score
1	Land elevation	4
2	Soil Type	1
3	Distance from Beach	10
4	Distance from River	3
5	Land cover	2
6	Slope	5

Table 1 is the weight of each criterion of tidal flood vulnerability consisting of land height, soil type, distance from the coast, distance from rivers, land cover and slope. The amount of weight is adjusted to the size of the influence of a parameter on the potential for tidal flooding. Next, the AHP calculation stage will be carried out, first determining the normalization value by dividing the value of each criterion by the total value of each column. Then add each row of normalized values so that the priority vector value will be obtained. Next, calculate the weight per criterion (W) by dividing the value per priority vector by the total number of priority vectors and finally perform an AHP consistency test. The AHP consistency test starts from calculating the matrix multiplication between the weight (W) and the criterion score (A), the result of the matrix multiplication divided by the weight (W) of the criterion, calculating values λmax, with Equation (2), then determine the random consistency value (RI), Then calculate the consistency index (CI) value like equation (3), and finally calculate the consistency ratio (CR) value like equation (4) (Saputra et al., 2020).

$$\lambda_{max} = \frac{\sum_{i=1}^{n}(A \times W)t}{n} \tag{2}$$

Where λ_{max} is the largest eigenvector value, A is the value of the criterion score, W is the weight value, n is the number of criteria.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{3}$$

Where CI is the consistency index, λ_{max} is the largest eigenvector value, n is the number of criteria.

$$CR = \frac{CI}{RI} < 0{,}1 \qquad 4)$$

Where CR is the consistency ratio, CI is the consistency index, RI is a random consistency value.

Table 2. Classification of each criterion (Wirayudaa et al., 2020)

Criterion	Score	Criterion	Score	Criterion	Score
Land elevation		Soil type		Distance from beach	
> 4 m	1	Very rude	1	> 750 m	1
3 – 4 m	2	The State	2	500 – 750 m	2
2 – 3 m	3	Keep	3	250 – 500 m	3
0 – 2 m	4	Soft	4	0 – 250 m	4
Distance from river		Land cover		Slope	
> 300 m	1	Forests and plantations	1	> 15%	1
200 – 300 m	2	Pasture/Rice Field	2	8 – 15%	2
100 – 200 m	3	Open ground	3	3 – 8%	3
0 – 100 m	4	Settlement	4	0 – 3%	4

Table 2 is a sub-criterion of each criterion of vulnerability to tidal floods, each sub-criterion has a different range of score values, which describe the level of vulnerability to tidal floods. The score assigned to each of these criteria will be used to calculate a total vulnerability score to tidal flooding at a location. The higher the total score, the higher the level of vulnerability to tidal flooding in that location.

Table 3. Random consistency values (RI)

Matrix Size	1	2	3	4	5	6	7	8	9	10
R!	0	0	0,58	0,9	1,12	1,24	1,32	1,41	1,45	1,49

Table 3 shows the Random Index (RI) values used in the Analytic Hierarchy Process (AHP) method to assess the consistency of answers in a paired comparison matrix (Sato & Tan, 2023). To determine the value of vulnerability, a value calculation is carried out by summing the scores on all parameters. To obtain the value of vulnerability, the equation (5) is used.

$$K = \sum_{i=1}^{n} (W_i \times X_i) \qquad (5)$$

Where K is the value of vulnerability, W_i is a weight on the i criterion, and X_i is the score on the i criterion. The level of vulnerability is divided into 3 classes, that is high, medium, and low (Feloni et al., 2020).

Evaluation Model

The algorithm will be configured based on the parameters that have been optimized. The developed model will be evaluated using a test data set to measure its accuracy. Evaluation metrics will include, among others, Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Testing the results of tidal flood vulnerability predictions was carried out by comparing the prediction results with flood vulnerability maps prepared by the Regional Disaster Management Agency (BPBD) of Tegal City.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \qquad (6)$$

Where n is the amount of data, i is the order of data on the database, $\hat{y}_i$ is actual and $\hat{y}_i$ is the predicted value.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{n} \times 100 \quad (7)$$

Where n is the amount of data, i is the order of data on the database, y_i is actual and $\hat{y}_i$ is the predicted value.

Results and Discussions

This research integrates Simple Moving Average (SMA) and Analytic Hierarchy Process (AHP) methods to develop a predictive model in assessing flood vulnerability in Tegal City. The analysis begins with the examination of historical rainfall data, which serves as a critical input for understanding patterns and trends that influence flood risks. The monthly rainfall data for Tegal City from 2017 to 2022, as shown in Table 4.

Table 4. Rainfall by Month in Tegal City (mm) in 2017 – 2022

Year	Jan	Feb	Mar	Apr	Mei	Jun	Jul	August	Sep	Oct	Nov	Dec
2017	363,2	394,3	149,5	108,1	86,1	46,6	73,4	4	49,8	21,6	173,7	228,2
2018	83,4	551,4	225,3	154,3	53,2	30,4	0	0	7,2	14,8	35	193,3
2019	492,5	365,2	372,3	257,1	8,1	0	7	0	0	89,1	30,3	385
2020	524,2	669,4	465,2	194,1	93,1	4,4	81	20,8	13,1	25,5	174,8	392,3
2021	273,4	479,7	415,4	111,8	36	55,7	33,9	46,4	81	54,1	262,3	302,7
2022	311,4	184,7	320,5	237,6	152,5	119,9	151,1	16,5	64	138,7	279,1	208,4

Table 4 shows monthly rainfall data from 2017 to 2022. This data will be calculated using the Simple Moving Average method with a period of 3 years which will help in analyzing long-term trends and planning ahead based on average annual rainfall. From the calculation results using the Simple Moving Avarage method for historical rainfall data for 2017 – 2022 with the python programming language produces prediction data as in Figure 3.

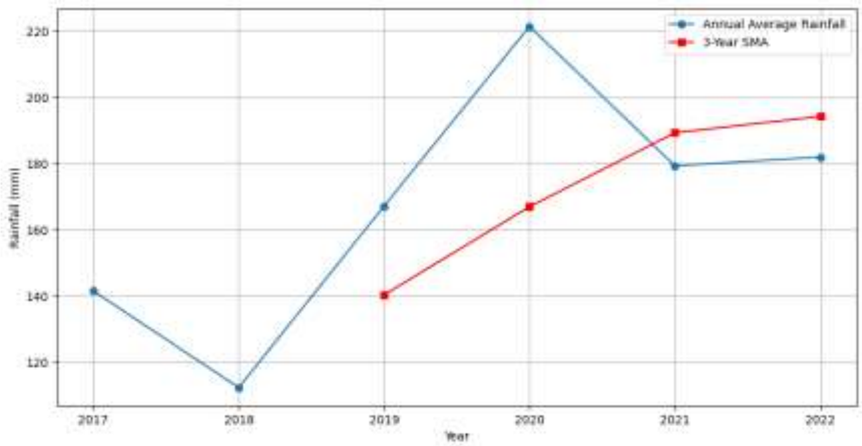

Figure 3. Rainfall prediction result

Figure 3 is the result of rainfall predictions that have been calculated using the Simple Moving Anger method. The rainfall prediction uses a 3-year period which results in an average Mean Absolute Error (MAE) value of around 25.89 and a Mean Absolute Percentage Error (MAPE) of around 13.24% which means a forecasting accuracy of 86.76%. These values indicate that the average, predicted SMA method deviates from the actual value by 25.89, and the relative error in percentage is about 13.24%.

After obtaining the results of rainfall predictions, the next step is to conduct a tidal flood vulnerability analysis using the Analytic Hierarchy Process (AHP) method which starts with making a comparison matrix based on the weighting that has been done, then determining the normalization value by dividing the value of each criterion by the total value of each column, then add each row of normalized values so that the priority vector value will be obtained, then calculate the weight per criterion by dividing the value per priority vector by the total number of priority vectors and finally perform the AHP consistency test.

Table 5. Priority value of tidal flood vulnerability criteria

Criterion	Priority
Land elevation	0,16
Soil type	0,04
Distance from beach	0,40
Distance from river	0,12
Land cover	0,08
Slope	0,20

Table 6. Sub-criteria priority value of tidal flood vulnerability

Criterion	Priority	Criterion	Priority	Criterion	Priority
Land elevation		Soil type		Distance from beach	
> 4 m	0,1	Very rude	0,1	> 750 m	0,1
3 – 4 m	0,2	The State	0,2	500 – 750 m	0,2
2 – 3 m	0,3	Keep	0,3	250 – 500 m	0,3
0 – 2 m	0,4	Soft	0,4	0 – 250 m	0,4
Distance from river		Land cover		Slope	
> 300 m	0,1	Forests and plantations	0,1	> 15%	0,1
200 – 300 m	0,2	Pasture/Rice Field	0,2	8 – 15%	0,2
100 – 200 m	0,3	Open ground	0,3	3 – 8%	0,3
0 – 100 m	0,4	Settlement	0,4	0 – 3%	0,4

Table 5 and Table 6 show the priority weight of criteria and sub-criteria for tidal flood vulnerability that have been calculated using the AHP method. The priority weight has been tested for consistency of AHP according to equation formula (4) which results in a CR value smaller than 0.1, namely 0.0 for tidal flood vulnerability criteria and 0.0 for each sub-criterion of tidal flood vulnerability which can be stated that the AHP calculation is consistent. Furthermore, it will do calculations to determine the level of tidal flood sanity according to the equation formula (5) which is divided into 3 levels, namely high, medium and low.

Table 7. The value of the scale of tidal flood vulnerability

Vulnerability level	Value
High	≥ 0,3
Medium	0,2 – 0,3
Low	≤ 0,2

Table 7 illustrates the value of the tidal flood vulnerability scale which is categorized into three levels based on the vulnerability value. The vulnerable category includes areas with a vulnerability value of 0.3 or more, indicating a high level of risk for tidal flooding. The moderately vulnerable category includes vulnerability values between 0.2 to 0.3, indicating areas of moderate risk. Meanwhile, the non-vulnerable category includes areas with a vulnerability value of 0.2 or less, indicating a low risk level for tidal flooding. This classification helps in identifying the level of risk and formulating appropriate mitigation strategies for each category.

Table 8, Data on criteria for tidal flood vulnerability in each village

Village name	Land elevation	Soil type	Distance from beach	Distance from river	Land cover	Slope
Debong Lor	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%
Kemandungan	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Kraton	2 - 3 m	The State	>750 m	200 - 300 m	Settlement	3 - 8%
Muarareja	2 - 3 m	The State	0 - 250 m	0 - 100 m	Settlement	0 - 3%

Pekauman	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%
Pesurungan Kidul	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Tegalsari	2 - 3 m	The State	0 - 250 m	0 - 100 m	Settlement	0 - 3%
Kejambon	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Mangkukusuman	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Mintaragen	2 - 3 m	The State	0 - 250 m	0 - 100 m	Settlement	0 - 3%
Panggung	2 - 3 m	The State	0 - 250 m	0 - 100 m	Settlement	0 - 3%
Slerok	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Cabawan	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Kaligangsa	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Kalinyamat Kulon	3 - 4 m	The State	>750 m	0 - 100 m	Rice Field	8 - 15%
Krandon	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Margadana	2 - 3 m	The State	>750 m	0 - 100 m	Settlement	3 - 8%
Pesurungan Lor	2 - 3 m	The State	>750 m	0 - 100 m	Settlement	3 - 8%
Sumurpanggang	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Bandung	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%
Debong Kidul	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%
Debong Kulon	3 - 4 m	The State	>750 m	0 - 100 m	Settlement	8 - 15%
Debong Tengah	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%
Kalinyamat Wetan	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%
Keturen	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%
Randugunting	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%
Tunon	3 - 4 m	The State	>750 m	> 300 m	Settlement	8 - 15%

Table 8 provides data on tidal flood vulnerability criteria for each village in Tegal City based on the results of the analysis. To determine the level of tidal flood vulnerability, each sub-criterion is weighted according to the degree of influence on tidal flood vulnerability. This weight is then multiplied by the value of each sub-criterion, with this method can identify which villages have a high, medium, or low level of vulnerability to tidal flooding.

Table 9. The level of tidal flood vulnerability of each village

No	Village name	The value of vulnerability	Information
1	Debong Lor	0,164	Low
2	Kemandungan	0,2	Low
3	Kraton	0,212	Medium
4	Muarareja	0,376	High
5	Pekauman	0,164	Low
6	Pesurungan Kidul	0,2	Low
7	Tegalsari	0,376	High
8	Kejambon	0,2	Low
9	Mangkukusuman	0,2	Low
10	Mintaragen	0,376	High
11	Panggung	0,376	High
12	Slerok	0,2	Low
13	Cabawan	0,2	Low
14	Kaligangsa	0,2	Low
15	Kalinyamat Kulon	0,184	Low
16	Krandon	0,2	Low
17	Margadana	0,236	Medium
18	Pesurungan Lor	0,236	Medium
19	Sumurpanggang	0,2	Low
20	Bandung	0,164	Low
21	Debong Kidul	0,164	Low
22	Debong Kulon	0,2	Low
23	Debong Tengah	0,164	Low
24	Kalinyamat Wetan	0,164	Low
25	Keturen	0,164	Low
26	Randugunting	0,164	Low
27	Tunon	0,164	Low

Table 9 presents the level of tidal flood vulnerability for each kelurahan in Tegal City based on the calculated vulnerability value. Muarareja, Tegalsari, Mintaragen, and Panggung villages show a high level of vulnerability with a vulnerability value of 0.376, which is categorized as a vulnerable area. This indicates that these areas require more intensive attention and mitigation actions. Meanwhile, Kraton, Margadana, and Pesurungan Lor villages have vulnerability values of 0.212 and 0.236 respectively, which are categorized as quite vulnerable areas. These areas also require preventive measures, although not as intensive as areas with vulnerable categories. Most other village, with a vulnerability value between 0.164 and 0.2, are categorized as non-vulnerable areas.

The prediction results for tidal flood vulnerability using the Simple Moving Average (SMA) and Analytic Hierarchy Process (AHP) methods were tested by comparing the predictions with the flood vulnerability map created by BPBD Kota Tegal. The BPBD map includes information about areas affected by runoff floods, inundation, and tidal floods. The prediction results using the AHP method categorize the villages of Muarareja, Tegalsari, Mintaragen, and Panggung as areas with high vulnerability to tidal floods, consistent with the BPBD map categories. The villages of Kraton, Margadana, and Pesurungan Lor are categorized as areas with medium vulnerability by the AHP method, which also aligns with the BPBD map categories. Meanwhile, the other 20 sub-districts are categorized as low vulnerability, consistent with the BPBD map indicating these areas as having low or no flood vulnerability. The alignment between the AHP prediction results and the BPBD map shows that the combination of SMA and AHP methods can provide accurate predictions of tidal flood vulnerability in Tegal City. This proves that this approach can be used as an effective tool in disaster mitigation planning. With this validation, the research results not only contribute theoretically to disaster vulnerability modeling but also have significant practical implications for decision-making and spatial planning in tidal flood-prone areas.

The results of this study show significant improvements in predictive accuracy and practical application compared to previous research. Prior studies often used single-method approaches, such as hydrological modeling or GIS-based assessments, which, while useful, are less integrative than the combination of SMA and AHP. Traditional flood risk assessments typically focus on historical data trends or multi-criteria analysis independently, thereby overlooking the comprehensive interaction of various tidal flood determinants. This research, however, leverages the strengths of both SMA and AHP, enabling a more nuanced understanding of flood vulnerability by incorporating long-term rainfall trends with a detailed evaluation of multiple vulnerability criteria. The alignment of the study's predictions with the BPBD map further underscores the robustness of the combined method, demonstrating its practical applicability and reliability.

The innovative incorporation of SMA and AHP in this study addresses the void in predictive modeling of flood vulnerability, particularly in coastal urban environments such as Tegal City. SMA's ability to analyze historical rainfall trends combined with AHP's comprehensive assessment of various flood determinants improved the accuracy of model predictions. In addition, these findings highlight the importance of integrating multiple methodologies to understand complex phenomena such as tidal flood vulnerability. This approach not only improves predictive accuracy but also offers versatile applications, enabling adaptation to other coastal areas with similar geographical and climatic conditions. The practical implications of this research for urban planning and disaster mitigation are profound. By predicting flood events with greater accuracy, urban planners and policymakers can formulate more effective strategies to reduce flood impacts, optimize resource allocation, and improve community resilience.

Conclusions

This study successfully integrated the Simple Moving Average (SMA) and Analytic Hierarchy Process (AHP) methods to predict tidal flood vulnerability in Tegal City with high accuracy. The results indicate that this method combination is effective in producing more accurate predictions compared to conventional methods. Villages such as Muarareja, Tegalsari, Mintaragen, and Panggung were identified as highly vulnerable and require more intensive mitigation attention. The practical application of these research results can aid the government and related parties in making more informed decisions regarding tidal flood disaster mitigation. The expected specific impacts include improved city planning and more effective resource allocation, as well as enhanced community resilience to tidal flood disasters. For future research, it is recommended to integrate real-time weather data and consider socio-economic factors in the predictive model to further improve accuracy and relevance in disaster mitigation, ensuring better planning and resource allocation.

References

Ali, S. A., Parvin, F., Vojteková, J., Costache, R., Linh, N. T. T., Pham, Q. B., Vojtek, M., Gigović, L., Ahmad, A., & Ghorbani, M. A. (2021). GIS-based landslide susceptibility modeling: A comparison between fuzzy multi-criteria and machine learning algorithms. *Geoscience Frontiers*, *12*(2), 857–876.

Antwi-Agyakwa, K. T., Afenyo, M. K., & Angnuureng, D. B. (2023). Know to predict, forecast to warn: a review of flood risk prediction tools. *Water*, *15*(3), 427.

Boukerche, A., & Wang, J. (2020). Machine learning-based traffic prediction models for intelligent transportation systems. *Computer Networks*, *181*, 107530.

Buchori, I., Pramitasari, A., Pangi, P., Sugiri, A., Maryono, M., Basuki, Y., & Sejati, A. W. (2021). Factors distinguishing the decision to migrate from the flooded and inundated community of Sayung, Demak: A suburban area of Semarang City, Indonesia. *International Journal of Disaster Risk Reduction*, *52*, 101946.

Ciampa, F., Seifollahi-Aghmiuni, S., Kalantari, Z., & Ferreira, C. S. S. (2021). Flood mitigation in Mediterranean coastal regions: Problems, solutions, and stakeholder involvement. *Sustainability*, *13*(18), 10474.

Coffey, L., & Claudio, D. (2021). In defense of group fuzzy AHP: A comparison of group fuzzy AHP and group AHP with confidence intervals. *Expert Systems with Applications*, *178*, 114970.

Dedekorkut-Howes, A., Torabi, E., & Howes, M. (2020). When the tide gets high: A review of adaptive responses to sea level rise and coastal flooding. *Journal of Environmental Planning and Management*, *63*(12), 2102–2143.

Enríquez, A. R., Wahl, T., Baranes, H. E., Talke, S. A., Orton, P. M., Booth, J. F., & Haigh, I. D. (2022). Predictable changes in extreme sea levels and coastal flood risk due to long-term tidal cycles. *Journal of Geophysical Research: Oceans*, *127*(4), e2021JC018157.

Feloni, E., Mousadis, I., & Baltas, E. (2020). Flood vulnerability assessment using a GIS-based multi-criteria approach—The case of Attica region. *Journal of Flood Risk Management*, *13*, e12563.

Fitriyani, N. L., Syafrudin, M., Alfian, G., & Rhee, J. (2020). HDPM: an effective heart disease prediction model for a clinical decision support system. *IEEE Access*, *8*, 133034–133050.

Hughes, M. G., Glasby, T. M., Hanslow, D. J., West, G. J., & Wen, L. (2022). Random forest classification method for predicting intertidal wetland migration under sea level rise. *Frontiers in Environmental Science*, *10*, 749950.

Knoth, S., Tercero-Gómez, V. G., Khakifirooz, M., & Woodall, W. H. (2021). The impracticality of homogeneously weighted moving average and progressive mean control chart approaches. *Quality and Reliability Engineering International*, *37*(8), 3779–3794.

Li, S., Wahl, T., Talke, S. A., Jay, D. A., Orton, P. M., Liang, X., Wang, G., & Liu, L. (2021). Evolving tides aggravate nuisance flooding along the US coastline. *Science Advances*, *7*(10), eabe2412.

Liu, Y., Eckert, C. M., & Earl, C. (2020). A review of fuzzy AHP methods for decision-making with subjective judgements. *Expert Systems with Applications*, *161*, 113738.

Merz, B., Kuhlicke, C., Kunz, M., Pittore, M., Babeyko, A., Bresch, D. N., Domeisen, D. I. V, Feser, F., Koszalka, I., & Kreibich, H. (2020). Impact forecasting to support emergency management of natural hazards. *Reviews of Geophysics*, *58*(4), e2020RG000704.

Park, S.-J., & Lee, D.-K. (2020). Prediction of coastal flooding risk under climate change impacts in South Korea using machine learning algorithms. *Environmental Research Letters*, *15*(9), 094052.

Pereira, J., Simpkin, A. J., Hartmann, M. D., Rigden, D. J., Keegan, R. M., & Lupas, A. N. (2021). High-accuracy protein structure prediction in CASP14. *Proteins: Structure, Function, and Bioinformatics*, *89*(12), 1687–1699.

Rahman, B., Karmilah, M., Kautsary, J., & Ridlo, M. A. (2021). THE TIDAL FLOODING CAUSES IN THE NORTH COAST OF CENTRAL JAVA: A SYSTEMIC LITERATURE REVIEW. *Journal of Southwest Jiaotong University*, *56*(6).

Rudiarto, I., & Pamungkas, D. (2020). Spatial exposure and livelihood vulnerability to climate-related disasters in the North Coast of Tegal City, Indonesia. *International Review for Spatial Planning and Sustainable Development*, *8*(3), 34–53.

Rusdiana, S., Yuni, S. M., & Khairunnisa, D. (2020). Comparison of Rainfall Forecasting in Simple Moving Average (SMA) and Weighted Moving Average (WMA) Methods (Case Study at Village of Gampong Blang Bintang, Big Aceh District-Sumatera-Indonesia. *Journal of Research in Mathematics Trends and Technology*, *2*(1), 21–27.

Saputra, N. A., Perwira, A., Tarigan, M., & Nusa, A. B. (2020). Penggunaan Metode AHP dan GIS Untuk Zonasi Daerah Rawan Banjir Rob di Wilayah Medan Utara. In *Media Komunikasi Teknik Sipil* (Vol. 26, Issue 1). https://doi.org/10.14710/mkts.v26i1.26211

Sato, Y., & Tan, K. H. (2023). Inconsistency indices in pairwise comparisons: an improvement of the Consistency Index. *Annals of Operations Research*, *326*(2), 809–830.

Sitorus, Z., Hariyanto, E., & Kurniawan, F. (2023). Analysis of Artificial Intelligence Machine Learning Technology for Mapping and Predicting Flood Locations in Pahlawan Batu Bara Village. *International Journal Of Computer Sciences and Mathematics Engineering*, *2*(2), 281–288.

Sutrisno, D., Rahadiati, A., Rudiastuti, A. W., Dewi, R. S., & Munawaroh. (2020). Urban coastal flood-prone mapping under the combined impact of tidal wave and heavy rainfall: a proposal to the existing national standard. *ISPRS International Journal of Geo-Information*, *9*(9), 525.

Tredennick, A. T., Hooker, G., Ellner, S. P., & Adler, P. B. (2021). A practical guide to selecting models for exploration, inference, and prediction in ecology. *Ecology*, *102*(6), e03336.

Valsamos, G., Larcher, M., & Casadei, F. (2021). Beirut explosion 2020: A case study for a large-scale urban blast simulation. *Safety Science*, *137*, 105190.

Wirayudaa, I. K. A. K., Nuarsa, I. W., & Putra, I. D. N. N. (2020). Pemetaan Potensi Kerawanan Banjir Rob di Kabupaten Gianyar. *JOURNAL OF MARINE RESEARCH AND TECHNOLOGY*, *3*(2), 94–101. https://doi.org/10.24843/JMRT.2020.v03.i02.p06

Wu, T. (2021). Quantifying coastal flood vulnerability for climate adaptation policy using principal component analysis. *Ecological Indicators*, *129*, 108006.