FLOOD SUSCEPTIBILITY ASSESSMENT IN CENTRAL REGION OF VIETNAM BASED ON ENSEMBLE FUZZY LOGIC AND MULTIVARIATE ANALYSIS

Duc-Loc NGUYEN
Ph. D Candidate, PhD Program for Civil Engineering, Water Resources Engineering, and Infrastructure Planning, College of Construction and Development, Feng Chia University, Taichung 40724, Taiwan; Faculty of Natural Resources and Environment, Vietnam National University of Agriculture, Trau Quy, Gia Lam, Hanoi, Vietnam, 10000, e-mail: st_loc@gis.tw

Tien-Yin CHOU
Distinguished Professor, Geographic Information Systems Research Center, Feng Chia University, Taichung 40724, Taiwan, e-mail: jimmy@gis.tw

Mei-Hsin CHEN
Associate Professor, Geographic Information Systems Research Center, Feng Chia University, Taichung 40724, Taiwan, e-mail: ivy@gis.tw

Thanh-Van HOANG
Associate Professor, Geographic Information Systems Research Center, Feng Chia University, Taichung 40724, e-mail: van@gis.tw

Trong-Phuong TRAN
Associate Professor, Faculty of Natural Resources and Environment. Vietnam National University of Agriculture, Trau Quy, Gia Lam, Hanoi, Vietnam, 10000, e-mail: ttphuong@vnua.edu.vn

Thanh-Son NGO
PhD, Faculty of Natural Resources and Environment. Vietnam National University of Agriculture, Trau Quy, Gia Lam, Hanoi, Vietnam, 10000, e-mail: ntson@vnua.edu.vn

Ngoc-Anh DO THI
BSc, Faculty of Geography, VNU University of Science, Vietnam National University, Hanoi, 334 Nguyen Trai, Thanh Xuan, Hanoi, Vietnam, 10000, e-mail: dothingocanh269@gmail.com

Thu-Huong BUI
BSc, Faculty of Geography, VNU University of Science, Vietnam National University, Hanoi, 334 Nguyen Trai, Thanh Xuan, Hanoi, Vietnam, 10000, e-mail: buithuhuong_t62@hus.edu.vn

Quoc-Huy NGUYEN
PhD, Faculty of Geography, VNU University of Science, Vietnam National University, Hanoi, 334 Nguyen Trai, Thanh Xuan, Hanoi, Vietnam, 10000, e-mail: huyquoc2311@hus.edu.vn

Abstract. Flooding is the most damaging natural hazard in the world. A better understanding of floods is a fundamental element in guiding the development of policies for managing and reducing flood risk. The main objective of this research is to contribute to the improvement of knowledge on flood susceptibility by combining Fuzzy AHP and Multivariate Analysis. Ha Tinh province in Vietnam was selected as the case study in which many floods have occurred in recent years. To accomplish this goal, 14 factors and 1427 flood locations were used to establish the flood susceptibility model. The area under the curve (AUC) was applied to assess the model accuracy. The results showed that rainfall, NDVI, NDBI, density of river, elevation, slope and aspect are the main factors influencing the occurrence of flooding. The models are efficient in analyzing the flood susceptibility in study area with AUC=0.87. Approximately 36% of the study area was recognized as Very High and High flood susceptibility, which focused on the littoral zone and along the river. The results of this research could be used as a scientific platform for better land use planning and sustainable development in areas highly vulnerable to floods.

Key words: flood, fuzzy AHP, GIS, Ha Tinh, Vietnam

1. Introduction

Flood is the most dangerous natural disaster and affects the greatest number of people (Samanta *et al*., 2018; Robi *et al*., 2019; Msabi and Makonyo, 2021; Diaconu *et al.,* 2021). Over the last few decades, they represent nearly 43% of all-natural disasters recorded (Nguyen *et al*., 2021), which affected approximately 2.8 billion people. Among them, nearly 95% of the deaths and almost 60% of the economic losses were recorded in developing countries, particularly in Asia. This heavy toll is largely due to an increasing population density and intensification of urbanization in flood-prone areas, combined with a high vulnerability of populations exposed to this hazard (Bui *et al*., 2020).

Various research has shown that the increase in extreme weather phenomena linked to climate change, combined with inadequate urban planning (deforestation and waterproofing of surfaces) will lead to an essential increase in river and coastal flooding phenomena (Rahmati *et al*., 2019; Stoleriu *et al*., 2020; Yariyan *et al*., 2020; Nguyen *et al*., 2021) in the future. It was estimated that approximately 40% of the world's cities will be in areas at highly exposed of flooding by 2030 (Güneralp and Seto, 2013) and 20% of the world's population will be at an increased risk of flooding in the horizons by 2080 (Arnell and Lloyd-Hughes, 2014). Since governments and municipalities must equip the knowledge and tools to anticipate, manage, and resilient to the flood risk, understanding the complex relationships between causal factors and the occurrence of floods is becoming increasingly crucial in effective flood risk management strategies (Yang *et al*., 2018; Nguyen *et al*., 2021; Petrişor *et al*., 2020).

Evidence, which found in the literature, has proven that many indicators be used flood risk assessment in the context of urban sprawl, and flood susceptibility being considered the crucial components. It is defined as the probability of spatial occurrence of a flood as a function of known predisposing factors (explanatory variables), without considering their temporal occurrence (Vojtek and Vojteková, 2019; Bui *et al*., 2020). Various research has employed the hydraulic model such as (Feng *et al*., 2020; Jacob *et al*., 2020) to calculate flood susceptibility. However, these models require complex data such as cross-sections of rivers and time series of meteorological and flow data that are not available in many regions. Therefore, their methods are not carried out at the global level. Remote sensing and GIS application in flood susceptibility mapping have also contributed to various research projects in this field (Meyer *et al*., 2009; Tran *et al*., 2009; Saha and Agrawal, 2020). Even when a Geographic Information System (GIS) can display submerged areas, it is limited in the display of impact and drifting forces of floods. To restrict these limits, GIS has integrated with other models like Support Vector Machine, Random Forest, Bagging, Deep Neural Network (Tehrany *et al*., 2014; Lee *et al*., 2017; Hong *et al*., 2018; Talukdar *et al*., 2020). However, these methods depend on locations of the flood in history and based on the relationships with the explanatory variables. Therefore, they are very difficult to apply in regions with data limits.

Besides hierarchical multi-criteria analysis, Analytic Hierarchy Process (AHP) and analytic network process (ANP) have established and integrated into GIS for flood susceptibility mapping (Alilou *et al*., 2019; Souissi *et al*., 2020; Swain *et al*., 2020; Stavropoulos *et al*., 2020). To make the best decision, AHP allows quantifying flood occurrence criteria and is considered the best-known Multi-criteria Decision Analysis (MCDA) technique for assessing flood sensitivity (Msabi and Makonyo, 2021; Nguyen *et al*., 2021). However, subjective evaluations by experts are the basis for the critical limitations of the AHP technique, resulting in bias or inconsistency possibility during pairs comparison (Das and Pal, 2019; Tella and Balogun, 2020). To resolve these limitations, Van Laarhoven and Pedrycz (1983) proposed improvement of Fuzzy AHP's (F-AHP) ability to quantify criteria more accurately, and the requirements for selecting alternatives. The main advantage of these methods over other commonly used machine learning methods is that they do not rely on training samples, but require only local expert knowledge to make predictions in the absence of samples. So, this method is a suitable tools which have been used widely to analyze flood susceptibility with good precision (Costache *et al.,* 2020). Therefore, various research have been used this methodology to map different geo-hazards like flooding. Tella and Balogun (2020) used the MCDA fuzzy to analyze flood susceptibility in Ibadan, Nigeria, while Lyu *et al*., 2019 combined F-AHP and fuzzy clustering analysis to flood risk assessments in Shanghai, China. However, studies are rarely implemented in Southeast Asia, particularly Vietnam, which often experiences flooding and with limited data. Moreover, according to the "No free lunch" theory, no model can solve all regions' problems (Bui *et al*., 2020) because each region presents its own particularity with all the varies in physical, climatic and human conditions. So, it is necessary to find a promising technique to establish a reasonable flood susceptibility map, especially in regions with data limits for supporting decision-makers as they formulate informed decisions for sustainable planning.

The novelty of this research is that, this study develops a state-of-the-art approach based on Remote Sensing and F-AHP for the flood susceptibility assessment in a Ha Tinh province, Vietnam based on environmental, hydrological, climatic and anthropogenic factors; such that the F-AHP methods is applied to assess the weights of the criteria that matches the districts. This is really important because F-AHP is considered to be one of the most influential multi-criteria decision-making (MCDM) tools on alternative criteria and evaluations.

In October 2020, it was plagued by severe flooding, which resulted in 6 people sharing death and injuries amongst themselves, and damage to the tune of approximately $23 million. To formulate mitigation strategies with high precision, understand the variable that influences flooding is significant. Land-use and land-cover changes are widely recognized as one of the major causes of increased flooding. By understanding areas with high and very high susceptibility to flooding, this study aims to help minimize the impacts of flooding on socio-economics. In addition, the study can contribute to land use planning and sustainable development as well as land use planning in urban areas in Vietnam. The finding of this study contributes towards an essential reference to flood susceptibility assessment in other regions, particularly for the national government to formulate preparation and emergency intervention strategies.

2. Data sources and flood influenced factors

2.1. Historical flood database

The flood inventory map is the first requirement and has a significant role in the flood assessment. It shows the past records of flood events in the study area and can be used as the input data for developing the flood susceptibility model. In this research, 1427 flood locations were collected from two main sources (Fig. 1).

The first source is from statistical report of Vietnam Disaster Management Authority. The second source is the flood marks from field survey. In addition, Sentinel-1 was also used in this stage to enrich the flood database. Sentinel-1 is an imaging radar mission, which is launched from 2014 under the ESA Copernicus program. It provides continuous all-weather, day-and-night imagery at C-band. The Sentinel-1 has high reliability, improved revisit time and geographical coverage. It also provides the rapid data dissemination to support various applications in the priority areas including land monitoring, marine monitoring and emergency services. The data was acquired from Sentinel-1 SAR instrument in four exclusive modes: Interferometric Wide Swath (IW), Stripmap (SM), Extra Wide Swath (EW), Wave (WV). The method which was proposed by Ben De Vries *et al*. (2020) was used to extract flood occurrence locations from Sentinel-1. All of the historical flood locations will be used to assess the performance of model output.

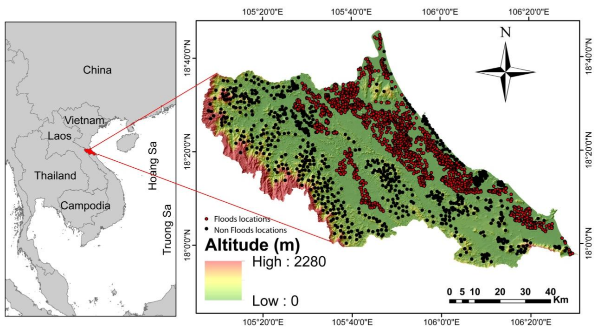

Fig. 1. Location of the study area.

2.2. Flood influenced factors

The selection of conditioning variables is the important steps in constructing the flood susceptibility model (Chowdhuri *et al*., 2020). According to previous studies, the selection of these factors usually changes from place to place due to environmental differences (Chowdhuri *et al*., 2020). However, the causal factors have separated the four categories; topography, climate, vegetation, and social-economic (Bui *et al*., 2020). To establish a flood susceptibility model in this research, variables similar to those in prior research were selected including elevation, slope, aspect, curvature, Topographic Wetness Index (TWI), Stream Power Index (SPI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), distance from rivers (DFRI), distance from road (DFRO), density of river (DORI), density of road (DORO), land use, and rainfall (Fig. 2).

Elevation, slope, aspect, curvature, TWI, SPI with a resolution of 10m were extracted from DEM, constructed from the topography map (1:10,000 scale). The environmental factors such as NDVI, NDBI with a resolution of 30m and resampled 10m computed from the Landsat 8 OLI image, while land use data was obtained from the Department of Natural Resources and the Environment in Ha Tinh Province. DFRI, DFRO, DORI, DORO with a resolution of 10m extracted from the topographic map (1:10,000 scale). Rainfall with a resolution of 10m was built from the 7 rainfall stations, which is distributed throughout the province. All factors will be divided into 5 groups using Natural Break method.

2.2.1. Elevation

In general, elevation plays a vital role in identifying flood susceptible zones, and has a major impact on the propagation, depth and direct flow of floods (Souissi *et al.*, 2019). Higher ground is less prone to flooding than areas of low elevation (Das *et al.*, 2019). The elevation map in this research was produced from topography contours of scale 1: 10,000.

2.2.2. Slope

Slope is a significant variable in flood risk research since water circulation speed heavily relies on the slope. Compared to steeper slopes which naturally increase runoff (Nachappa *et al.*, 2020; Shahabi *et al.*, 2020), gentle slopes are more likely to flood since water would move more slowly.

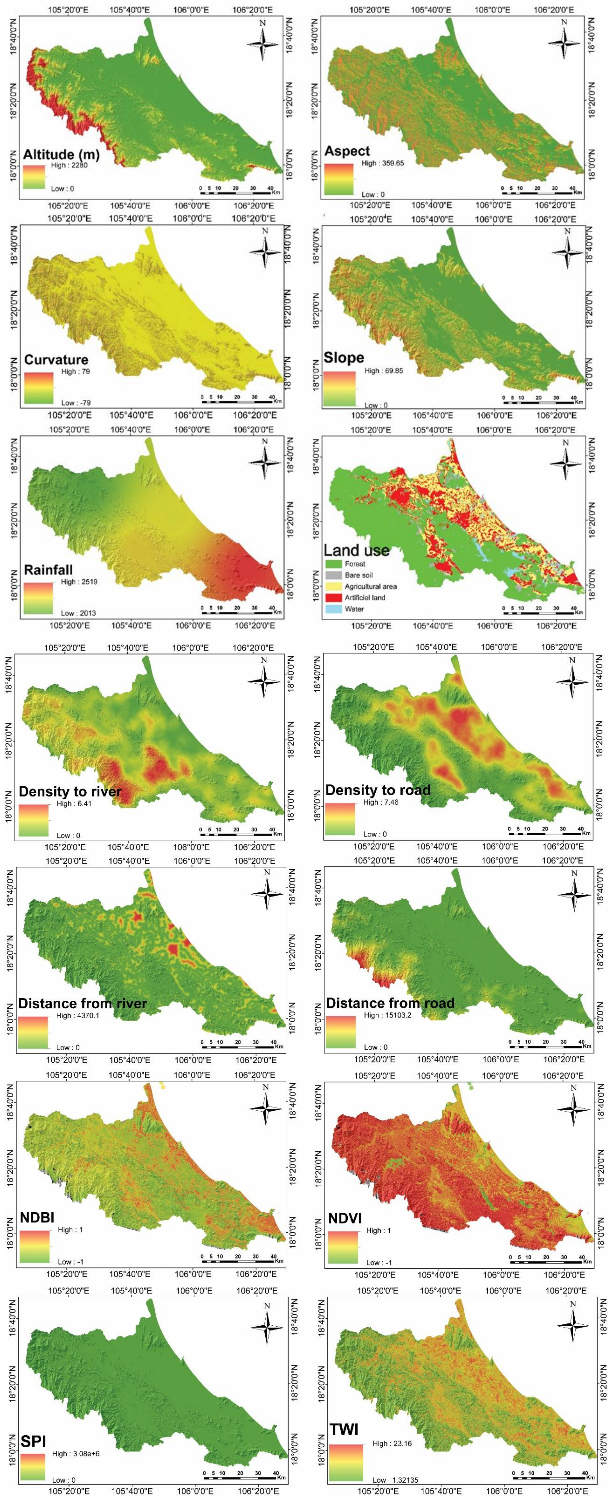

Fig. 2. Maps of flood susceptibility factors for the Ha Tinh province.

2.2.3. Aspect

Aspect has a considerable effect on evapotranspiration and also influences the direction of precipitation. It impacts vegetation and is a significant influencing factor in erosion and other weather-induced phenomena (Nachappa *et al.*, 2020).

2.2.4. Curvature

Curvature is considered a key variable in the evaluation of flood susceptibility. Various research demonstrated that regions with curvature value 0 usually have more potential for flood occurrence (Costache *et al.*, 2020).

2.2.5. Topographic wetness index

Representing the spatial variations in humidity within an area, TWI is the more significant variable in the construction of flood susceptibility models. It is used to compute the infiltration capacity of water in the area. Indeed, TWI value is usually higher in low elevation regions, where there is appreciable water accumulation capacity (Costache *et al*. 2020).

2.2.6. Stream power index

SPI is a significant variable in analyzing river environments and represents the potential for erosion and sediment transport from a specific area within a watershed. Its value is inversely proportional to floods (Khosravi *et al.*, 2019).

2.2.7. Normalized difference vegetation index (NDVI) and normalized difference built-up index (NDBI)

NDVI is a significant influencing variable susceptibility to flooding. It represented the indices in estimating vegetation cover or density in an area. High vegetation density reduces the potential for flooding. While NDBI represents the distribution characteristic of urban areas and reflects the fact that the urbanized area is higher in upstream region, then the quantity of runoff will pass higher through it during a flooding event. It therefore highlights the areas of concentration of flow downstream of urbanized areas (Nguyen *et al.*, 2020; Mohajane *et al.*, 2018; Randazzo *et al.*, 2021). The values of NDVI and NDBI vary in [-1, 1].

2.2.8. Distance from rivers

Various studies showed that areas, where are closer to rivers, are easily affected by inundation (Predick and Turner, 2008; Pham *et al.*, 2020).

2.2.9. Distance from roads

Road construction increases the waterproof surface, changes the topography and causes changes in the hydrological regimes closer to it. For flood susceptibility modelling, distance from roads is an important conditioning element since all these factors influence runoff or its accumulation (Band *et al.*, 2020; Nachappa *et al.*, 2020).

2.2.10. Density of rivers

Flood susceptibility models utilize river density since it influences surface runoff generation. It is contrasted to low-density areas, river areas with high-density are more affected by inundation (Arabameri *et al.*, 2020; Tella and Balogun, 2020).

2.2.11. Density of roads

The road system plays a significant role since it facilitates mobility between different places in a watershed. In a bid to have the best access possible, residents tend to build infrastructure near roads. A few cases have shown that roads behave like dams blocking the waters. Where roads were flooded, there was notable disruption of the daily way of life in mobility. Therefore, areas with high road density are more vulnerable to floods and disruption of normal way of life (Band *et al.*, 2020).

2.2.12. Land-use/Land-cover

Land use and land cover are utilized for flood susceptibility modeling since they determine many regions' water infiltration capacity. Vegetation density and flood occurrence show a negative correlation. Areas with excellent vegetation density portray high water infiltration, decreasing the possibility of flooding. On the contrary, urban zones and regions with low vegetation density portend weak percolation and higher water hoarding, increasing the possibility of experiencing flooding (Samanta *et al.*, 2018; Chowdhuri *et al.*, 2020).

2.2.13. Rainfall

Rainfall is an important triggering factor for flooding. Compared to regions of low rainfall intensity, the possibility of flooding in areas of higher rainfall intensity is greater (Wu *et al.*, 2016; Nachappa *et al.*, 2020). The study area has an annual precipitation of approximately 2,500 mm in the mountainous areas and 1,800 mm in the plains.

All influenced factors including elevation, slope, aspect, curvature, TWI, SPI, NDVI, NDBI, DFRI, DFRO, DORI, DORO, land use, and rainfall will be transformed to raster format data and normalized before analyzing the susceptibility of floods in the study area.

3. Methodology

The initial step for flood mapping is the identification of the factors influencing. In this study, a total 14 factors were used to build the flood susceptibility model, namely elevation, slope, aspect, curvature, TWI, SPI, TWI, NDBI, NDVI, DFRI, DFRO, DORI, DORO, land-use (LU), and rainfall. Each factor was analyzed the spatial distribution based on GIS technique. They are then converted into raster data for flood analysis.

The second step, these factors are ranked by their significance in the sensitivity of flooding levels. The selection and ranking processes are carried based on literature review, experts' knowledge and the specific features of study area. The AHP method is used to evaluate the weights for each factor. In addition, we scale all value of the factors to range of [0-1].

Finally, the flood susceptibility map is created from the weighted linear model combined with GIS framework. The results from F–AHP model are evaluated by Receiver Operating Characteristic (ROC) method. The overall process could be illustrated in Fig. 3.

3.1. Mapping susceptibility to floods based on Fuzzy Analytical Hierarchy Process method

3.1.1. Analytic Hierarchy Process (AHP)

The AHP is used to determine the weights and hierarchies of many factors that are directly susceptible to flooding. The factors were compared in pairs and the scale is used in ranged from 1 to 9. All of these assessments were based on the knowledge of local experts by questionnaire. The consistency of AHP process is evaluated using the consistency index (CI) and consistency ratio (CR) (Ghorbanzadeh *et al.*, 2018). CI is calculated by (Equation 1).

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad \text{(Equation 1)}$$

CI is the consistency index, λ_{max} is the maximum eigenvalue and n is the number of rows in the matrix. CR can be calculated from CI as (Equation 2).

$$CR = \frac{CI}{RI} \qquad \text{(Equation 2)}$$

CR is the consistency rate, and RI is the random index for the randomly generated pair comparison matrix where n = 2, 3, 4, 5, 6, 7, 8 and 9. CR < 0.10 indicates accepted consistency, while a CR > 0.10 indicates an inconsistency.

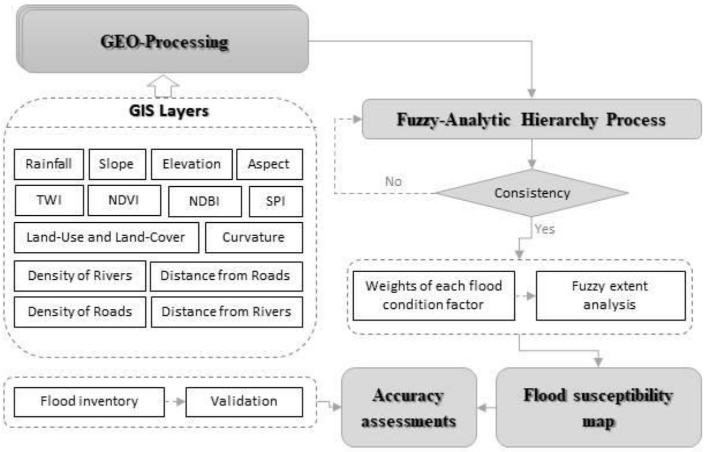

Fig. 3. Overall process of the proposed approach.

3.1.2. Fuzzy Analytic Hierarchy Process (F-AHP)

The calculation process of F–AHP method is only possible when CR ≤ 0.10. This method is carried by combining AHP method and fuzzy theory by comparing AHP with the triangular fuzzy number (TFN). The calculation process of F-AHP is summarized as follows.

- Fuzzy set

A fuzzy set A in the dimension U is represented by a function μ_A, U → [0,1]. Function μ_A is a function of the fuzzy set A, is the dependence proportion of x in the fuzzy set A. Thus, the fuzzy set is the generalization of the set by allowing the dependent function to take any value in the range [0,1]. The dependent function of the specified set takes only two values 0 or 1. The fuzzy set A is calculated by Equation 3.

$$A = \{(x, \mu_A(x)) | x \in U\} \qquad \text{(Equation 3)}$$

- Triangular fuzzy numbers

A triangular fuzzy number (TFN) is a special class of fuzzy numbers, where the dependent function is defined by a set of three real values and is often denoted (l; m; u) where (l) represents the represents the smallest value; (m) is the most likely value and (u) is the maximum value of a fuzzy set. The affiliate function of each TFN is defined by:

$$\mu_A(x) = \begin{cases} 0, x < l \ or \ x > u \\ \frac{x-l}{m-l}, x \in (m, l) \\ \frac{u-x}{u-m}, x \in (u, m) \end{cases} \qquad \text{(Equation 4)}$$

- Fuzzy extent analysis method

The experts' evaluation in the Fuzzy–AHP method is represented by the fuzzy triangular numbers and the fuzzy match matrix, which could be defined by:

$$\tilde{A} = (\tilde{a}_{ij})_{n \times n} = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) & \cdots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & \cdots & (1,1,1) \end{bmatrix}$$

(Equation 5)

Where:

$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ and $\tilde{a}_{ij}^{-1} = (1/l_{ij}, 1/m_{ij}, 1/u_{ij})$; $i, j = 1, \ldots, n$ and $i \neq j$

The processes in the fuzzy analysis are summarized according to the following 2 main steps:

Step 1: Calculate the sum of each row in the match matrix Ã, then normalize the rows just calculated by the fuzzy arithmetic operation (Equation 6).

$$S_i = \sum_{j=1}^{n} \tilde{a}_{ij} \otimes \left[\sum_{k=1}^{n} \sum_{j=1}^{n} \tilde{a}_{kj} \right]^{-1} = \left(\frac{\sum_{j=1}^{n} l_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} u_{kj}}, \frac{\sum_{j=1}^{n} m_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} m_{kj}}, \frac{\sum_{j=1}^{n} u_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} l_{kj}} \right)$$

(Equation 6)

Table 1. Variables and corresponding fuzzy numbers.

Degree of preference	The corresponding TFNs	Inverse TFNs
Extremely more important	(9,9,9)	(1/9,1/9,1/9)
Very strongly more important	(6,7,8)	(1/8,1/7,1/6)
Strongly more important	(4,5,6)	(1/6,1/5,1/4)
Moderately more important	(2,3,4)	(1/4,1/3,1/2)
Equally important	(1,1,1)	(1,1,1)
Intermediate	(7,8,9); (5,6,7); (3,4,5); (1,2,3)	(1/9,1/8,1/7); (1/7,1/6,1/5); (1/5,1/4,1/3); (1/3,1/2,1)

Where i = 1,…,n; ⊗ is the extended multiplication of two fuzzy triangular numbers. These fuzzy numbers are considered to be the correlation weights for each choice on a given condition and the weight of each condition. Then, the total weight will be calculated to evaluate for each choice.

Step 2. Calculate the probability to compare the relationship between two fuzzy numbers ($\check{S}_i$, $\check{S}_j$) (Equation 7).

$$V(\tilde{S}_i \geq \tilde{S}_j) = sup_{y \geq x}\left[min\left(\tilde{S}_j(x), \tilde{S}_i(y)\right)\right]$$
(Equation 7)

$\check{S}_i = (l_i, m_i, u_i)$ and $\check{S}_j = (l_j, m_j, u_j)$; $i = 1, \ldots, n$ and $j = 1, \ldots, m$ and $i \neq j$ (Equation 8)

$$V(\check{S}_i \geq \check{S}_j) = \begin{Bmatrix} 1\ if\ m_i > m_j \\ (u_i - l_j)/(u_i - m_i) + (m_j - l_j)\ otherwise \\ 0\ if\ l_j > u_i \end{Bmatrix}$$
(Equation 8)

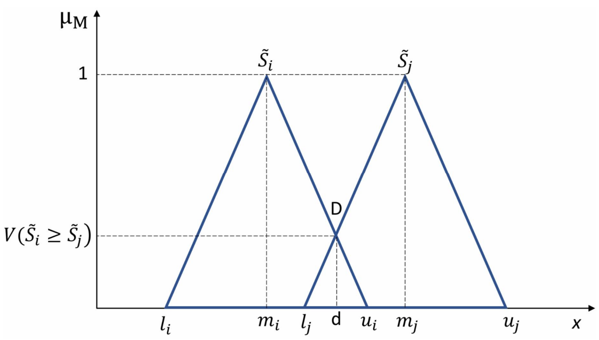

Fig. 4. The intersection of two TFNs.

To compare $\check{S}_i$ and $\check{S}_j$, we need both the values of $V(\check{S}_i \geq \check{S}_j)$ and $V(\check{S}_j \geq \check{S}_j)$.

Step 3. Estimate the priority vector $W = (w_1, \ldots, w_n)^T$ of match matrix Ã, which is defined by Equation 9:

$$W_i = \frac{V(\check{S}_i \geq \check{S}_j | j = 1, \ldots, n;\ j \neq i)}{\sum_{k=1}^{n} V(\check{S}_k \geq \check{S}_j | j = 1, \ldots, n;\ j \neq k)}, i = 1, \ldots, n$$
(Equation 9)

Where: $V(\check{S}_i \geq \check{S}_j \mid j = 1, \ldots, n) = V(\check{S}_i \geq \check{S}_1) \cap V(\check{S}_i \geq \check{S}_2) \cap \ldots \cap V(\check{S}_i \geq \check{S}_n) = min\ V(\check{S}_i \geq \check{S}_j), j = 1, \ldots, n$

Thus:

$$W_i = \frac{min\ V(\check{S}_i \geq \check{S}_j), j = 1, \ldots, n;\ j \neq i)}{\sum_{k=1}^{n} min\ V(\check{S}_k \geq \check{S}_j), j = 1, \ldots, n;\ j \neq k)}, i = 1, \ldots, n$$
(Equation 10)

In this study, to compare pairs of fuzzy parameters, linguistic variables are defined corresponding to the rating levels in Table 1. Table 1 variables can be shown in Fig. 5.

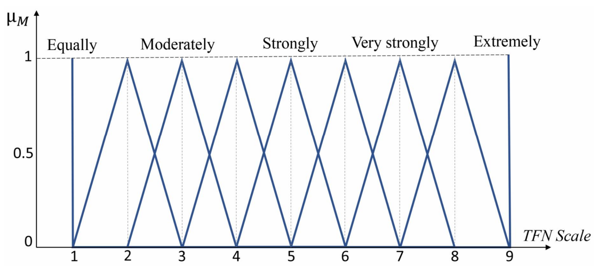

Fig. 5. The fuzzy number corresponding to linguistic variables for the importance of each criterion.

3.1.3. Overall flood susceptibility index (OFSI)

The susceptibility to flooding is expressed as a sum of factors (14 factors). The overall flood susceptibility index was then used to evaluate spatial differences of flood-sensitive areas. The map uses weights of all factors obtained from the F-AHP process and were estimated by Equation 11. In addition, all criteria are classified into five flood sensitivity levels based on the "natural break" algorithm and improved by experts. Flood susceptibility levels are related to the susceptibility indicators and are divided into five levels: (i) very low, (ii) low, (iii) moderate, (iv) high and (v) very high.

$$OFSI = \sum_{i=1}^{n} F_i \times w_i \qquad \text{(Equation 11)}$$

Where: F_i is a rating of the factor in each point, w_i is the weights of each factor, and n is the number of the criteria.

3.2. Validation and accuracy assessments of the flood susceptibility maps

Validation of the modelling results is a fundamental step in elaborating flood susceptibility maps and assessing their quality (Pourghasemi *et al.*, 2012). It is generally conducted by comparing the obtained results against information derived from past events through satellite images, field surveys, etc. In this study, the results of F-AHP model were evaluated using the receiver operating characteristic curve (ROC) model, which is widely employed in validating geospatial models. The ROC curve is constructed by plotting the "specificity" and the ordinate the "sensitivity" on the abscissa. The area under the ROC curve (AUC) is usually computed to quantify the model performance. AUC value indicates the prediction accuracy as follows: (0.9-1) excellent, (0.8-0.9) very good, (0.7-0.8) good, (0.6-0,7) average, and (0.5-0,6) poor.

4. Results

4.1. The level of indicators and weight assessment for flood susceptibility analysis

4.1.1. The level of indicators in flood susceptibility analysis

The data of indices was obtained base on Remote Sensing and GIS integration. In which, 14 factors were divided into 5 levels including (i) very low, (ii) low, (iii) moderate, (iv) high and (v) very high. However, each factor will be classified base on different characteristics. Elevation, slope, aspect, curvature, TWI, SPI, NDVI, NDBI, DFRI, DFRO, DORI, DORO, Land-Use and rainfall were split by Natural Break method. While land use factor was grouped by spatial distribution and characteristics, which is affected to flood susceptibility in different levels in the study area. It was classified as follows: very low (forestland), low (un-used land), moderate (rice land), high (non-agriculture land), and very high (aquaculture land and surface water). Table 2 showed the flood susceptibility levels of influenced factors.

4.1.2. Ranking the alternatives

The process of calculating flood susceptibility weights was performed using F-AHP methods as described in the previous section. Weightings are computed for groups of indicators from a pair comparison matrix, weighted values and the results of indicator consistency ratios including: Elevation (0.069), Slope (0.064), Aspect (0.062), Curvature (0.047), TWI (0.058), SPI (0.04), NDBI (0.09), NDVI (0.114), DFRI (0.047), DFRO (0.054), DORI (0.08), DORO (0.056), Land-use (0.06), and Rainfall (0.154).

- With λ_{max} = 14.919, CI = 0.071, RI = 1.58, and CR = 0.045 (<0.10 satisfied).

Accordingly, the consistency ratio (CR = 0.045) is less than 10%, satisfying the pair comparison matrix's requirements. Rainfall, NDVI, NDBI, and DORI with weights of 0.154, 0.114, 0.09, 0.08, respectively, were found to be the most critical flood conditioning factors in the Central Region of Vietnam based on Fuzzy AHP.

Table 2. The flood susceptibility level.

	Flood susceptibility level				
	(i) Very low	(ii) Low	(iii) Moderate	(iv) High	(v) Very high
(Elevation)	> 1124	1124 - 652	652 - 309	309 - 105	< 105
(Slope)	> 33.44	33.44 - 24.11	24.11 - 15.1	15.1 - 5.43	< 5.43
(Aspect)	> 282.2	282.2 - 202.3	202.3 - 118.4	118.4 - 38.7	< 38.7
(Curvature)	> 11	11 - 3	3 - (-4)	(-4) - (-12)	< (-12)
(TWI)	< 4.73	4.73 - 7.89	7.89 - 11.04	11.04 - 13.6	> 13.6
(SPI)	> 979135	979135 - 447259	447259 - 169233	169233 - 36246	< 36246
(NDBI)	< (-0.38)	(-0.38) - (-0.27)	(-0.27) - (-0.15)	(-0.15) - (-0.078)	> (-0.078)
(NDVI)	> 0.75	0.75 - 0.56	0.56 - 0.34	0.34 - 0.003	< 0.003
(Distance from River)	> 2073.65	2073.65 - 1182.49	1182.49 - 616.95	616.95 - 239.92	< 239.92
(Distance from road)	> 8765.76	8765.76 - 5212.07	5212.07 - 2665.25	2665.26 - 888.42	< 888.42
(Density to river)	< 1.08	1.08 - 1.96	1.96 - 2.86	2.86 - 4.15	> 4.15
(Density to road)	< 0.76	0.76 - 1.9	1.9 - 3.13	3.13 - 4.47	> 4.47
(Land Use)	Forestland	Un-used land	rice land	Non-agriculture land	Aquaculture land and surface water
(Rainfall)	< 2126	2126 - 2229	2229 - 2332	2332 - 2437	> 2437

4.2. Accuracy assessment and flood susceptibility mapping

The performance of the model was evaluated by the receiver operating characteristic (ROC) with 1427 flood points and 761 non-flood points. It is presented by the 1-sensitivity on the x-axis and sensitivity on the y-axis.

The area under the curve (AUC) is a synthetic index, which is calculated for ROC curves. AUC is the probability that a positive event will be classified as positive by the test over the range of possible threshold values. The model is more accurate when the AUC value approaches 1. In general, if this value is less than 0.5, the model cannot predict the flood susceptibility. When the AUC value ranges from 0.6 to 0.7, the model is weak. The model is good when the AUC value is greater than 0.7. A well discriminating model must have an AUC between 0.87 and 0.9. A model with an AUC greater than 0.9 is excellent (Lobo *et al.*, 2008; Bui *et al.*, 2020). The result shows that with AUC = 0.87 (Fig. 6), the model proposed in our research can be used to generate the flood susceptibility assessment in Ha Tinh province of Vietnam.

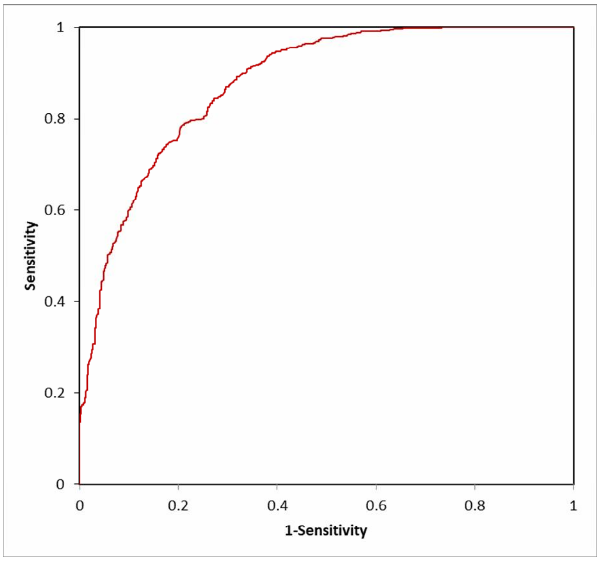

Fig. 6. The AUC value of F-AHP.

After validating the F-AHP model, the flood susceptibility map was constructed in Ha Tinh province of Vietnam (Fig. 6). To understand the spatial distribution of flood susceptibility, the map of this model has been grouped into five classes: very low

(1.0-1.75), (ii) low (1.75-2.65), (iii) moderate (2.65-3.27), (iv) high (3.27-3.7), and (v) very high (3.7-4.58).

Areas with very high susceptibility to flooding covered approximately 766.85 km², are located in the south of the province where the heavy precipitation. At the same time, the high susceptibility area with 1339.52 km² is found in the lower reaches of the river. The moderate susceptibility zone with 1408 km² is located in the region to the province's North West. In the end, the zone with low and very low susceptibility with 2330 km² is located in the mountain zone. This map is an essential science-based solution to support local authorities who can build early warning systems to reduce damage (Fig. 7).

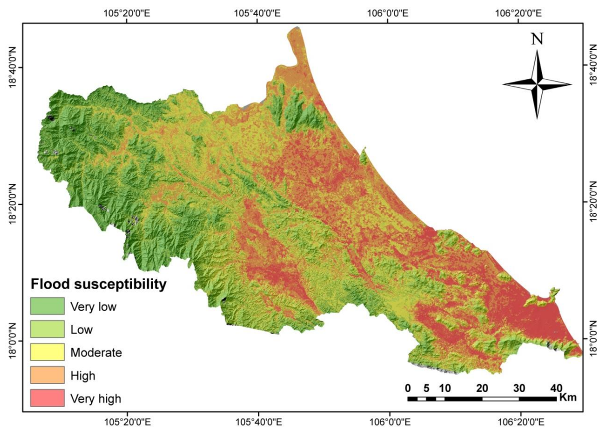

Fig. 7. Flood susceptibility in the Ha Tinh province.

5. Discussion

In recent years, the flood risk has increased significantly in general and Vietnam due to socio-economic growth and climate change (Nguyen *et al.*, 2021; Pham *et al.*, 2021). However, research on assessing the risk of complete flooding at the local level is still very limited. This study presented a comprehensive approach to assess the susceptibility of flooding using integrand fuzzy-AHP and Geographic Information Systems (GIS), which has offered decision-making support to reduce flood damage and sustainable development of the territory in Ha Tinh province, the Central region of Vietnam. A literature review allows us to identify the criteria of susceptibility to flooding, including environmental, hydrological, climatic, anthropogenic criteria (Nachappa *et al.*, 2020; Pham *et al.*, 2021). The F-AHP method calculated the weights of parameters to assess flood susceptibility.

Based on the basic weights gathering from the pairwise comparison, we observed the conservation of the hierarchy in the importance of the criteria, which are established by this approach. We can therefore notice that the essential criteria remain rainfall and NDVI. The other factors that follow and are also not less are NDBI, DORI, elevation, slope, aspect, land use/land cover, TWI, DORO, DFRO, DFRI, curvature and SPI. Precipitation (or rainfall) in the study area is the most important factor because it is the trigger, affects surface runoff and causes flooding. Regions with high rainfall potentially submerge faster than areas with low precipitation. Many study areas is covered by the vegetation surface. These surfaces help to retain excessive rainwater, prevent extreme runoff, reduce damage in the event of flooding. The volume of water retained by forests would depend on the forest area. However, currently the forest in the study area has been replaced by agricultural land or construction land. Thus, when the rain is heavy, the water flows quickly from the up-streams of the river where the altitudes are higher to the lower regions which caused the great floods, particularly in the area with high density to river such as the study area.

The final results obtained for the flood susceptibility map reveal that the potential flood sites are the littoral zone and the province's southern region. It is necessary to have more attention from the local authorities because these areas are in the worst alternative sites. In addition, the flood susceptibility analysis highlights the more important role of criteria such as rainfall, human activities, elevation, slope in estimating the spatial distribution of flood risk. These results showed that the removal of a causes such as road density does not significantly influence the potential of flood occurrence for Ha Tinh province.

The analysis of the results is an essential step because it allows to further consolidate the validity of the results by specifying the limits within which the conclusions remain robust with regard to the variation of the parameters of the method used. It also makes it possible to compare the marginal effect on the final decision, which reflects a personalization on a few criteria or on the weighting associated with them (Nguyen *et al.*, 2020; Nguyen *et al.*, 2021). The several previous studies thus specify that it is at this stage of the multicriteria analysis for decision support that we find the best potential for the interpretation of the results assisted by experts and actors in the field of flood risk. The F-AHP method to calculate the weight to be assigned to each criterion used shows reliable results for the scale of the area studied.

The flood susceptibility map produced using this approach can be used as an instrument for sustainable land use planning and to optimize resource use. Indeed, GIS combined with F-AHP constitutes one of the best decision-making tools for land use planning. However, the combined use of F-AHP and GIS has identified potential areas for flooding. However, difficulties were encountered in this study. One of the problems of this method is the choice of the limits of the factor classes. It operates on the one hand based on the operator's ability to discern and on his judgment, and on the other hand, on the values of the criteria. Therefore, the limits of the chosen classes are not fixed, but stem from the reality on the ground and the objectives to be achieved.

5. Conclusion

Flood susceptibility assessment is a very high topical scientific subject because of its research with great potential to propose alternative solutions to reduce the damage to the economy and humans. This study presents an approach to assess the susceptibility of flooding at the local level of Ha Tinh Province using F-AHP and GIS. The results show that the areas with high and very high flood susceptibility, covering approximately 2000 km², are located in the coastal region, where has heavy precipitation and touched by deforestation. Understanding the flood susceptibility distribution can support local authorities in implementing flood control strategies and activities. The approach developed in this research is essential because it contributes a comprehensive overview and a method to assess the flood susceptibility quickly using the available data. The applied technique could be extended to other fields of application or other factors depending on the availability of data hence its flexibility and scalability.

REFERENCES

Alilou H., Rahmati O., Singh V. P., Choubin B., Pradhan B., Keesstra S., Ghiasi S. S., Sadeghi S. H. (2019), *Evaluation of Watershed Health Using Fuzzy-ANP Approach Considering Geo-environmental and Topo-hydrological Criteria*, Journal of Environmental Management **232**: 22-36.

Arabameri A., Saha S., Chen W., Roy J., Pradhan B., Bui D. T. (2020), *Flash Flood Susceptibility Modelling Using Functional Tree and Hybrid Ensemble Techniques*, Journal of Hydrology **587**: 125007.

Arnell N. W., Lloyd-Hughes B. (2014), *The Global-Scale Impacts of Climate Change on Water Resources and Flooding under New Climate and Socio-economic Scenarios*, Climatic Change **122(1)**: 127-140.

Band S. S., Janizadeh S., Chandra P. S., Saha A., Chakrabortty R., Melesse A. M., Mosavi A. (2020), *Flash Flood Susceptibility Modeling Using New Approaches of Hybrid and Ensemble Tree-Based Machine Learning Algorithms,* Remote Sensing **12(21)**: 3568.

Bui Q. T., Nguyen Q. H., Nguyen X. L., Pham V. D., Nguyen H. D., Pham V. M. (2020), *Verification of Novel Integrations of Swarm Intelligence Algorithms into Deep Learning Neural Network for Flood Susceptibility Mapping,* Journal of Hydrology **581**: 124379.

Chowdhuri I., Pal S. C., Chakrabortty R. (2020), *Flood Susceptibility Mapping by Ensemble Evidential Belief Function and Binomial Logistic Regression Model on River Basin of Eastern India,* Advances in Space Research **65(5)**: 1466-1489.

Costache R., Țîncu R., Elkhrachy I., Pham Q. B., Popa M. C., Diaconu D. C., Avand M., Costache I., Arabameri A., Bui D. T. (2020), *New Neural Fuzzy-Based Machine Learning Ensemble for Enhancing the Prediction Accuracy of Flood Susceptibility Mapping,* Hydrological Sciences Journal **65(16)**: 2816-2837.

Costache R., Popa M. C., Bui D. T., Diaconu D. C., Ciobotaru N., Minea G., Pham Q. B. (2020), *Spatial Predicting of Flood Potential Areas Using Novel Hybridizations of Fuzzy Decision-Making, Bivariate Statistics, and Machine Learning*, Journal of Hydrology **585**: 124808.

Das B., Pal S. C. (2019), *Combination of GIS and Fuzzy-AHP for Delineating Groundwater Recharge Potential Zones in the Critical Goghat-II Block of West Bengal, India,* HydroResearch **2**: 21-30.

Das B., Pal S. C., Malik S., Chakrabortty R. (2019), *Living with Floods Through Geospatial Approach: a Case Study of Arambag CD Block of Hugli District, West Bengal, India,* SN Applied Sciences **1(4)**: 1-10.

DeVries B., Huang C., Armston J., Huang W., Jones J. W., Lang M. W. (2020), *Rapid and Robust Monitoring of Flood Events Using Sentinel-1 and Landsat Data on the Google Earth Engine,* Remote Sensing of Environment **240**: 111664.

Diaconu D. C., Costache R., Popa M. C. (2021), *An Overview of Flood Risk Analysis Methods,* Water **13(4)**: 474.

Feng B., Wang J., Zhang Y., Hall B., Zeng C. (2020), *Urban Flood Hazard Mapping Using a Hydraulic–GIS Combined Model*, Natural Hazards **100(3)**: 1089-1104.

Ghorbanzadeh O., Feizizadeh B., Blaschke T. (2018), *An Interval Matrix Method Used to Optimize the Decision Matrix in AHP Technique for Land Subsidence Susceptibility Mapping,* Environmental Earth Sciences **77(16)**: 1-19.

Güneralp B., Seto K. (2013), *Futures of Global Urban Expansion: Uncertainties and Implications for Biodiversity Conservation,* Environmental Research Letters **8(1)**: 014025.

Hong H., Panahi M., Shirzadi A., Ma T., Liu J., Zhu A X., Chen W., Kougias I., Kazakis N. (2018), *Flood Susceptibility Assessment in Hengfeng Area Coupling Adaptive Neuro-Fuzzy Inference System with Genetic Algorithm and Differential Evolution,* Science of the Total Environment **621**: 1124-1141.

Jacob X. K., Bisht D. S., Chatterjee C., Raghuwanshi N. S. (2020), *Hydrodynamic Modeling for Flood Hazard Assessment in a Data Scarce Region: a Case Study of Bharathapuzha River Basin*, Environmental Modeling & Assessment **25(1)**: 97-114.

Khosravi K., Shahabi H., Pham B. T., Adamowski J., Shirzadi A., Pradhan B., Dou J., Ly H. B., Gróf G., Ho H. L. (2019), *A Comparative Assessment of Flood Susceptibility Modeling Using Multi-Criteria Decision-Making Analysis and Machine Learning Methods,* Journal of Hydrology **573**: 311-323.

Lee S., Kim J. C., Jung H. S., Lee M. J., Lee S. (2017), *Spatial Prediction of Flood Susceptibility Using Random-Forest and Boosted-Tree Models in Seoul Metropolitan City, Korea*, Geomatics, Natural Hazards and Risk **8(2)**: 1185-1203.

Lobo J., Jiménez-Valverde A., Real R. (2008), *AUC: a Misleading Measure of the Predictive Distribution Models*, Global Ecology and Biogeography **17(2):** 145-151.

Lyu H. M., Shen S. L., Zhou A. N., Zhou W. H. (2019), *Flood Risk Assessment of Metro Systems in a Subsiding Environment Using the Interval FAHP-FCA Approach,* Sustainable Cities and Society **50**: 101682.

Meyer V., Scheuer S., Haase D. (2009), *A Multicriteria Approach for Flood Risk Mapping Exemplified at the Mulde River, Germany*, Natural Hazards **48(1)**: 17-39.

Mohajane M., Essahlaoui A., oudija F., Hafyani E. M., Hmaidi A. E., Ouali E. A., Randazzo G., Teodoro A. C. (2018), *Land Use/Land Cover (LULC) Using Landsat Data Series (MSS, TM, ETM+ and OLI) in Azrou Forest, in the Central Middle Atlas of Morocco*, Environments **5(12)**: 131.

Msabi M. M., Makonyo M. (2021), *Flood Susceptibility Mapping Using GIS and Multi-Criteria Decision Analysis: a Case of Dodoma Region, Central Tanzania*, Remote Sensing Applications: Society and Environment **21** : 100445.

Nachappa T. G., Piralilou S. T., Gholamnia K., Ghorbanzadeh O., Rahmati O., Blaschke T. (2020), *Flood Susceptibility Mapping with Machine Learning, Multi-Criteria Decision Analysis and Ensemble Using Dempster Shafer Theory*, Journal of Hydrology **590**: 125275.

Nguyen H. D., Pham V. D., Nguyen Q. H., Pham V. M., Pham M. H., Vu V. M., Bui Q.-T. (2020), *An Optimal Search for Neural Network Parameters Using the Salp Swarm Optimization Algorithm: a Landslide Application*, Remote Sensing Letters **11(4)**: 353-362.

Nguyen H. D., Fox D., Dang D. K., Pham L. T., Viet Du Q. V., Nguyen T. H. T., Dang T. N., Tran V. T., Vu P. L., Nguyen Q. H., Nguyen T.G., Bui Q.-T., Petrişor A.-I. (2021), *Predicting Future Urban Flood Risk Using Land Change and Hydraulic Modeling in a River Watershed in the Central Province of Vietnam*, Remote Sensing **13(2)**: 262.

Nguyen H. X., Nguyen A. T., Ngo A. T., Phan V. T., Nguyen T. D., Do V. T., Dao D. C., Dang D. T., Nguyen A. T., Hens L. (2020), *A Hybrid Approach Using GIS-Based Fuzzy AHP–TOPSIS Assessing Flood Hazards along the South-Central Coast of Vietnam*, Applied Sciences **10(20)**: 7142.

Nguyen T. G., Tran N. A., Vu P. L., Nguyen Q. H., Nguyen H. D., Bui Q. T. (2021), *Salinity Intrusion Prediction Using Remote Sensing and Machine Learning in Data-Limited Regions: A Case Study in Vietnam's Mekong Delta*, Geoderma Regional **27**: e00424.

Petrişor A.-I., Hamma W., Nguyen H. D., Randazzo G., Muzirafuti A., Stan M.-I., Tran V. T., Aştefănoaiei R., Bui Q.-T., Vintilă D.-F., Truong Q. H., Lixăndroiu C., Țenea D.-D., Sîrodoev I., Ianoş I. (2020), *Degradation of Coastlines under the Pressure of Urbanization and Tourism: Evidence on the Change of Land Systems from Europe, Asia and Africa*, Land **9(8)**: 275.

Pham B. T., Avand M., Janizadeh S., Phong T. V., Al-Ansari N., Ho L. S., Das S., Le H. V., Amini A., Bozchaloei S. K. (2020), *GIS Based Hybrid Computational Approaches for Flash Flood Susceptibility Assessment*, Water **12(3)**: 683.

Pham B. T., Luu C., Van Dao D., Van Phong T., Nguyen H. D., Le V. H., von Meding J., Prakash I. (2021), *Flood Risk Assessment Using Deep Learning Integrated with Multi-Criteria Decision Analysis*, Knowledge-Based Systems **219**: 106899.

Pham B. T., Luu C., Van Phong T., Nguyen H. D., Le V. H., Tran T. Q., Ta H. T., Prakash I. (2021), *Flood Risk Assessment Using Hybrid Artificial Intelligence Models Integrated with Multi-Criteria Decision Analysis in Quang Nam Province, Vietnam*, Journal of Hydrology **592**: 125815.

Pourghasemi H. R., Pradhan B., Gokceoglu C. (2012), *Application of Fuzzy Logic and Analytical Hierarchy Process (AHP) to Landslide Susceptibility Mapping at Harazd Watershed, Iran*, Natural Hazards **63(2)**: 965-996.

Predick K. I., Turner M. G. (2008), *Landscape Configuration and Flood Frequency Influence Invasive Shrubs in Floodplain Forests of the Wisconsin River (USA)*, Journal of Ecology **96(1)**: 91-102.

Randazzo G., Cascio M., Fontana M., Gregorio F., Lanza S., Muzirafuti A. (2021), *Mapping of Sicilian Pocket Beaches Land Use/Land Cover with Sentinel-2 Imagery: a Case Study of Messina Province,* Land **10(7)**: 678.

Rahmati O., Darabi H., Haghighi A. T., Stefanidis S., Kornejady A., Nalivan O. A., Tien Bui D. (2019), *Urban Flood Hazard Modeling Using Self-Organizing Map Neural Network*, Water **11(11)**: 2370.

Robi M. A., Abebe A., Pingale S. M. (2019), *Flood Hazard Mapping under a Climate Change Scenario in a Ribb Catchment of Blue Nile River Basin, Ethiopia*, Applied Geomatics **11(2)**: 147-160.

Saha A. K., Agrawal S. (2020), *Mapping and Assessment of Flood Risk in Prayagraj District, India: a GIS and Remote Sensing Study*, Nanotechnology for Environmental Engineering **5**: 1-18.

Samanta S., Pal D. K., Palsamanta B. (2018), *Flood Susceptibility Analysis Through Remote Sensing, GIS and Frequency Ratio Model*, Applied Water Science **8(2)**: 1-14.

Shahabi H., Shirzadi A., Ghaderi K., Omidvar E., Al-Ansari N., Clague J. J., Geertsema M., Khosravi K., Amini A., Bahrami S. (2020), *Flood Detection and Susceptibility Mapping Using Sentinel-1 Remote Sensing Data and a Machine Learning Approach: Hybrid Intelligence of Bagging Ensemble Based on K-Nearest Neighbor Classifier*, Remote Sensing **12(2)**: 266.

Souissi D., Zouhri L., Hammami S., Msaddek M. H., Zghibi A., Dlala M. (2020), *GIS-Based MCDM - AHP Modeling for Flood Susceptibility Mapping of Arid Areas, Southeastern Tunisia*, Geocarto International **35(9)**: 991-1017.

Stavropoulos S., Zaimes G. N., Filippidis E., Diaconu D. C., Emmanouloudis D. (2020), *Mitigating Flash Floods with the Use of New Technologies: a Multi-Criteria Decision Analysis to Map Flood Susceptibility for Zakynthos Island, Greece*, Journal of Urban and Regional Analysis **12(2)**: 233-248

Stoleriu C. C., Urzica A., Mihu-Pintilie A. (2020), *Improving Flood Risk Map Accuracy Using High-Density Lidar Data and the HEC□RAS River Analysis System: a Case Study from North-Eastern Romania*, Journal of Flood Risk Management **13**: e12572.

Swain K. C., Singha C., Nayak L. (2020), *Flood Susceptibility Mapping Through the GIS-AHP Technique Using the Cloud*, ISPRS International Journal of Geo-Information **9(12)**: 720.

Talukdar S., Ghose B., Salam R., Mahato S., Pham Q. B., Linh N. T. T., Costache R., Avand M. (2020), *Flood Susceptibility Modeling in Teesta River Basin, Bangladesh Using Novel Ensembles of Bagging Algorithms*, Stochastic Environmental Research and Risk Assessment **34(12)**: 2277-2300.

Tehrany M. S., Pradhan B., Jebur M. N. (2014), *Flood Susceptibility Mapping Using a Novel Ensemble Weights-Of-Evidence and Support Vector Machine Models in GIS*, Journal of Hydrology **512**: 332-343.

Tella A., Balogun A. L. (2020), *Ensemble Fuzzy MCDM for Spatial Assessment of Flood Susceptibility in Ibadan, Nigeria*, Natural Hazards **104(3)**: 2277-2306.

Tran P., Shaw R., Chantry G., Norton J. (2009), *GIS and Local Knowledge in Disaster Management: a Case Study of Flood Risk Mapping in Viet Nam*, Disasters **33(1)**: 152-169.

Van Laarhoven P. J., Pedrycz W. (1983), *A Fuzzy Extension of Saaty's Priority Theory*, Fuzzy Sets and Systems **11(1-3)**: 229-241.

Vojtek M., Vojteková J. (2019), *Flood Susceptibility Mapping on a National Scale in Slovakia Using the Analytical Hierarchy Process*, Water **11(2)**: 364.

Wu Y., Li W., Wang Q., Liu Q., Yang D., Xing M., Pei Y., Yan S. (2016), *Landslide Susceptibility Assessment Using Frequency Ratio, Statistical Index and Certainty Factor Models for the Gangu County, China*, Arabian Journal of Geosciences **9(2)**: 84.

Yang W., Xu K., Lian J., Bin L., Ma C. (2018), *Multiple Flood Vulnerability Assessment Approach Based on Fuzzy Comprehensive Evaluation Method and Coordinated Development Degree Model*, Journal of Environmental Management **213**: 440-450.

Yariyan P., Avand M., Abbaspour R. A., Torabi Haghighi A., Costache R., Ghorbanzadeh O., Janizadeh S., Blaschke T. (2020), *Flood Susceptibility Mapping Using an Improved Analytic Network Process with Statistical Models, Geomatics*, Natural Hazards and Risk **11(1)**: 2282-2314.

Received: 20 October 2021 • **Revised**: 3 November 2021 • **Accepted**: 24 November 2021