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Flood susceptibility mapping using analytic hierarchy process and ranking method with remote sensing and geographic information system for river basin - Case study in the Ca river basin, Vietnam

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Abstract:

Floods are among the most severe natural hazards, causing significant loss of life, property damage, and environmental destruction. Therefore, it is essential to develop a flood susceptibility map as a foundation for proposing solutions to mitigate the impact of floods. The Ca river basin serves as the typical study area. This research utilises data from various remote sensing satellite images, including the shuttle radar topography mission (SRTM) digital elevation model (DEM), Sentinel-1,2, and flood thematic classes such as topography, geomorphology, and hydrometeorological conditions. These were prepared and combined using a geographic information system (GIS) - based analytic hierarchy process (AHP) and ranking method (RM) to delineate flood susceptibility areas within the basin. The two final flash flood hazard maps were validated against the October 2020 flood map using the sentinel application platform (SNAP). The results produced a spatial distribution of flood susceptibility with four levels: low, moderate, high, and very high. In the lower part of the Ca river basin, including districts such as Can Loc, Duc Tho, Loc Ha, Huong Khe, Do Luong, and Nam Dan, the areas highly susceptible to floods range from 16.81 to 18.81%. The research results demonstrated the appropriateness of the methods and the integration of remote sensing and GIS techniques, highlighting significant flood susceptibility areas in the Ca river basin.

Keywords: **analytic hierarchy process, flood susceptibility, geographic information system, ranking method.**

Classification numbers: **4.1, 5.3**

1. Introduction

The increasing risk and vulnerability to floods arise from more frequent extreme events linked to climate change, shifts in land use patterns, encroachment into floodplains, and the growing economic value of assets and businesses [1]. Since the early 21st century, the integration of GIS, remote sensing, and watershed modelling systems to create flood risk maps has been consistently enhanced and expanded as the availability of GIS and spatial databases improves [2]. Flooding is a complex dynamic phenomenon; hence, the GIS or remote sensing database can predominantly be utilised to assess the scope of flooded regions [3]. The utilisation of satellite data can aid in identifying, assessing, and monitoring the impact of hazards, as well as mitigating the effects of floods. Satellite sensors can now directly and indirectly measure almost all parts of the hydrological cycle. Satellite data sources such as meteorological data, land use, land cover, terrain, and soil are collected, extracted, and identified. These data are gathered, analysed, synthesised, and organised to support system models and evaluation methods to achieve established outcomes.

In the 1970s, R.W. Saaty (1987) [4] pioneered the AHP, establishing a mathematical framework that revolutionised systematic decision-making analysis. He defined the AHP as a method for mathematically analysing decision-making problems. AHP is widely recognised as a method now utilised globally in various sectors, including transportation, energy, healthcare, and technology projects [5]. The AHP method converts problems into quantifiable relationships that are weighted and measurable. The factors involved in flood susceptibility modelling vary between regions and are selected based on their individual importance and impact. Key factors such as slope, elevation, land use, rainfall, and proximity to water bodies are essential for effective flood susceptibility analysis and modelling [2]. The AHP can also be utilised to develop a decision-making framework tailored for flood susceptibility mapping [6], resulting in different flood-vulnerable parameters being ranked based on their impact using a pairwise comparison matrix (PCM) [7].

Multi-criteria analysis (MCA) provides a framework that allows the identification of the different elements of a complex decision-making problem, organising them into

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a hierarchical structure, and analysing the relationships between those factors. In MCA, goals are specified and aligned with identified attributes or indicators. Indexes are determined based on quantitative analysis through scoring, ranking, and measurement of various types and criteria. In the RM, each factor or criterion under consideration is ranked according to the decision maker's priority. MCA and GIS methods have been applied in many studies assessing vulnerability and risk due to floods [7, 8]. A study of the Hadejia-Jama'are river basin in Nigeria considered multiple factors contributing to flooding, including annual rainfall, basin slope, drainage networks, land cover, and soil type [7]. Another study expanded this approach by incorporating additional factors, such as watershed size and the gradient of the main drainage channel [8]. Since this method accounts for various regional conditions, its results are specific to those conditions and inherently include a degree of subjectivity in the weighting process [8].

In recent years, flood monitoring using SAR data from the Sentinel-1 satellite has advanced significantly, particularly when integrated with the Google earth engine (GEE) cloud computing platform [9-12]. This approach also plays a crucial role in verifying flood calculation results obtained through other tools [13].

The Ca river basin, located in Vietnam's North Central region, is one of the country's major river basins and was selected as the study area. Floods in the Ca river basin rank among the most destructive natural disasters [13]. In Vietnam, the Central region is consistently the area most affected by floods. In 2020, extensive rainfall, flash floods, and landslides in this region resulted in the deaths or disappearance of 249 people and the collapse of 1,531 houses, with damages exceeding 36,000 billion VND. Between 2007 and 2019, the Ca river basin experienced eight extreme flood events, each causing widespread flooding that lasted approximately 10 days [14].

Research on floods in the Ca river basin has predominantly concentrated on weather patterns and rainfall, neglecting factors such as soil, vegetation cover, and other related elements [15], or related studies focusing on hydraulic hydrological modelling [13, 16].

Flood phenomena are largely associated with heavy rain during storms and the topographic differentiation of basins. They depend on the area and morphology of the basin, the density of flow in each basin, the elevation and slope of the terrain, the thickness and properties of the soil layer along with the weathered crust, the condition of the basin, the status of vegetation cover, and the current status of resource exploitation and use in the basin.

The collected data, combined with GIS technology, the aforementioned factors, and the AHP and RM, are utilised to create flood susceptibility maps based on the best current understanding of influencing factors. This study on the Ca river basin focuses on selecting factors that influence flooding in the area. It employs the AHP and RM to develop flood susceptibility maps and compares their results. Additionally, it examines the advantages of using Sentinel-1 satellite imagery to construct flood maps for result validation.

2. Materials and methods

2.1. Study area

The Ca river basin is one of the largest river basins in Vietnam, with coordinates between 18°33′10″N and 20°01′43″N latitude, and 103°52′53″E to 105°48′50″E longitude [17]. The Ca river is a significant international river in the North Central region, playing an important role in the socio-economic development, defence, and security of Nghe An and Ha Tinh provinces (Fig. 1). The river is abundant, but its spatial and temporal distribution is uneven. Streamflow is greatly accumulated during the flood season, while water shortages paradoxically occur during periods of scarce water resources in the dry season.

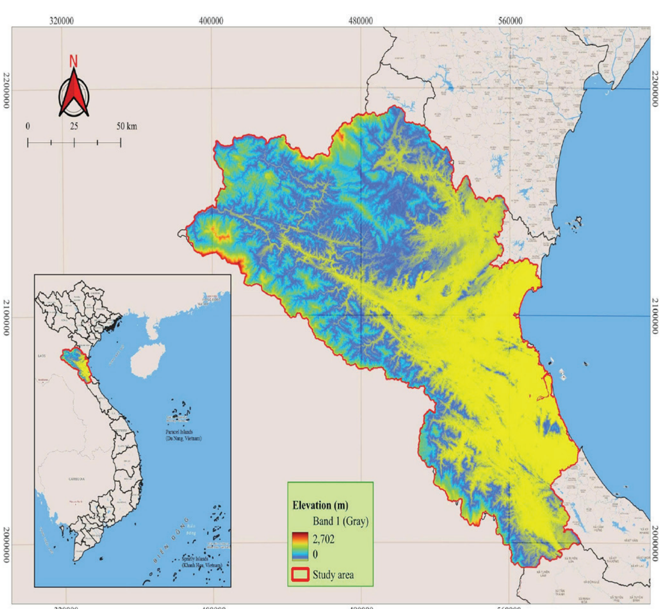

Fig. 1. Location of the study area (the Ca river basin in Nghe An and Ha Tinh provinces).

The Ca river basin's expansive area allows for a variety of climatic and hydrological flow characteristics. In the higher areas, the rainy season typically lasts from May to August, whereas in the lower regions, it extends from August to November. According to flood data, widespread flooding and inundation frequently occur in August and September. This is largely attributed to the extended periods of intense rainfall and the occurrence of tropical storms during these months [14]. This study will focus on the Ca river basin across Nghe An and Ha Tinh provinces, chosen based on the availability and quality of collected hydrometeorological data.

2.2. Data processing

In this study, ten criteria were identified as critical for creating floods and were thus concentrated on for predicting flood-susceptible sites [18, 19]. This study uses a set of factors primarily related to the hydrology and geographic features of the study area for measurement and evaluation. The factors used include (1) TWI - topographic wetness index, (2) Slope, (3) Elevation, (4) Rainfall, (5) Land use/land cover (LULC), (6) NDVI - normalised difference vegetation index, (7) Distance from rivers, (8) Distance from roads, (9) Drainage density, and (10) Soil type. In this step, the data are collected and processed using GIS and GEE. The next step involves AHP and RM, assigning weights to the thematic classes for classification. In phase 3, we utilise the overlap tool in GIS with varying weights of the two methods to create a flood sensitivity map and then compare the results from both methods. The last step involves verifying the results using the actual flood map through SNAP/GIS. The entire process of developing a flood susceptibility map for the Ca river basin is illustrated in Fig. 2.

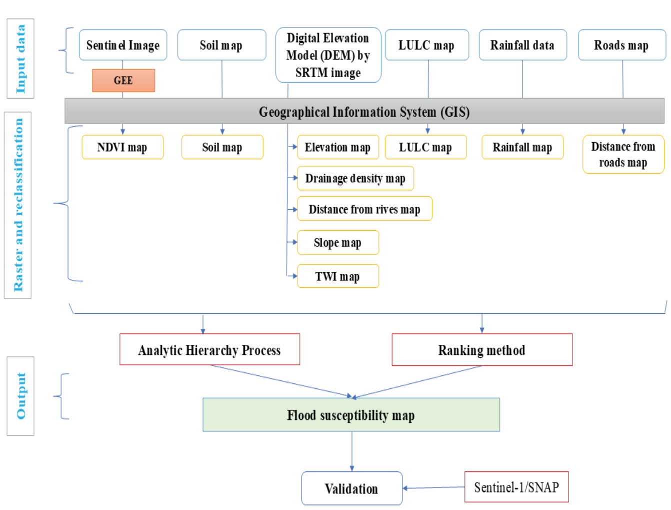

Fig. 2. Flowchart showing the methodology used in this study.

Each river basin has unique hydrometeorological, geological, and soil conditions, which influence the selection of factors affecting floods. In the case of this study, the Ca river basin extends in a northwest-southeast direction, with a gradual slope toward the East Sea. The characteristics of flood formation in the Ca river basin are primarily influenced by widespread heavy rainfall, coupled with the terrain features that lead to an uneven distribution of rainfall [15]. Rainfall is the primary factor contributing to floods in the Ca river basin as a whole, and particularly in the downstream areas [20, 21]. Prolonged heavy rainfall over a large area, combined with the basin's slope and river network, are the primary drivers of major floods in the Ca river basin [21]. Most of the terrain in the region is highly fragmented, featuring rivers and streams with steep gradients. The midland transition zone between the mountains and plains is relatively short, causing floodwaters to concentrate rapidly during heavy rainfall. This lack of natural regulation results in floodwaters flowing swiftly to the plains, where they often coincide with heavy downstream rain and high tides, leading to widespread flooding [22]. It is evident that the selection of factors influencing floods in the Ca river basin, based on available data conditions, is quite appropriate.

Many remote sensing data sources and other datasets have been gathered to aid in constructing flood susceptibility maps in the Ca river basin. SRTM DEM data is then selected to generate the topographical map and compute catchment parameters. Sentinel-2 is used on the GEE platform to create NDVI maps (Table 1).

Table 1. Datasets used for flood susceptibility mapping.

Data	Resolution/ Scale	Source	Relevance	Data availability statement
Rainfall data	30 years (1986-2015)	Vietnam Meteorological and Hydrological Administration	Average rainfall	
Shuttle radar topography mission (Digital elevation model)	30 m	https://earthexplorer.usgs.gov/	Elevation; Slope; Topographic Wetness index; Drainage density; Distance from rivers	
Sentinel-2	10 m	https://livingatlas.arcgis.com/landcover/	Land use/Land cover	October 11 2023
Sentinel-2	10 m	https://code.earthengine.google.com	Normalised difference vegetation index	
Soil type data	-	https://www.fao.org/	Soil type	
Roads	-	https://data.opendevelopmentmekong.net	Distance from roads	
Sentinel-1	10 m	https://scihub.copernicus.eu/dhus/#/home	Flood map	

Rainfall data, spanning 30 years (1986-2015), were collected from the Vietnam Meteorological and Hydrological Administration, providing a sufficiently long dataset for evaluation. The SRTM DEM has been widely utilised in various studies to determine elevation, slope, and the TWI [23-25]. The SRTM demonstrates higher accuracy compared to several other DEMs, including ASTER GDEM2, GMTED2010, EarthEnv-DEM90, and GTOPO30 [23]. Utilising deep learning and cloud computing advancements on 10m-resolution Sentinel-2 data enables the creation of a global LULC map with enhanced accuracy [26]. Flood monitoring with Sentinel-1 SAR has been conducted through various case studies [11, 27, 28]. The flash flood hazard maps will be compared with the flood hazard maps of a typical flood event through the SNAP.

2.3. Geospatial layers for flood susceptibility mapping

Topographic wetness index refers to the topographic humidity index. It is commonly used to quantify topographic control over hydrological processes. High values of TWI indicate favourable conditions for water accumulation and runoff. A high TWI value suggests a low quantity of drainage, representing more saturated soil, which can lead to flooding [3]. TWI is calculated using the formula in Eq. 1 [3].

$$\text{TWI} = \text{Ln}\ (\alpha/\tan\beta) \quad (1)$$

where α is the cumulative flow value and β is the slope value.

2.3.1. Slope

Topographic slope and morphological patterns of flood slopes are decisive factors for flow direction and water concentration time, which directly affect the risk of flood formation. Areas with low slopes (lowlands) have a high probability of flooding due to the stagnation of large amounts of water, leading to severe flooding [2].

2.3.2. Elevation

Lowland morphology is highly susceptible to flooding, while higher terrestrial areas are less susceptible. Low-lying areas are more likely to be flooded because water is more likely to flow to low-lying areas than to high-lying areas.

2.3.3. Rainfall

Rainfall is an important climatic factor that affects the frequency of flood occurrence [29]. The greater the rainfall, the stronger the flow and the higher the flood intensity. In addition, in the delta, specifically river mouths adjacent to the sea, high tides exacerbate flooding. The wider the area, the slower the flood flow will rise and recede, whereas if the basin is narrow and elongated, the flood flow will rise faster.

2.3.4. Land use/land cover

The role of land use types in flow and flood studies is very important. In nature, the ability to regulate water varies among different land types, but in the exploitation of land for economic development due to human impact, each type of land use has a different capacity to regulate water.

2.3.5. Normalised difference vegetation index

The NDVI is a measure of an area's vegetation characteristics that affect both surface runoff and the permeation capacity of an area. This study used Sentinel-2 images and calculated the NDVI index as described in Eq. 2 [30].

$$NDVI = (\text{Band 8 - Band 4})/(\text{Band 8 + Band 4}) \quad (2)$$

Google earth engine is a cloud-based platform specifically developed for processing satellite imagery and other geospatial and observational data. It offers access to a vast repository of satellite imagery and provides the computational power necessary for detailed image analysis. The NDVI map for 2022 has been constructed for the Ca river basin on the GEE platform.

2.3.6. Distance from rivers

Floods often occur near riverbanks and inundate floodplains. The distance from the river significantly impacts the flood and its intensity.

2.3.7. Distance from roads

Roads are impermeable and quickly create runoff or inundation during floods, so areas near them are prone to flooding.

2.3.8. Drainage density

Drainage density affects flooding during rainy periods. Sites with high drainage density are less prone to flooding than areas with low drainage density [5].

2.3.9. Soil

Soil acts as a mediator between climate and flow. An area's susceptibility to flooding is influenced by its soil type and structure, which determine its water retention and permeability characteristics. Clay soils are more likely to experience faster and greater runoff from intense rainfall than sandy soils.

Factor classes are frequently determined by expert knowledge, the characteristics, and the level of each factor affecting floods, as mentioned above, as well as the specific characteristics of each region and basin (Table 2). Each flood-related factor has been selected and calculated, and

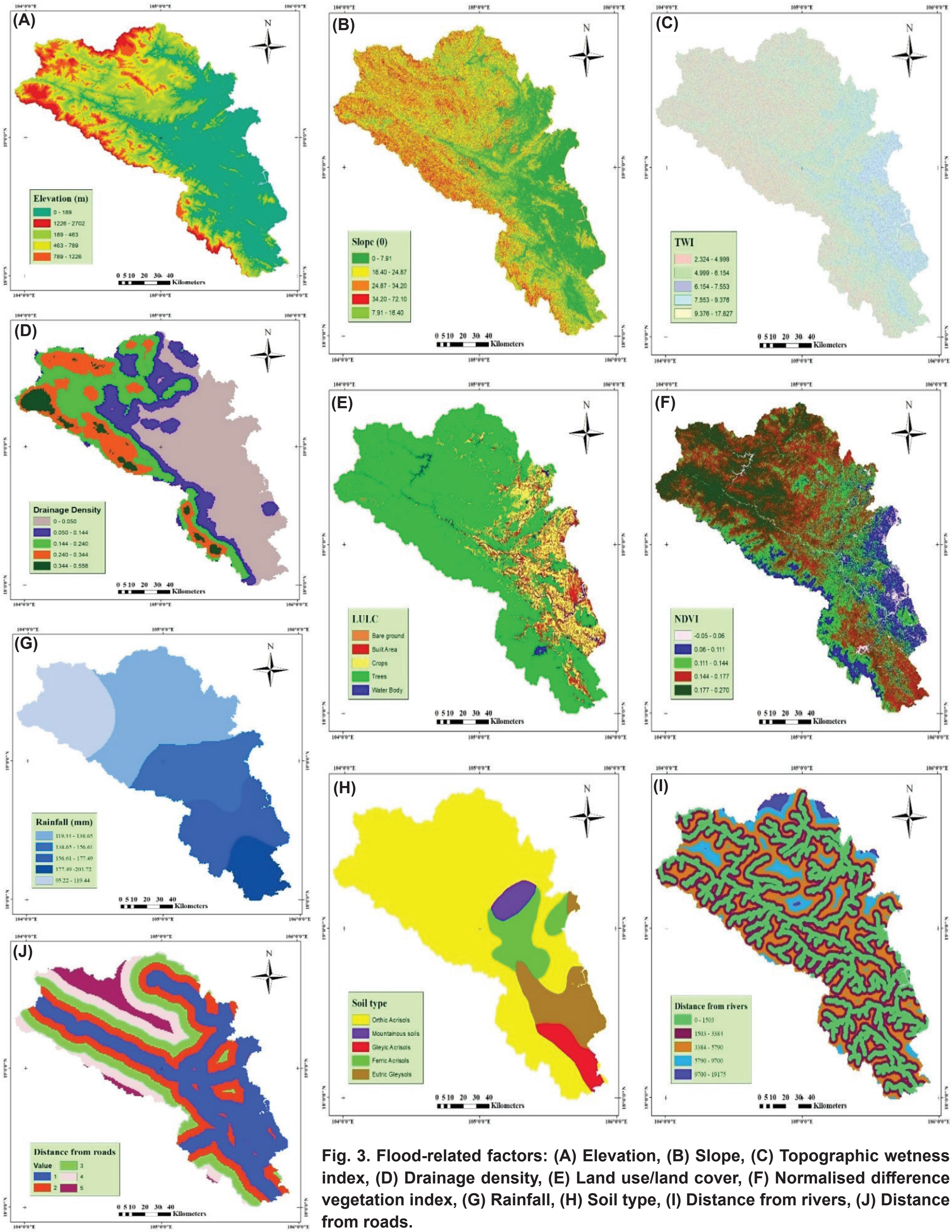

Fig. 3. Flood-related factors: (A) Elevation, (B) Slope, (C) Topographic wetness index, (D) Drainage density, (E) Land use/land cover, (F) Normalised difference vegetation index, (G) Rainfall, (H) Soil type, (I) Distance from rivers, (J) Distance from roads.

within each factor, it is divided into five classes using the Reclassify tool in ArcGIS. Each element is categorised into classes, with each element further divided into five layers based on its susceptibility to flooding, as shown in Fig. 3. These layers are categorised into five levels of susceptibility: very high (5 points), high (4 points), moderate (3 points), low (2 points), and very low (1 point).

Table 2. Flood related factors, including respective classes and rating.

Factors	Factor's classes	Importance of factor classes	Factors	Factor's classes	Importance of factor classes
Topographic wetness index	2.324-4.999	1	Normalised difference vegetation index	-0.05-0.06	5
	4.999-6.154	2		0.06-0.111	4
	6.154-7.553	3		0.111-0.144	3
	7.553-9.376	4		0.144-0.177	2
	9.376-17.827	5		0.177-0.270	1
Elevation (m)	0-189	5	Distance from rivers (m)	0-1503	5
	189-463	4		1503-3384	4
	463-789	3		3384-5790	3
	1226-2702	2		5790-9700	2
	1226-2702	1		9700-19175	1
Slope (%)	0-7.91	5	Distance from roads (km)	5	5
	7.91-16.40	4		10	4
	16.40-24.87	3		15	3
	24.87-34.20	2		20	2
	34.20-72.10	1		>20	1
Rainfall (mm)	95.22-119.44	1	Drainage density (km/km^2)	0-0.050	1
	119.44-138.65	2		0.050-0.144	2
	138.65-156.61	3		0.144-0.240	3
	156.61-177.49	4		0.240-0.344	4
	177.49-201.72	5		0.344-0.558	5
Land use/land cover	Waterbody	5	Soil type	Orthic acrisols	1
	Crops	4		Ferric acrisols	2
	Built area	3		Mountainous soils	3
	Bare ground	2		Gleyic acrisols	4
	Trees	1		Eutric gleysols	5

2.4. Analytic hierarchy process

In the early 1970s, R.W. Saaty (1987) [4] developed a decision-making method known as the AHP to address multidisciplinary decision-making problems and complex standards. AHP is often used to rank factors based on expert opinions, which can introduce some uncertainties [3]. As presented above, this study selected 10 factors influencing floods for flood susceptibility mapping. To apply the AHP method, the following key steps are carried out. First, the decision-making problem is broken down into individual factors. These factors are then arranged hierarchically based on their importance. Numerical values are assigned to each component to reflect their relevance in the decision-making process.

A comparison matrix is built to analyse the relationships between the components. Finally, the normalised eigenvector is computed to determine the weights of each component, guiding the decision-making process in a systematic and logical manner [31]. The importance of each criterion is assessed based on its contribution to flood susceptibility, with its weighting determined by an AHP PCM. R.W. Saaty (1987) [4] concluded that a PCM method was used to construct weighting factors for individual criteria by applying a ranking scale. This method was also used to estimate and assess a random consistency index. The significance of each criterion is assessed according to its influence on flood susceptibility, as determined by an AHP PCM. R.W. Saaty (1987) [4] introduced a PCM method for establishing weighting factors for individual criteria through a ranking scale, which was evaluated using a random consistency index. The average random index (RI) varies depending on the number of factors or the order of the matrix (Table 3). The consistency ratio (CR) is defined for validation (Eq. 3) [4, 19].

$$\mathrm{CR} = \frac{CI}{RI} \tag{3}$$

To validate the weightage, if CR=0, the matrix is consistent; however, a value greater than 0 indicates inconsistency. The CR value should be less than 0.1; if it exceeds this threshold, the weights of the comparison matrix must be recalculated. The researchers employed an approximation technique to compute the final weights and normalised the PCM using the consistency index (CI) ratio. The following equation was used to calculate CI (Eq. 4) [4, 19].

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n-1} \tag{4}$$

where λ is the average value of the consistency vector; n is the number of criteria; and RI is the random CI for a randomly generated PCM. The RI can be accessed from the table of random inconsistency indices.

Table 3. Randon consistency index [19].

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

RI: The random CI for a randomly generated PCM.

2.5. Ranking method

In the RM, decision makers prioritise factors or criteria based on their perceived importance. Coefficient values for each assessment unit are calculated according to the assessed significance of flood hazards. The ranking sum method is used to determine the flood risk index (RI) after assigning a weight to each factor, which is a sensitive index. The normalised weight for each key factor is assigned and normalised using the rank sum and is calculated as (Eq. 5) [32].

$$W = n - r_j + 1 \tag{5}$$

where n is the number of criteria being considered (k=1,2,..., n) and r_j is the ranking position of the criteria.

Each criterion has a weight of $n - r_j + 1$ and then normalised by the weighted sum, specifically: $\sum(n-r_k+1)$. The normalised weight W_j of criterion j is calculated (Eq. 6) [32].

$$W_j = \frac{n - r_j + 1}{\sum(n-r_k+1)} \tag{6}$$

The total weight to estimate flood risk in a specific area is equal to the sum of each factor calculated as follows (Eq. 7) [32].

$$R = \sum(C_1W_{1,j} + C_2W_{2,j} + C_3W_{3,j} + C_4W_{4,j} + C_5W_{5,j}) \tag{7}$$

where C_1, C_2, C_3, C_4 and C_5 are the criteria corresponding to $C_1W_{1,j}$, $C_2W_{2,j}$, $C_3W_{3,j}$, $C_4W_{4,j}$, $C_5W_{5,j}$, normalised weight of each criteria.

3. Results and discussion

3.1. Flood susceptibility mapping

3.1.1. The weight given to the factors of methods

The AHP method: As presented above, the study considered ten main influencing factors related to flood susceptibility (TWI, Slope, Elevation, Rainfall, LULC, NDVI, drainage density, soil type, distance from roads, and distance from rivers). For the AHP method, a pairwise comparison matrix is performed. The rows reflect the inverse score of each factor and its importance relative to other factors, as shown in Table 4.

Table 4. Comparison matrix and the relative score of each factor.

Criteria	TWI	Elevation	Slope	Rainfall	LULC	NDVI	Distance from rivers	Distance from roads	Drainage density	Soil type
TWI	1	1	1	1	3	3	1	3	1	2
Elevation	1	1	1	1	3	3	2	3	1	1
Slope	1	1	1	1	3	2	2	3	1	1
Rainfall	1	1	1	1	3	3	1	3	2	2
Land use	1/3	1/3	1/3	1/3	1	1	2	2	1	1
NDVI	1/3	1/3	1/2	1/3	1	1	2	2	1	1
Distance from rivers	1	1/2	1/2	1	1/2	1/2	1	2	1	1
Distance from roads	1/3	1/3	1/3	1/3	1/2	1/2	1/2	1	2	2
Drainage density	1	1	1	1/2	1	1	1	1/2	1	1
Soil type	1/2	1	1	1/2	1	1	1	1/2	1	1

TWI: Topographic wetness index, LULC: Land use/cover, NDVI: Normalised difference vegetation index.

The weights of the factors are determined based on the comparison matrix. Through weighting, we can ascertain the importance of each factor in affecting the research problem (Table 4). Table 5 shows the importance of factors according to the AHP method. The results in Table 5 indicate that rainfall (14.6%) is the most important factor in determining flood-sensitive areas. Following rainfall are TWI (13.8%), elevation (13.8%), slope (13.2%), drainage density (8.3%), distance from rivers (7.9%), soil type (7.7%), NDVI (7.4%), LULC (7.2%), and distance from roads (6.3%).

Table 5. Weight given to the factors according to the analytic hierarchy process method.

Criteria	Weight	Criteria	Weight
Topographic wetness index	0.138	Normalised difference vegetation index	0.074
Elevation	0.138	Distance from rivers	0.079
Slope	0.132	Distance from roads	0.063
Rainfall	0.146	Drainage density	0.083
Land use/land cover	0.072	Soil type	0.077

The Central region is characterised by its long coastline and heavy rainfall, resulting in an average of more than 10 major floods per year [33]. Natural disasters are expected to become more severe due to a combination of extreme weather and hydrological conditions, such as the impact of storms, short concentration times, and the steep slopes of

Table 6. Weight given to the factors according to the ranking method.

Factors	Ranking	Weight (W)	The normalised weight (W_j)	Percentage (%)
Rainfall	1	10	0.182	18.18
Topographic wetness index	2	9	0.164	16.36
Slope	3	8	0.145	14.55
Elevation	4	7	0.127	12.73
Drainage density	5	6	0.109	10.91
Soil type	6	5	0.091	9.09
Distance from rivers	7	4	0.073	7.27
Land use/land cover	8	3	0.055	5.45
Normalised difference vegetation index	9	2	0.036	3.64
Distance from roads	10	1	0.018	1.82

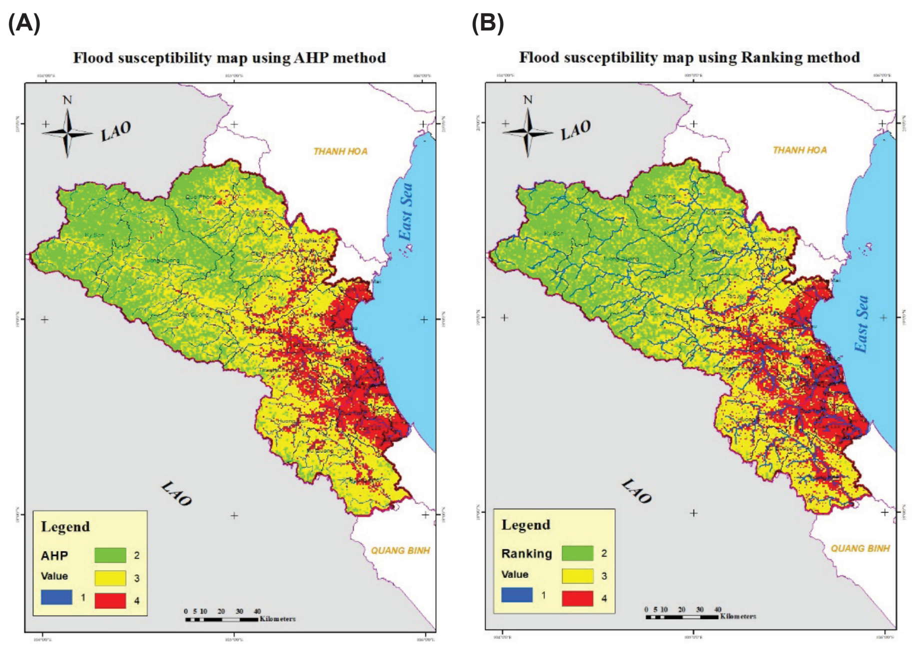

Fig. 4. Flood susceptibility map using (A) analytic hierarchy process method and (B) ranking method.

upstream rivers and downstream flood plains [34]. Along with the assessment above and considering the actual conditions in the study area and Vietnam, the contribution rate of the factors in determining flood-sensitive areas is quite reasonable.

When determining the weights of the adaptive factors, the parameters of the comparison matrix are established to verify the accuracy of the expert opinion. With a CR value of 0.06<0.1, these weights are accepted.

Ranking method: The importance of each criterion in relation to other criteria can be demonstrated through weighting according to criteria. If ordinal information on the importance of criteria is available, the RM is utilised.

Based on the results from the two tables using the AHP and RM, significant differences can be observed in the evaluation of factors. With the AHP method, the priority order is determined more precisely through the use of pairwise comparison matrices, allowing for an assessment of the relative importance among factors (Table 6). Factors such as "Rainfall", "Topographic wetness index", and "Slope" have higher weights, but the differences in weights are more evenly distributed, reflecting a comprehensive analysis. In contrast, the RM focuses on directly prioritising the factors, with weights more distinctly separated and a sharper decline between the most important and the least important factors. While this method is quicker and simpler, it lacks the detailed assessment of inter-factor relationships. Therefore, AHP is more suitable for in-depth analysis and deriving precise weights, whereas ranking is more appropriate for situations requiring quick evaluations based on priority levels.

3.1.2 Flood susceptibility mapping

The final map was produced by integrating the AHP method and RM, which considered ten factors and categorised them into five classes using the equal interval technique within the ArcGIS environment, as shown in Fig. 4.

Four levels of flood susceptibility were identified in the findings: low, moderate, high, and very high (Table 7).

Table 7. Degree of flood susceptibility.

Ranking	Level	Analytic hierarchy process method	Ranking method
1	Low	0.03	0.03
2	Moderate	30.48	30.31
3	High	52.68	50.85
4	Very high	16.81	18.81

The results indicate the similarity between the two methods in identifying areas prone to flooding. The portion of the basin area susceptible to floods is notably higher with the RM method at 18.81% compared to 16.81% with the AHP method. The flood-sensitive area for low and medium floods is nearly identical between the two methods. Both approaches indicated that the downstream area of the Ca river basin is prone to flooding, including Can Loc, Duc Tho, Loc Ha, Thach Ha, Huong Khe, Do Luong, Hung Nguyen, Thanh Chuong, and Nam Dan districts (before 1st July 2025).

These results are also quite similar to previous studies in this basin using the AHP method, with six factors selected, including Rainfall, Soil, Slope, Land cover, Drainage density, and Relative slope length, in highly sensitive areas such as Can Loc, Thach Ha, Thanh Chuong, Huong Son, Vu Quang, Huong Khe, and Nam Dan districts (before 1st July 2025) [35]. Both studies determined that the factors greatly influencing flood sensitivity are rainfall and slope. However, there are some differences between this study and previous studies, mainly the selection of more factors affecting floods, such as TWI, NDVI, Elevation, Distance from rivers, and Distance from roads. By integrating and evaluating many factors, the level of detail, specificity, and accuracy of each flood-sensitive area is displayed on the map.

The results are also quite consistent with studies on hydraulic models in the Ca river basin, focusing on calculating the amount of rain causing flooding in the Ca river basin in the following cases: starting to flood, flooding at alarming levels 2 and 3 under natural conditions, and with the operation of the reservoir system [16]. One of the advantages of hydraulic modelling is that it can include structures and reservoir systems in the basin to simulate and concentrate the formation of floods on the river. However, in this study, identifying factors that form floods is an advantage and is also a quick assessment method, with spatial factors given more attention.

Hydraulic models are useful for determining flood characteristics such as velocity and duration, but they often assume that water flows freely from rivers. In reality, however, rainfall is concentrated over fields, leading to flooding within the levee system. This assumption reduces the accuracy of the model, often resulting in predicted flood areas that are lower than actual areas. The accuracy of the model depends heavily on the quality of the input data, and simulating the entire hydraulic system is both complex and costly [13]. The results of constructing flood susceptibility maps using the AHP and RM show that the flood area is larger than that predicted by the modelling method. This aligns with the limitations of the hydraulic model in the study by V.A. Truong, et al. (2021) [13] on the downstream of the Ca river. Considering multiple influencing factors has enhanced the accuracy of identifying flood-risk areas.

3.2. Validation with Sentinel-1

The Central region flood of 2020 (also known as the historic flood) was a storm and flood that affected Central Vietnam from the night of 6 October 2020 to 1 December 2020. It mainly impacted the provinces of Thanh Hoa, Nghe An, Ha Tinh, Quang Binh, Quang Tri, and Thua Thien Hue in the North Central region, as well as parts of the South Central

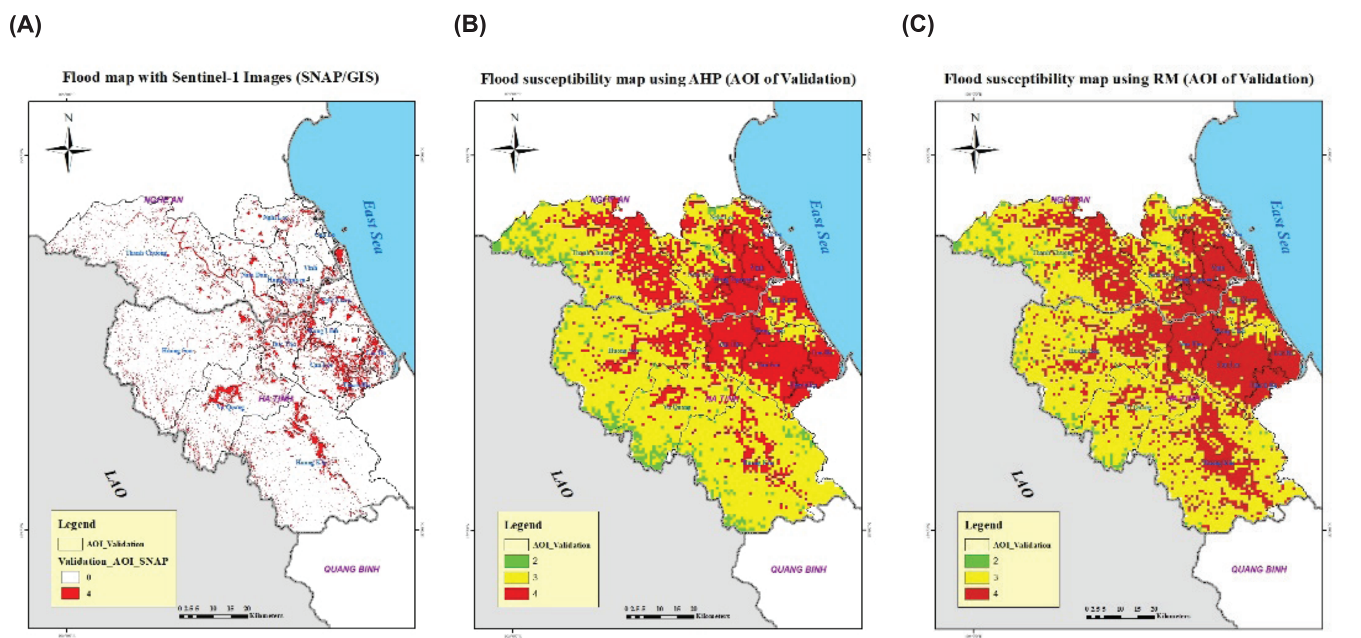

Fig. 5. (A) Flood map with Sentinel-1 images, and (B, C) Flood susceptibility map using analytic hierarchy process and ranking methods, respectively.

region including Da Nang, Quang Nam, Quang Ngai, Binh Dinh, Phu Yen, and the Northern Central Highlands (before 1st July 2025).

To enhance result accuracy, the study gathered Sentinel-1 images during heavy rainfall in the Ca river basin on 18 October 2020. Sentinel-1, a product of the European Space Agency, is used to identify flood patterns. Sentinel-1 contributes to flood mapping due to the sensitivity of its backscatter signal to open water [14]. SNAP software was employed to estimate VV (co-polarisation) and VH (cross-polarisation) backscatter values (dB) for both pre- and post-flood scenarios using a thresholding method. Together with QGIS software, SNAP generated a flood map of the Ca river basin for comparison with the flood susceptibility map (Fig. 5).

The findings from the comparative analysis of the three maps indicate that significant instances of major flooding occur in the vicinity where the rivers traverse. The results show the similarity between the two maps and the accuracy of the flood susceptibility map. This validates and enhances the effectiveness of using AHP and Ranking methods in combination with GIS techniques for flood susceptibility mapping in the study area. However, it is evident that flood susceptibility maps produced using the AHP and ranking methods display larger flood-prone areas compared to those derived from Sentinel-1 imagery. The accuracy could be enhanced by improving the quality of input data. Additionally, the flood map generated from Sentinel-1 images is limited by temporal constraints, as the data may not capture the peak flood period.

4. Conclusions

The final flood susceptibility map was prepared using the AHP method and RM combined with remote sensing and GIS techniques. Two different approaches, the standardisation and classification of criteria, were applied to construct flood susceptibility maps. Ten factors influencing flooding were considered for mapping flood-susceptible areas: TWI, elevation, slope, rainfall, LULC, NDVI, DD, soil type, distance from rivers, and distance from roads. The final flood susceptibility map was validated using the October 2020 flood map through the SNAP-GIS/RS technique. The two methods show similar results for areas likely to experience flooding. The area highly sensitive to floods, according to both methods, ranges from 16.81 to 18.81% and is mainly concentrated in the lower part of the Ca river basin, including the Can Loc, Duc Tho, Loc Ha, Huong Khe, Do Luong, and Nam Dan districts (before 1st July 2025).

Choosing methods and approaches to evaluate flood sensitivity is a complex task because of the unique data characteristics in each study, as well as the subjective nature of selecting criteria. The criteria and weights of the factors also need to be carefully considered. Improving the quality of the input data source and incorporating additional physical factors in the future will enhance the output quality of the map. The accuracy of the map results is highly dependent on the quality of input data. In this study, the SRTM 30m DEM data source, which is freely available, was used; however, many factors influencing flooding rely on DEM data. This suggests that future studies could benefit from higher-resolution data, such as DEM from LiDAR. Additionally, more accurate data sources for factors like LULC and soil properties could further improve the results. This study demonstrates the potential of integrating AHP method and RM with GIS/RS for evaluating flood vulnerability.

The results of the study can be useful for other research in understanding the impact of factors affecting floods in space and can also serve as a reference in the prevention and mitigation of natural disasters in the Ca river basin, especially in the downstream areas.

CRediT author statement

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COMPETING INTERESTS

The authors declare that there is no conflict of interest regarding the publication of this article.

REFERENCES

[1] S. Begum, M.J. Stive, J.W. Hall (2007), *Flood Risk Management in Europe: Innovation in Policy and Practice*, Springer Dordrecht, DOI: 10.1007/978-1-4020-4200-3.

[2] S.A.A.E. Magd, R.A. Amer, A. Embaby (2020), “Multi-criteria decision-making for the analysis of flash floods: A case study of Awlad Toq-Sherq, Southeast Sohag, Egypt”, *Journal of African Earth Sciences*, **162**, DOI: 10.1016/j.jafrearsci.2019.103709.

[3] K.C. Swain, C. Singha, L. Nayak (2020), “Flood susceptibility mapping through the GIS-AHP technique using the cloud”, *ISPRS Int. J. Geo-Inf.*, **9(12)**, DOI: 10.3390/ijgi9120720.

[4] R.W. Saaty (1987), "The analytic hierarchy process - what it is and how it is used", *Mathematical Modelling*, **9(3-5)**, pp.161-176, DOI: 10.1016/0270-0255(87)90473-8.

[5] C. Fountzoula, K. Aravossis (2021), "Analytic hierarchy process and its applications in the public sector: A review", *Academy of Accounting and Financial Studies Journal*, **25(6)**, pp.1-15.

[6] M. Vojtek, J.J.W. Vojteková (2019), "Flood susceptibility mapping on a national scale in Slovakia using the analytical hierarchy process", *Water*, **11(2)**, DOI: 10.3390/w11020364.

[7] S. Yahaya, N. Ahmad, R. Abdalla (2010), "Multicriteria analysis for flood vulnerable areas in Hadejia-Jama'are river basin, Nigeria", *European Journal of Scientific Research*, **42(1)**, pp.71-83.

[8] G. Yalcin, Z. Akyurek (2004), "Analysing flood vulnerable areas with multicriteria evaluation", *20th ISPRS Congress*, pp.359-364.

[9] F.C. Conde, M.D.M. Muñoz (2019), "Flood monitoring based on the study of Sentinel-1 SAR images: The Ebro river case study", *Water*, **11(12)**, DOI: 10.3390/w11122454.

[10] T. Klein, M. Nilsson, A. Persson, et al. (2017), "From open data to open analyses - New opportunities for environmental applications?", *Environments*, **4(2)**, DOI: 10.3390/environments4020032.

[11] F. Roth, B.B. Marschallinger, M.E. Tupas, et al. (2022), "Sentinel-1 based analysis of the Pakistan flood in 2022", *EGUsphere*, DOI: 10.5194/egusphere-2022-1061.

[12] M. Singha, J. Dong, S. Sarmah, et al. (2020), "Identifying floods and flood-affected paddy rice fields in Bangladesh based on Sentinel-1 imagery and Google earth engine", *ISPRS Journal of Photogrammetry and Remote Sensing*, **166**, pp.278-293, DOI: 10.1016/j.isprsjprs.2020.06.011.

[13] V.A. Truong, A.Q. Duong, N.Q. Bui, et al. (2021), "The advantage of using satellite data together with the hydraulic model in flood hazard assessment: A case study in Ca river downstream", *Vietnam Journal of Hydrometeorology*, **8(8)**, pp.28-43, DOI: 10.36335/VNJHM.2021(8).28-43 (in Vietnamese).

[14] X.H. Le, L.N. Van, G.V. Nguyen, et al. (2023), "Towards an efficient streamflow forecasting method for event-scales in Ca river basin, Vietnam", *Journal of Hydrology: Regional Studies*, **46**, DOI: 10.1016/j.ejrh.2023.101328.

[15] T.D. Thien, L.T.H. Linh (2023), "Assessing flooding features for reservoir flood prevention in Ca river", *Environment Magazine*, **I**, pp.73-76 (in Vietnamese).

[16] N.X. Tien, N.T. Son, N.V. Linh (2020), "Application of hydrologic and hydraulic modeling for flood inundation simulation on downstream of the Ca river", *Vietnam Journal of Hydrometeorology*, **710(2)**, pp.1-13, DOI: 10.36335/VNJHM.2020(710).1-13.

[17] D.Q. Tri, Q.T.T. Tuyet (2016), "Effect of climate change on the salinity intrusion: Case study Ca river basin, Vietnam", *Journal of Climate Change*, **2(1)**, pp.91-101, DOI: 10.3233/JCC-160010.

[18] A. Beckers, B. Dewals, S. Erpicum, et al. (2013), "Contribution of land use changes to future flood damage along the river Meuse in the Walloon region", *Natural Hazards and Earth System Sciences*, **13(9)**, pp.2301-2318, DOI: 10.5194/nhess-13-2301-2013.

[19] T.L. Saaty, L.G. Vargas (2012), *Models, Methods, Concepts & Applications of The Analytic Hierarchy Process*, Springer New York, DOI: 10.1007/978-1-4614-3597-6.

[20] N.T. Son, T.N. Anh, D.D. Kha, et al. (2014), "Testing the impact assessment of climate change flooding in the downstream area of Lam river", *Journal of Hydrometeorology*, **645**, pp.13-20 (in Vietnamese).

[21] T.D. Kieu, L.D. Thanh (2011), "A study on signals and zoning potential of high flood on Lam river basin", *Journal of Water Resources and Environmental Engineering*, **34(9)**, pp.3-8 (in Vietnamese).

[22] Nghe An Province Department of Natural Resources and Environment (2023), *2-Way Model Reporting and 1&2-Way Connectivity*, 86pp (in Vietnamese).

[23] X. Li, Y. Zhang, X. Jin, et al. (2017), "Comparison of digital elevation models and relevant derived attributes", *Journal of Applied Remote Sensing*, **11(4)**, DOI: 10.1117/1.JRS.11.046027.

[24] M.S. Chowdhury (2023), "Modelling hydrological factors from DEM using GIS", *MethodsX*, **10**, DOI: 10.1016/j.mex.2023.102062.

[25] T.A. Tesema (2021), "Impact of identical digital elevation model resolution and sources on morphometric parameters of Tena watershed, Ethiopia", *Heliyon*, **7(11)**, DOI: 10.1016/j.heliyon.2021.e08345.

[26] K. Karra, C. Kontgis, Z.S. Weil, et al. (2021), "Global land use/land cover with Sentinel 2 and deep learning", *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, pp.4704-4707, DOI: 10.1109/IGARSS47720.2021.9553499.

[27] S.P. Dhanabalan, S.A. Rahaman, R. Jegankumar (2021), "Flood monitoring using Sentinel-1 sar data: A case study based on an event of 2018 and 2019 Southern part of Kerala", *The International Archives of The Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIV-M-3-2021, pp.37-41, DOI: 10.5194/isprs-archives-XLIV-M-3-2021-37-2021.

[28] B. Ghosh, S. Garg, M. Motagh, et al. (2024), "Automatic flood detection from Sentinel-1 data using a nested UNet model and a NASA benchmark dataset", *PFG - Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, **92(1)**, pp.1-18, DOI: 10.1007/s41064-024-00275-1.

[29] K. Dandapat, G.K. Panda (2017), "Flood vulnerability analysis and risk assessment using analytical hierarchy process", *Modeling Earth Systems and Environment*, **3**, pp.1627-1646, DOI: 10.1007/s40808-017-0388-7.

[30] O. Strashok, M. Ziemiańska, V. Strashok (2022), "Evaluation and correlation of Sentinel-2 NDVI and NDMI in Kyiv (2017-2021)", *Journal of Ecological Engineering*, **23(9)**, pp.212-218, DOI: 10.12911/22998993/151884.

[31] M.M. Msabi, M. Makonyo (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**, DOI: 10.1016/j.rsase.2020.100445.

[32] M. Blistanova, M. Zelenakova, P. Blistan, et al. (2016), "Assessment of flood vulnerability in Bodva river basin, Slovakia", *Acta Montanistica Slovaca*, **21(1)**, pp.19-28, DOI: 10.3390/ams21010019.

[33] M.P. Quang, K. Tallam (2022), "Predicting flood hazards in the Vietnam Central region: An artificial neural network approach", *Sustainability*, **14(19)**, DOI: 10.3390/su141911861.

[34] T.T. Vu, R. Ranzi (2017), "Flood risk assessment and coping capacity of floods in central Vietnam", *Journal of Hydro-environment Research*, **14**, pp.44-60, DOI: 10.1016/j.jher.2016.06.001.

[35] N.B. Dung, N.Q. Long, D.T. An, et al. (2021), "Multi-geospatial flood hazard modelling for a large and complex river basin with data sparsity: A case study of the Lam river basin, Vietnam", *Earth Systems and Environment*, **6**, pp.715-731, DOI: 10.1007/s41748-021-00215-8.