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GIS-BASED ANALYTICAL HIERARCHY PROCESS MODELING FOR FLOOD-PRONE AREA MAPPING IN VIETNAM

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ABSTRACT:

Flood is a more frequent natural hazard, having destroying effects on human life and property around the world. Water resource management strategies require understanding of the flood susceptibility. This study's objective is to develop an effective new approach to the construction of a flood susceptibility map (FSM) in the Nhat Le-Kien Giang River watershed in Vietnam, based on the analytical hierarchy process (AHP) technique. AHP was used to calculate the weighting of each of nine conditioning factors to build a flood susceptibility map. The results showed that the AHP technique would be successful in constructing a FSM with an AUC value of 0.95. The area of high and very high flood susceptibility in the residential area increased from 95 km² in 2005 to 251 km² in 2020. While the area of high and very high flood susceptibility in the agricultural area increased from 239 km² in 2005 to 245 km² in 2020. The findings of this study can support decision-makers and planners working in flood management and the development of mitigation strategies. Although the approach in this study has been applied to construct a flood susceptibility map for one area in Vietnam, it can be applied both to other types of natural hazards and in other countries.

Key-words: *Flood susceptibility, AHP, Nhat Le–Kien Giang River, Vietnam, flood management.*

1. INTRODUCTION

Flood is now the most common and the most damaging of natural hazards globally, with occurrences having increased by around 40% over the past two decades (Hirabayashi et al. 2013, Prasad et al. 2021). According the United Nations Office for Disaster Risk Reduction (UNISDR), 150,061 floods occurred globally between 1995 and 2016, causing approximately 157,000 deaths and affecting 200 million people every year (Towfiqul Islam et al. 2021, UNISDR 2015). Asia is particularly exposed: nine of the top ten countries affected by floods are Asian (Pham et al. 2020). In addition, Vietnam is often affected by major floods and typhoons every year, causing significant damage to people, agriculture, and housing. Although the Vietnamese government has focused on structural measures like dikes, dams, and early warning systems, flood prediction tools are still limited (Luu et al. 2021). Climate change combined with socio-economic growth has had a significant effect on flood and is set to further increase the risk of flood in the future (Costache 2019, Nachappa et al. 2020). Therefore, the assessment of FS is important steps when preparing management and mitigation strategies regarding future emergencies.

Various methods have been carried out by the global scientific community to construct flood susceptibility maps. Various studies have employed the MIKE hydraulic model (Patro et al. 2009, Tansar et al. 2020) and the SWAT model (Narsimlu et al. 2015, Rajib et al. 2020), which have both proven effective in analyzing the effects of flood on a given territory. However, these models utilized detailed field data such as river cross-river, meteorological, and hydrological data series, so they have mainly been applied in smaller regions with good data quality. In addition, the remote sensing and geographic information systems (GIS) in FSM have contributed to a variety of studies in the field (Dewan et al. 2007, Kabenge et al. 2017). However, flood usually occurs quickly, following bad weather, so in many cases the sensors cannot accurately identify flood time and are often affected by

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cloud cover. All of this prevents adequate monitoring. Although remote sensing and GIS can show the spatial distribution of flood, they are limited in their ability to detect the driving forces behind the flood. These models require further development or replacement with more powerful methods, to reduce the restrictions of hydrological models (Hostache 2010).

The causes of flood depend on natural conditions, and anthropogenic activities (Bui et al. 2020). We have reviewed several studies that employed AI methods to predict FS. They can be categorized two approaches: machine learning methods and expert knowledge. Identifying the correlations between these factors enables screening for suitable flood prediction models. Machine learning approaches include support vector machine (Tehrany et al. 2014), bagging (Chen et al. 2019), dagging (Yariyan et al. 2020), random forest (Chen et al. 2020, Lee et al. 2017), adaboost (Bui et al. 2016, Hong et al. 2018), artificial neural network (Falah et al. 2019, Khoirunisa et al. 2021), and K-nearest neighbor (Abu El-Magd et al. 2021, Ren et al. 2019). The calculation principle of these methods is very complex and involves a significant workload when applied to a large area. Moreover, the overfitting and global optimization problems are important limitations when using machine learning to construct flood susceptibility maps. A database management system has recently been integrated with decision support systems to build flood susceptibility maps. Multiple-criteria decision-making (MCDM) makes it possible to determine the optimal variables that influence the probability of flood occurrence (Nguyen et al. 2020). In particular, the analytical hierarchy process (AHP) is widely applied to comprehensively assess susceptibility. It is a simpler technique which can accurately determine flood-susceptible areas by careful evaluation of different influencing factors (Vojtek and Vojteková 2019a). This technique, particularly when combined with GIS, can take into account a large number of parameters in order to obtain precise results that closely represent reality. This method can be applied in large regions. Luu et al. (2020) used MCDM to assess the flood risk in Quang Binh Province in Vietnam. Das (2020) mapped susceptibility in the Western Ghat coastal belt in India utilizing AHP and multi-source geospatial data. Vojtek and Vojteková (2019a) also constructed a map for Western Ghat, using AHP and multi-source geospatial data, and used AHP and GIS to assess flood susceptibility in Slovakia. Dano (2020) used AHP to determine flood-susceptible areas and propose mitigation strategies in Jeddad in Saudi Arabia using expert judgements. However, there is no previous research in the study area that used expert opinion to analyze the factors causing flood. Expert opinion can support deciders to construct necessary strategies to reduce flood damage. Therefore, the application of the AHP method combined with GIS is appropriate for a medium-sized watershed such as Nhat Le‑Kien Giang, which lies in a humid tropical region that is characterized by rugged topography, high urban growth, and the effects of climate change.

The assessment of flood susceptibility in regions in the process of spatial planning has been an important part of previous research. It is particularly important in the context of urban growth. Spatial planning is a tool for managing adaptation to, and the effects of, climate change, as well as reducing the negative effects of flood. For developed areas, flood risk can be reduced by developing effective early warning systems and response and adaptation plans, while for developing areas, building restrictions in areas prone to flood is necessary for sustainable spatial planning.

This study aimed to identify the areas most vulnerable to flood in the Nhat Le‑Kien Giang River basin using AHP and GIS to reduce the consequences of flood. The novelty of this study is that the first time the flood susceptibility map is constructed in the Nhat Le – Kien Giang watershed using the AHP technique. This technique in this study can be applied in other regions in Vietnam. AHP will be established using the conditioning factors and the evaluation of their importance for the probability of flood occurrence. GIS facilitates the analysis and processing of spatial data, as well as facilitating the analysis and evaluation of the AHP results. This is the first time the proposed method has been used. The hypothesis is that the AHP technique would be successful in constructing the FSM. It was also hypothesized that the proportion of urban land in the high and very high flood susceptibility areas would increase. The findings of this study can be used to support planners in developing strategies for managing and mitigating flood risks in Vietnam and around the world.

2. MATERIALS AND METHODS

2.1. Study area and Flood inventory mapping

The Nhat Le-Kien Giang River basin in central Vietnam covers approximately 2,650 km^2 (**Fig. 1**) with the mean altitude about 234 m and the mean slope 20.7 m. The climate divided by the rainy season lasts from August to November and the dry season from December to July. The average annual precipitation is 2000‑2500 mm; however, 65‑70% is focused in the rainy season.

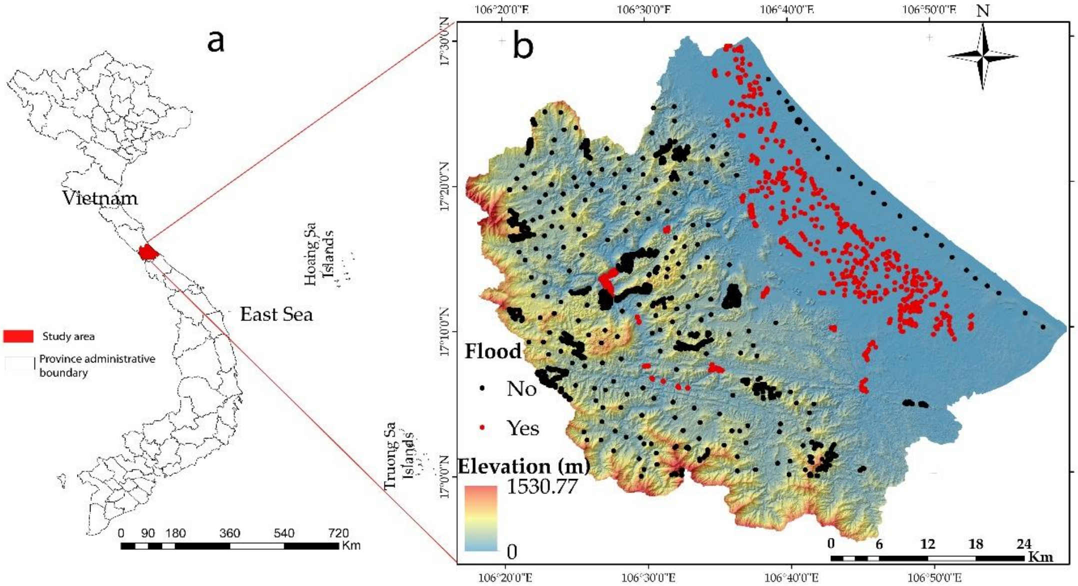

Fig. 1. – a) The location of the Nhat Le – Kien Giang basin in the Vietnam; b) The flood mark and the elevation of the Nhat Le – Kien Giang River basin.

Approximately 75% of the study area is covered by forest, although this coverage has been shrinking rapidly in recent years due to urban expansion, agricultural development, and illegal logging. This increases the likelihood of flood. The region was affected by three major floods in October 2020, which caused significant damage to property and loss of life (**Fig. 2**).

Fig. 2. – The flood marks in the Nhat Le – Kien Giang in 2020 (left) and 2013 (right). These flood marks were recorded by GPS with X and Y coordinates in 2015 and 2022 in Hong Thuy commune – Le Thuy district, Quang Binh, Vietnam. These are two historic floods in Vietnam, have significant effects on human life and the country's economy. *Source: Huu Duy Nguyen 2022 and 2015.*

Floods generally occur from September to November; this is also the period when extreme climatic events such as storms and tropical depressions occur. In many cases, floods occur in combination with these major flood events. Major floods in the study area, such as in 1999, 2010, 2013, 2016, 2020 and 2021 cause major material and human damage. The development of a GIS flood location database is a fundamental step in analyzing flood susceptibility. It shows an overview of the relationship between historical flood locations and input variables. In this study, flood locations were extracted from the Vietnam Disaster Management Authority archives. Flood marks were also collected from the field mission. In addition, to improve the accuracy of the method, flood samples were obtained using a Sentinel 1A image on 18 October 2020. In final, 502 flood samples were obtained in the basin. Also, to improve the quality of the FSM, 1462 non-flood points were selected in high-altitude areas which did not flood. All points were used to build flood inventory mapping using ArcGIS 10.4 software.

2.2. Flood conditioning factors

Conditioning factors play a crucial role in constructing a flood susceptibility model because they represent the connections between past flood events and topographical, climatic, hydrological, and anthropogenic conditions (Gudiyangada Nachappa et al. 2020, Nguyen et al. 2021). In this study, the conditioning factors were collected from sources such as official data from government organizations and remote sensing data. Nine conditioning factors were selected from the literature reviews: elevation, slope, aspect, curvature, rainfall, land use and land cover (LULC), normalized difference vegetation index (NDVI), distance to river, and distance to road (**Fig. 3**).

Elevation, slope, aspect, and curvature – at a resolution of 10m – were obtained from DEM, which was constructed using a 1/50,000 m topographical map. Distance to river and distance to road were extracted from a 1/50,000m topographic map, which is available from Ministry of Natural Resources and Environment of Vietnam. The Euclid Distance method in GIS was used to create the Distance to Road and Distance to River for the flood assessment. The LULC map is also available from this department. Rainfall was built from data collected from ten hydrological stations in the province. The IDW method in GIS was used for the interpolation of rainfall data to build the rainfall map. While NDVI was calculated from a Landsat 8 OLI map (disponible in https://earthexplorer.usgs.gov/). All these factors were analyzed spatial distribution and converted to GRID raster format with 10 m resolution using GIS. Each factor was reclassified and flood susceptibility impact was ranked from *very low* to *very high*, using the natural break method, on the ArcGIS platform (**Tab. 1**).

Table 1.

Flood susceptibility impact of each factor.

	Flood susceptibility level				
	Very low	**low**	**Moderate**	**High**	**Very high**
Elevation	> 728.79	469.5–728.79	270.51–469.5	101.67–270.51	0–101.67
Slope	> 37.5	27.32–37.57	17.36–27.32	6.8–17.36	0–6.8
Aspect	> 286.58	211.76–286.58	141.17–211.76	70.58–141.17	0–70.58
Curvature	> 1.88	0.42–1.88	-0.74–0.42	-2.2–(-0.74)	- 52–(-2.2)
Rainfall	< 2816.7	2816.7–2986.2	2986.2–3159.4	3159.4–3347.4	3347.4–3573
NDVI	> 0.55	0.36–0.55	0.13–0.36	-0.05–0.13	-0.3–(-0.05)
Distance to river	> 2641	1579.9–2641	896–1579.9	377.29 - 896	0–377.29
Distance to road	> 7952.5	4696.7–7952.5	2455.13–4696.7	907.33–2455.13	0–907.33
LULC	Forest	Barren	Agricultural	Urban	Water

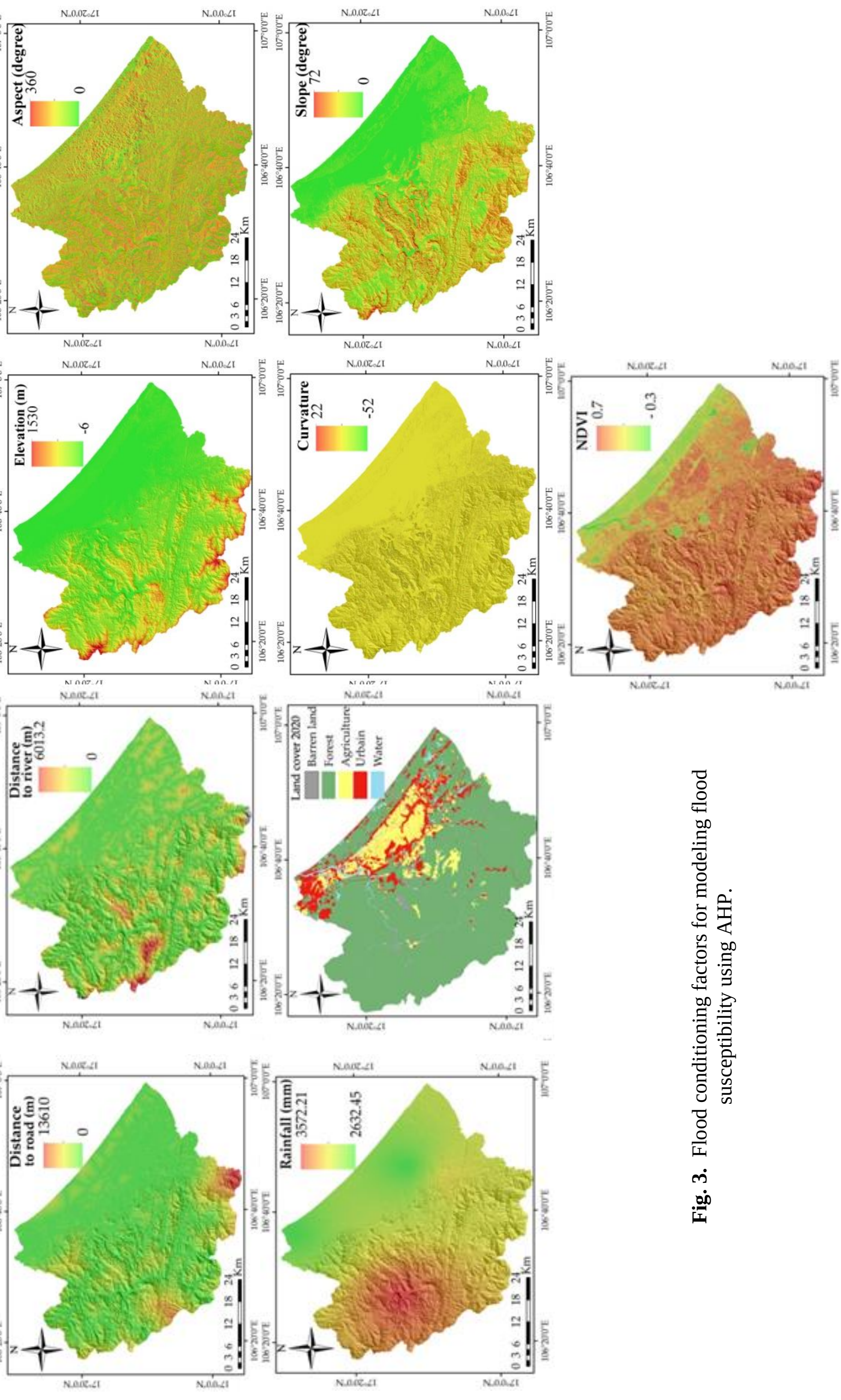

Fig. 3. Flood conditioning factors for modeling flood susceptibility using AHP.

It should be noted that areas with very low flood susceptibility is roped in by 1 and very high is roped in by 5. The natural break method is based on Jenk's optimization formulation to reduce the variability of each class. It generates clusters that have similar values separated by breakpoints and suits values that have been distributed irregularly or have a tendency to cluster at an end point in the distribution. The natural break method has been used in several previous studies on flood susceptibility. LULC was grouped by the spatial distribution and characterization of each type of LULC. It was classified as very low (forest), low (barren land), moderate (agriculture), high (urban) and very high (water). **Table 1** shows the impact of flood susceptibility of each factor.

3. ANALYTIC HIERARCHY PROCESS (AHP)

In this study, AHP was used to compute the weights of the criteria to build the FSM. The advantage of this method is the direct use of expert opinions, the simple integration of the GIS and the consistency of judgment. However, this method has general limitations related to subjective opinions in the evaluation. It is considered the limit in most MCDA methods.

AHP is the theoretical measure of tangible criteria, which was proposed by T. Saaty in 1980. The weights of the criteria were evaluated by pairwise comparison matrices. AHP can support decision-making processes by quantifying alternative priorities by decision makers. This technique has been widely applied in several fields such as economy, environment, transport. In recent years, it is applied in the study of flood susceptibility.

The AHP technique is carried out by four main steps: i) construction of the hierarchical model; ii) the construction of the matrices for the pairs for the criteria based on the subjective judgment of the experts; iii) calculation of criteria weights; iv) model consistency assessment.

i) Construction of the hierarchical model: In the Nhat Le – Kien Giang River basin, several factors influence the flood occurrence. These factors have been divided into four groups: Geo-environment, hydrology, climate and anthropogenic activity. So, nine factors elevation, rainfall, LULC, distance to river, NDVI, slope, aspect, curvature, and distance to road were selected for the hierarchical model.

ii) the construction of the matrices for the pairs based on the subjective judgment of the experts: nine factors conditionings are compared in pairs to calculate the weighting of each factor; the importance of each factor is measured on a scale of 1 to 9 (**Tab. 2**). The weights of the criteria in the AHP method have been evaluated based on the subjective judgment of several experts (Li et al. 2013) or on the experience of the author (Luu et al. 2020). In this study, we used the author's experience.

iii) calculation of the weights of the criteria: after the construction of the matrices for the pairs, several techniques are used to calculate the weights like normalization and vector. In this study, we applied the normalization technique (**Tab. 3**). It should be noted that the higher the weights of the criteria, the more the criteria influence the flood susceptibility.

Table 2.

Pair-wise comparison matrix.

Factors	Elevation	Rainfall	LULC	Distance to river	NDVI	Slope	Aspect	Curvature	Distance to road
Elevation	1	2	3	3	4	4	5	6	8
Rainfall	0.5	1	2	2	3	3	4	5	6
LULC	0.33	0.5	1	2	3	3	3	4	5
Distance to river	0.33	0.5	0.5	1	2	2	2	3	4
NDVI	0.25	0.33	0.33	0.5	1	2	2	2	3
Slope	0.25	0.33	0.33	0.5	0.5	1	2	2	2
Aspect	0.2	0.25	0.33	0.5	0.5	0.5	1	2	2
Curvature	0.16	0.2	0.25	0.33	0.5	0.5	0.5	1	2
Distance to road	0.125	0.16	0.2	0.25	0.33	0.33	0.5	0.5	1

Table 3.

Normalized factor weights

Factors	Elevation	Rainfall	LULC	Distance to river	NDVI	Slope	Aspect	Curvature	Distance to road	Weight (w_i)
Elevation	0.31	0.37	0.37	0.29	0.26	0.24	0.25	0.23	0.24	0.29
Rainfall	0.15	0.18	0.25	0.19	0.20	0.18	0.2	0.19	0.18	0.2
LULC	0.10	0.09	0.12	0.19	0.20	0.18	0.15	0.15	0.15	0.15
Distance to river	0.10	0.09	0.06	0.09	0.13	0.12	0.1	0.11	0.12	0.1
NDVI	0.07	0.06	0.04	0.04	0.06	0.12	0.1	0.07	0.09	0.08
Slope	0.07	0.06	0.04	0.04	0.03	0.06	0.1	0.07	0.06	0.06
Aspect	0.06	0.04	0.04	0.04	0.03	0.03	0.05	0.07	0.06	0.05
Curvature	0.05	0.03	0.03	0.03	0.03	0.03	0.025	0.03	0.06	0.04
Distance to road	0.03	0.03	0.02	0.02	0.02	0.02	0.025	0.01	0.03	0.03

iv) Model consistency assessment: Consistency ratio (CR) is used to examine consistency in expert judgment in the process of comparing factors. CR < 0.10 indicates acceptable consistency, while CR > 0.10 indicates inconsistency. It is measured by the following equation (Hammami et al. 2019):

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

The following equation calculates the consistency index (CI) (Hammami et al. 2019):

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

λ_{max} is the maximum eigenvalue of the pairwise comparison matrix (n x n). The maximum eigenvalue λ_{max} is always greater than or equal to the number of rows or columns n. The more consistent the rating, the closer the calculated value of λ_{max} is to n (Ghosh et al. 2018):

$$\lambda_{\max} = \sum_{i=1}^{n} wi \; * \; \sum_{j=1}^{n} a_{ii}$$

RI is a random index which depends on the number of factors used in the comparison matrix.

In this study, λ max = 9.26, CI = 0.03, RI = 1.54, and CR = 0.023 (satisfying < 0.10), meeting the requirements of the pairwise comparison matrix. The flood susceptibility map was constructed using the following equations

Finally, the flood susceptibility index (FSI) was measured by the following equation:

FSI = elevation*0.29 + rainfall*0.2 + LULC*0.15+ distance to river*0.1 + NDVI*0.08 + slope*0.06 + aspect*0.05 + curvature*0.04 + distance to road*0.03*

The FSI was generated by multiplying the weights for each factor and then totaling the results. It should be noted that each factor has been divided by five classes: 1-very low, 2-low, 3-moderate, 4-high and 5-very high. The process was done using ArcGIS Spatial Analyst's raster calculator. FSI was separated into five levels: very low, low, moderate, high and very high, using the natural break method.

4. RESULTS

4.1. Validation of flood susceptibility mapping

The receiver operating characteristic (ROC) was used to validate the AHP model. It was drawn by 1-specificity on the X-axis and sensitivity on the Y-axis (Janizadeh et al. 2019). The area under the receiver operating curve (AUC) represents the accuracy of the model. If the AUC value is 1, then the model is perfort (Choubin et al. 2019, Dodangeh et al. 2020). **Fig. 4** shows the ROC and AUC of the AHP model. In this study, 1964 flood and non-flood points were overlaid on the FSM in ArcGIS software to assess the accuracy of the FSM. The result indicates the model's acceptable precision (AUC = 0.95) for predicting flood susceptibility (**Fig. 4**).

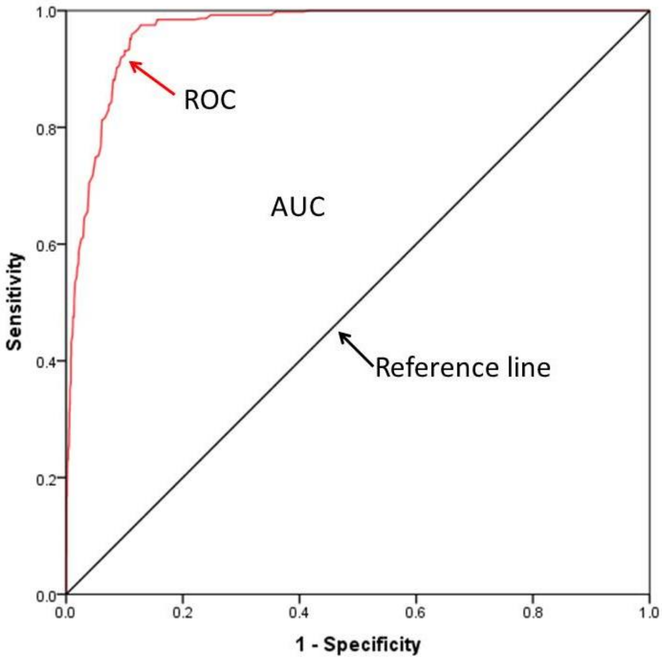

Fig. 4. ROC and AUC of the AHP model.

4.2. Flood susceptibility mapping

After the weighting calculation of all conditioning factors, the final FSM was produced using the AHP technique. The flood level was separated into five classes using the natural break method: very low, low, moderate, high, and very high (**Fig. 5**). The map was crossed with the land-use maps for 2005 and 2020 to understand the rate of each category of LULC corresponding to flood susceptibility levels (**Tab. 4**). Residential area in the high and very high flood susceptibility classes increased from 95 km² in 2005 to 251 km² in 2020. The area in the moderate class increased from 17.4 km² to 30.6 km² over the same period, with the low zone growing from 0.56 km² to 1.07 km². The agricultural area with very high flood susceptibility increased from 81.1 km² to 89.5 km².

On the other hand, in the high areas, these surfaces decreased from 164.2 km² to 150.3 km²; in the moderate areas, the fall was from 25.4 km² to 11.2 km²; and the low areas also saw a decline from 3.7 km² to 0.15 km². Regarding forested areas, the high and very high zone dropped from 638 km² to 610 km², the medium zone increased from 588 km² to 624 km², and surfaces in the low and very low zones increased 10 km².

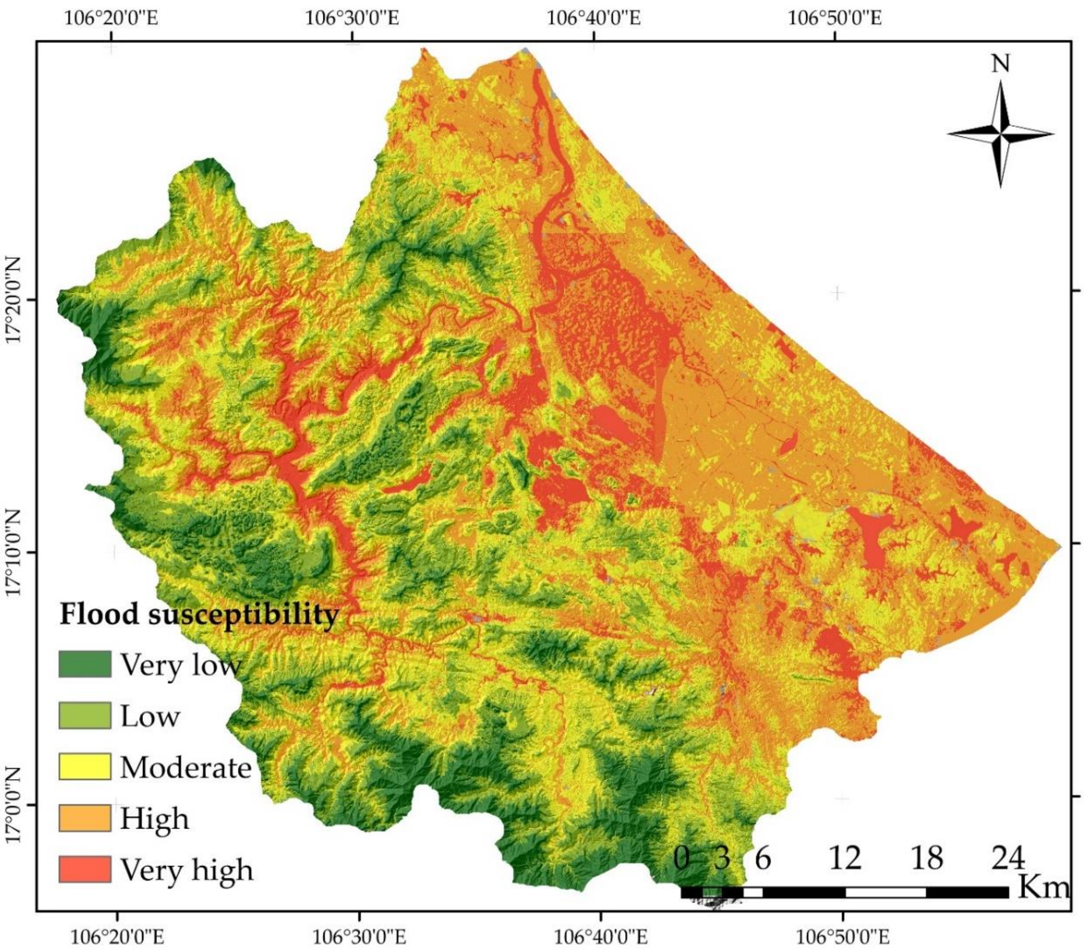

Fig. 5. Flood susceptibility in the Nhat Le–Kien Giang watershed.

Table 4.

LULC and their respective flood susceptibility classes.

	LULC	Flood susceptibility class				
		Very low (km²)	Low (km²)	Moderate (km²)	High (km²)	Very high (km²)
2020	**Agricultural**		0.15	11.2	150.3	89.5
	Residential	0.13	1.07	30.6	156.3	59
	Forest	227.5	496	623.9	532.9	77.9
2005	**Agricultural**	0	3.7	25.4	164.2	81.1
	Residential	0	0.56	17.4	77.1	18.1
	Forest	225.6	487.4	588	519.7	118.3

5. DISCUSSION

Flood is now the world's most dangerous natural hazard, both in terms of damage to humans and economies, and its impact is increasing as our climate changes (Khosravi et al. 2019). Although the number of studies on flood susceptibility has been increasing in Vietnam and around the world, there is still a lack of detailed research on flood susceptibility at the local level (Luu et al. 2020). Therefore, this study has developed a comprehensive approach to the construction of flood susceptibility maps, particularly in study area, using the AHP technique. The findings of this study can support planners in developing flood management and mitigation strategies.

Floods have significantly impacted the socio-economic conditions of the populations in the watershed and the wider Quang Binh province. A comprehensive approach to global and local flood management can reduce the negative effects of flood. Before a flood occurs, we can reduce risk and discuss mitigation activities in areas with high susceptibility to flood with the use of a highly accurate flood susceptibility map.

The residential area in the high and very high flood susceptibility zones increased. These areas are generally located in the littoral zone. This trend is typical of many regions around the world. Güneralp and Seto (2013) pointed out that around 40% of the world's cities will be in the high flood risk zone in 2030. Güneralp et al. (2015) anticipated that approximately 82% of the urban area of Southeast Asia would be located in areas with a high frequency of flood. Nguyen et al. (2018) reported that urbanization increased rapidly between 2003 and 2020 in the flood zone in Vietnam's Gianh River watershed. Abdelkarim et al. (2019) pointed out that urban expansion was increasingly rapid in Tabuk City, Saudi Arabia in the period 1975‐2018. Lin et al. (2020) calculated that the urban area would increase sharply between 2015 and 2050 in China's Pearl River Delta, especially in the flood zone. Our study provides further evidence of urban growth in the flood zone.

AHP is ostensibly a simple technique: it depends on the authors' experience in determining the weightings for each of the different criteria, which leads to some uncertainty. It is appropriate for local and regional flood susceptibility research; however, the problem for scientists is deciding the appropriate number of conditioning factors and the order of priority of these factors to best describe the flood phenomenon in the study area. In this study, ten conditioning factors were selected, which is similar to previous studies. Hammami et al. (2019) used eight conditioning factors ‐ namely land use, elevation, lithology, rainfall, drainage density, slope, soil, and groundwater level ‐ to assess flood susceptibility in Tunis. Vojtek and Vojteková (2019b) built a map in Slovakia using seven factors: river density, distance to river, elevation, slope, flow accumulation, curve number, and permeability level. Swain et al. (2020) used 22 factors, divided by physical, climatic, hydrological condition and human activity to assess the FM in Bihar, India. Souissi et al. (2020) constructed a map in an arid area of southeastern Tunisia using eight factors: drainage density, distance from drainage, elevation, slope, land use, rainfall, lithology, and groundwater. There is no universal guide to selecting conditioning factors for analyzing flood susceptibility. However, studies seem to show that it is best to use more than six factors to avoid single-factor dominance. In addition, the number of factors must also be modified based on the local topographical, climatic, hydrological, and anthropogenic conditions.

Key to correctly mapping the susceptible area is determining the importance of the conditioning variables. In this study, elevation and rainfall had the greatest influence on the probability of flood occurrence, because elevation represents the reaction to runoff and the capacity of water accumulation, and rainfall is the trigger for flood. The importance of the other factors (LULC, distance to river, NDVI, slope, aspect, curvature, and distance to road) were diminished. These results are consistent with previous studies (Santangelo et al. 2011, Souissi et al. 2020).

The flood susceptibility levels of the Nhat Le Kien Giang watershed obtained in this study is consistent with previous studies used machine learning to establish the flood susceptibility map. They showed that the eastern plain is sudden and has a high potential for the occurrence of flooding.

Faced with the effects of flood, people have three main strategies: withdrawal, resistance, or adaptation (Zaninetti et al. 2014). Withdrawal is only carried out when the actual or presumed effect of the flood passes a threshold of danger to life and/or irreversible damage to the territory in question. However, previous researchers have pointed out that planned personal withdrawal strategies are very expensive and rare. Resistance strategies, such as the construction of dykes and dams, are pursued to reduce the effects of flood. However, urban development and population growth in the flood zone increases the flood risk, and in many cases, the failure of dykes causes significant damage to human life, communities, and the local economy. In recent decades, adapting land use to encompass the potential flood hazard has been an appropriate strategy in many countries. In the Nhat Le–Kien Giang River watershed, although the local government has developed strategies to address the flood risk issue through mitigation, preparedness, response, and recovery, these efforts do not influence land-use planning in the absence of strong planning rules.

Flood susceptibility map in this study provides useful information which can support policymakers and planners in developing strategies for flood management and mitigation at both national and regional levels. The flood susceptibility map can also provide the inhabitants with crucial precise information on the flood situation in the region.

Multi-criteria decision analysis methods in general, and AHP in particular, face limitations due to the subjectivity involved in the selection of the order of importance of the conditioning factors. In addition, this study has limitations related to the data. Several conditioning factors (climatic, hydrological and anthropic factors) were extracted by Landsat 8 with 30m resolution. While previous studies have pointed out that Sentinel 2A with 10m resolution can exhibit more climatic, hydrological and anthropogenic characteristics (Nguyen et al. 2022). In recent years, floods strongly influence urban growth and climate change. Therefore, studies of the effects of these elements on flooding are very necessary in the future, can support land planning decision makers.

6. CONCLUSIONS

FSM is an essential tool for planners working toward more sustainable territory. Nine conditioning factors, namely elevation, slope, aspect, curvature, NDVI, rainfall, distance to river, and distance to road were selected to build FSM.

The AHP technique was utilized to establish the weighting of each of the conditioning factors. They were prioritized in the following order: elevation, LULC, distance to river, NDVI, slope, aspect, curvature, and distance to road. The results show that the AHP technique was able to establish a FSM, with the value of AUC of 0.95. The residential area in the high and very high susceptibility zones increased from 95 km^2 in 2005 to 251 km^2 in 2020. In recent years, flood risk management strategies have risen up the list of priorities for decision-makers around the world, especially in the context of global warming. However, a number of the world's watersheds and at-risk regions have yet to be assessed for flood risk mitigation and management plans. The methodology used in this study can be applied to assess flood susceptibility in any region. Therefore, the results of this study provide essential information to support local authorities as they plan to diminish damage to both human life and property.

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