Flood vulnerability assessment using a GIS-based multi-criteria approach—The case of Attica region

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Abstract

The identification of flood-prone areas is a fundamental component of rational urban planning and proper natural disaster management policy. The aim of the present study is to introduce a framework for the identification of flood-prone areas using geographical information systems techniques and decision-making, based on a comparative evaluation for various scenarios. As a case study, the Attica region in Greece is selected, which is occasionally affected by heavy rainfall, the main cause of flooding in the region, coupled with the fact that human activities and urbanization of recent years play a significant role in flood occurrence. In this context, the development and application of a GIS-based multi-criteria analysis method for the determination of areas susceptible to flood events is initially presented. The entire spatial analysis is performed using SAGA 6.3.0 and ArcMap 10.2 Desktop, by applying a number of alternative modifications and, finally, by evaluating different scenarios regarding methods for the criteria standardization, criteria hierarchy and factors' weighting estimation. The proposed framework has an advantage among other approaches, since it takes into account mainly static data that are linked to flooding, such as the topography and land cover distribution and it can be easily customized in ungauged catchments.

KEYWORDS

flood vulnerability mapping, flood-prone areas, fuzzy, GIS, k-means, multi-criteria analysis, ungauged catchments

1 | INTRODUCTION

Floods are one of the most significant types of natural disasters. By their nature floods are generated by the random coincidence of severe meteorological factors, but human activities also influence the severity and consequences of the events (Samuels, Borga, Baltas, & Casale, 1997). The observed escalation in magnitude, frequency, and intensity of flood events worldwide have led to a rise in global awareness for flood damage mitigation measurements (Hall et al., 2014). In recent decades, Europe has frequently been afflicted by numerous and disastrous flood events. Many studies suggest that the occurrence of flood events is increasing both in numbers and intensity (e.g., Madsen, Lawrence, Lang, Martinkova, & Kjeldsen, 2014), while, the scientific community sees a strong correlation between this trend and the rise in human activities, such as land occupancy and changes in land use (Tsakiris, Nalbantis, & Pistrika, 2009). Due to the escalation in magnitude, frequency, and intensity of the flood events, European Union established the Directive 2007/60/EC on the assessment and management of flood risk.
of flood risks (European Commission, 2007). The main goal of Flood Directive 2007/60/EC is the establishment of a generic framework for flood risk management and mapping within the European Union. Among the current requirements of the Directive implementation is the Second Flood hazard and risk maps submission by the end of the year 2019, while the first flood risk management cycle, including the Second Flood Risk Management Plans with specific requirements on climate change, will have been completed by the end of 2021. A primary component within the framework of the Flood Directive 2007/60/EC implementation is the detection and mapping of potentially flood-prone areas. Digital terrain modelling and terrain-derived geomorphological and hydrological attributes (i.e., slope, streams, drainage, and catchment areas), combined or not with remote sensing data, have become standard tools used for flood-prone area identification (Noman, Nelson, & Zundel, 2001). These approaches mainly consider a scheme of spatial multi-criteria decision analysis (MCDA), including the procedure of criteria standardization or classification and the determination of the corresponding factors’ weights before the spatial analysis. According to Khosravi, Nohani, Maroufinia, and Pourghasemi (2016), some of the most popular methods are frequency ratio (Lee, Kang, & Jeon, 2012; Rahmati, Pourghasemi, & Zeinivand, 2016; Tehrany, Pradhan, & Jebur, 2014), artificial neural network (Kia et al., 2012), analytical hierarchy process (AHP) (Chen, Yeh, & Yu, 2011), fuzzy analytical hierarchy process (FAHP) (Papaioannou, Vasiliades, & Loukas, 2015), support vector machine (Tehrany, Pradhan, & Jebur, 2015) and decision tree (Tehrany, Pradhan, & Jebur, 2013). Flood vulnerability and risk mapping using the AHP decision-making technique for the combination of various flood-related factors is widely adopted. Ouma and Tateishi (2014) used various physical and socio-economic criteria to estimate flood vulnerability in an urbanized environment in Kenya. A flood vulnerability map based on the digital terrain model, the terrain slope, aspect, land use distribution and geology is presented by Ozcan and Musaoglu (2010) for an urban area near riverbeds (Ayamama River in Istanbul). Siddayao, Valdez, and Fernandez (2014) also used the AHP in spatial modelling for floodplain risk assessment in the town of Enrile in northern Philippines. Furthermore, as AHP is inferior because the priorities derived from the decision-makers result in “subjective” judgments, the fuzzy version (FAHP) is also adopted for relevant spatial applications. Wang, Li, Tang, and Zeng (2011) used FAHP to determine five classes of flood risk (from very low to very high) in an urban area in Central China that frequently suffers from floods. Finally, in Greece, Papaioannou et al. (2015) used both AHP and FAHP for flood-prone area identification on a rural basin of 120 km² named Xerias, located in the Thessaly, region of Central Greece.

Therefore, the purpose of this work is to develop, implement and evaluate an integrated methodology that uses spatial MCDA for flood vulnerability mapping (FVM) at a regional level. Particularly, the methodology is performed at a River Basin District (RBD) level, for the continental part of the RBD of the Attica region in Greece, an area of about 2,960 km². All catchments of this RBD are ungauged and combine characteristics of urban and peri-urban environments. The proposed methodology includes investigation among different scenarios, regarding methods for criteria standardization, criteria hierarchy and factors’ weighting estimation. Each approach is evaluated through the available dataset of flood events and mainly the flood-affected properties that have been recorded during the last 15 years. Regarding criteria selection, the initial combination of criteria is based on Papaioannou et al. (2015) research and then modifications are introduced and tested for each individual scenario. Apart from the criteria selection, the method of each factor’s values transformation into a common scale is equally important. The first approach is the process where all criteria are standardized before the multi-criteria decision-making (MCDM), while the second approach is the method where all criteria are clustered in five classes and then, additive weighting is performed for the production of flood vulnerability maps. Regarding factors’ weights, these are also estimated with the AHP and FAHP techniques after considering three scenarios for the hierarchy of the criteria. The first scenario focuses on rainfall intensity and land morphology, the second scenario on the stream network attributes and the third is the average one. The proposed framework is developed for decision-makers to identify areas that are potentially prone to flash, urban and fluvial floods by applying a spatial MCDA, as a general guidance even for relevant application at a larger spatial scale (e.g., national) for both gauged and ungauged catchments. This is particularly important, as a GIS-based MCDM method for FVM is essentially useful at areas with limited available information, or at ungauged catchment areas where preliminary flood hazard evaluation or flood risk mapping is required and the adoption of typical hydrologic and hydraulic methods involves uncertainty.

2 STUDY AREA AND DATA USED

The RBD of Attica corresponds to an area of 3,186 km² and includes the continental Attica Region, the islands of Aegina, Salamina, and Makronisos and a small part of Sterea Ellada and the Peloponnisos (Figure 1). The human activities in the region are generally geographically more concentrated on the lowlands and semi-mountainous parts. The analysis is performed only in the continental part of the District, since the major economic activity of Greece, more than 50% of the country’s population, and the highest flood risk are observed. The area often suffers from extreme rainfall events, that is, high precipitation depth in short duration.
These rainfall systems are mainly WSW-ENE oriented (Feloni, Nastos, & Matsangouras, 2017) and they test the capacity of the drainage network, causing less or more extended flooding. Finally, human activities and mainly the urbanization of recent decades that resulted in the current land cover distribution have a significant effect on the occurrence of floods, as they reduce hydrological losses and the catchments' time of concentration, leading to high peak values of discharge. Specifically, based on the available information of the CORINE Land Cover (2012) dataset, 24.5% of the region corresponds to artificial surfaces (urban fabric, industrial, commercial, and transport units), while forests cover 50% and agricultural areas 25% of the region. Finally, wetlands and water bodies correspond to only 0.5% of the region. According to Köppen (1884), the climate of Attica can be characterized as Mediterranean, except for the highest altitudes, where it is mountainous. The mean annual precipitation is 411 mm and varies significantly with elevation (e.g., 350 mm in Attica basin, 1,000 mm in the Mount Parnitha). The mean annual temperature varies from 16 to 18°C, depending on the altitude and distance from the sea. The main rivers of the RBD of Attica are the Kifissos and Ilissos Rivers in Attica basin.

Apart from the CORINE Land Cover (CLC) shapefile, one of the main datasets used for multiple criteria is the digital elevation model (DEM; Figure 1), which is provided by the National Cadastre & Mapping Agency S.A. The format of the files is ERDAS Imaging, the pixel size on the ground is 5 m and the geodetic system is the Hellenic Geodetic Reference System 1987 (known as Greek Grid; “GGRS87”). This product is of the highest available resolution for the Greek territory, while its geometric accuracy is RMSEz ≤2.00 m and the absolute accuracy is ≤3.92 m for a 95% confidence level. In the entire procedure, rainfall time series provided by the Hellenic National Meteorological Service (HNMS) for the period 1987–2017 and for the available rainfall stations of the study area were also used in order to estimate a rainfall-relevant criterion.

A number of significant flood events have been recorded in recent years in the region. The most severe flood event of the previous century occurred on October 21–22, 1994, its return period was estimated to be approximately 100 years (Mimikou, Baltas, & Varanou, 2002) and due to this event 11 deaths were reported, while nine of them occurred in the greater Athens area. In the last decade, a severe flood took place on February 22, 2013 where more than 100 mm of rainfall were locally recorded in 5 hr. The heavy rain was the worst seen in Greece’s capital for the last 50 years. Later on, on October 22, 2015, many suburbs of Athens were affected by a two-phased storm, producing extended flash flood incidents, particularly in the northwest part of the
Attica basin, where four flood-related human fatalities occurred and over 1,300 citizens’ calls for operations were recorded by the Fire Service. Finally, the most recent and deadly flood event in the Attica region occurred in November 2017 in Mandra (Western Attica) marked by the loss of 24 people and numerous material damages. Flood history, together with satellite data which provide information on the spatial extent of floodplains, is considered as a reliable way to evaluate methodologies relevant to FVM. In this regard, data on the citizens’ calls to the Fire Service, provided by the Integrated Emergency Coordination Centre of the Hellenic Fire Service, were used for the evaluation of flood-prone areas, as Hellenic Fire Service reports its operations for water pumping and help aid. The overall evaluation was based on the fact that, as these incidents correspond to the postal address of the flood-affected properties, by applying a geocoding process one can obtain the exact location and the coordinates of all these incidents, in order to evaluate the resulting map with the five classes of flood vulnerability that are estimated using each spatial MCDM approach.

3 | METHODOLOGICAL FRAMEWORK

In the present study, a spatial MCDA was developed, implemented, and evaluated with the purpose of identifying the potentially flood-prone areas through creating maps of five classes of flood vulnerability (from very low to very high). The resulting maps differ from each other as various criteria, standardization, and weighting methods were adopted. Thus, the implementation of this analysis can be separated into the following steps; (a) an investigation concerning the selection of the MCDA criteria to propose the final number of them and the most suitable algorithm to determine some of them, (b) the application of MCDA by using two approaches: one based on standardized criteria and the other one based on classified criteria, and (c) the estimation of criteria weighting, after performing two different approaches regarding the criteria hierarchy and the process of weighting (i.e., the AHP and the FAHP technique). The analysis is performed in a pixel size equal to 5 m x 5 m. Each step of the corresponding analysis is presented in this section, while Figure 2 summarizes the process of the MCDA application.

3.1 | Selection of MCDA criteria

The GIS-based MCDA for FVM is a process mainly affected by the number of criteria selected and by what each criterion expresses. In relevant applications, these criteria are mainly DEM derived, in a way that they include all the geomorphological features that may influence flood occurrence, combined with hydrological features, such as the general pattern of hydrological losses and a rainfall-related index.

In the context of the present study, modifications are performed compared to existing approaches. First of all, the number of the selected criteria is reassessed, as the flow accumulation criterion is assumed as unnecessary because this information is embedded in the flow distance criteria that are linearly dependent (direct derivatives) on the flow direction and their values are proportional. In addition, instead of the Vertical Overland Flow Distance (VOFD, a SAGA-GIS Tool parameter; Olaya & Conrad, 2009), the Topographic Position Index (TPI; Weiss, 2001), the curve number, the aspect (A) and the Modified Fournier Index (MFI; Morgan, 2009) criteria that have been used previously, the vertical distance to channel network (VDCN, a SAGA-GIS Tool parameter), three criteria regarding curvature (curvature index, CI; Classification according to the area’s curvature, CCI; multi-scale topographic position index, msTPI), a composite version of curve number (CN_comp), the critical aspect criterion and the daily-modified Fournier Index (dMFI) are introduced in the context of this analysis. The reasons for the aforementioned modifications in the criteria are described as follows.

1. DEM: As generally areas of lower altitude are more vulnerable to flooding, the criterion of topography is incorporated in the process of flood vulnerability assessment (FVA). The criterion values are transformed (i.e., minimized) through Equation (3.b) (in “Standardization and

FIGURE 2 Overview of methodology
| Criterion | Tool | Software | Values before standardisation/classification | Standardised values | Centroids K-means |
|-----------|------|----------|---------------------------------------------|--------------------|------------------|
| 1. DEM | – | ArcMap | [0, 1,413] | [0, 1] | 1 868.79 |
|           |      |          |                                              |                    | 2 576.27       |
|           |      |          |                                              |                    | 3 370.75       |
|           |      |          |                                              |                    | 4 202.88       |
|           |      |          |                                              |                    | 5 60.34        |
| 2. Slope | ArcMap | [0, 246.346] | [0, 1] | 1 241.00 |
|           |      |          |                                              |                    | 2 216.08       |
|           |      |          |                                              |                    | 3 98.71        |
|           |      |          |                                              |                    | 4 41.12        |
|           |      |          |                                              |                    | 5 6.87         |
| 3. Aspect | ArcMap | North (337.5, 22.5) | 0.4 | 1 27.34 |
|           |      | Northeast (22.5, 67.5) | 0.2 | 2 105.32 |
|           |      | East (67.5, 112.5) | 0.2 | 2 105.32 |
|           |      | Southeast (112.5, 157.5) | 0.2 | 2 105.32 |
|           |      | South (157.5, 202.5) | 0.4 | 3 174.37 |
|           |      | Southwest (202.5, 247.5) | 1.0 | 4 321.49 |
|           |      | West (247.5, 292.5) | 0.8 | 4 321.49 |
|           |      | Northwest (292.5, 337.5) | 0.6 | 5 242.79 |
|           |      | Plane (–1) | 0.5 | 5 242.79 |
| 4. HOFD | Overland flow distance to channel network | SAGA | [0, 2,387.7] | [0, 1] | 1 721.42 |
|           |      |          |                                              |                    | 2 407.81       |
|           |      |          |                                              |                    | 3 247.79       |
|           |      |          |                                              |                    | 4 136.62       |
|           |      |          |                                              |                    | 5 43.07        |
| 5. VDCN | Vertical distance of channel network | SAGA | [0, 323.6] | [0, 1] | 1 102.50 |
|           |      |          |                                              |                    | 2 59.11        |
|           |      |          |                                              |                    | 3 33.42        |
|           |      |          |                                              |                    | 4 15.32        |
|           |      |          |                                              |                    | 5 1.90         |
| 6a. CI | Curvature | ArcMap | [−2065.0, 2060.2] | [0, 1] | - |
|           |      |          |                                              |                    | 1 0.125        |
|           |      |          |                                              |                    | 2 0.250        |
|           |      |          |                                              |                    | 3 0.375        |
|           |      |          |                                              |                    | 4 0.500        |
|           |      |          |                                              |                    | 5 0.625        |
|           |      |          |                                              |                    | 6 0.750        |
|           |      |          |                                              |                    | 7 0.875        |
|           |      |          |                                              |                    | 8 1.000        |
| 6b. CCI | Curvature classification | SAGA | 0 (convex / convex) | 0.000 | - |
|           |      | 1 (plane / convex) | 0.125 | - |
|           |      | 2 (concave / convex) | 0.250 | - |
|           |      | 3 (convex / plane) | 0.375 | - |
|           |      | 4 (plane / plane) | 0.500 | - |
|           |      | 5 (concave / plane) | 0.625 | - |
|           |      | 6 (convex / concave) | 0.750 | - |
|           |      | 7 (plane / concave) | 0.875 | - |
|           |      | 8 (concave / concave) | 1.000 | - |

(Continues)
classification of MCDA criteria” section). However, in some studies, some kind of inverse-scale measurement is used, that is, from the point of maximum elevation to the sea level, in order to maximize the criterion (Burrough, McDonnell, McDonnell, & Lloyd, 2015). In the present study, this criterion is the DEM of 5 m × 5 m spatial resolution, as described in the previous section. As the entire analysis is performed for an area of about 2,960 km², it is difficult to obtain a DEM of a better resolution for such a spatial extent. However, it should be noted that as the DEM is a fundamental component of the analysis that is also used for the production of additional criteria, the resulting map is expected to change when using a DEM of different resolution and accuracy.

2. Slope (Sl): It is the product of the mean slope in each pixel and is measured as a percentage (%) of the elevation change to the corresponding horizontal displacement. Slope is the main product of the elevation and gives information on the surface runoff and water concentration in a basin. Generally, the smaller the slope, the more vulnerable the flood area, that is, the criterion standardization follows Equation (3.b). All processing and mapping were performed in ArcMap 10.2 (ESRI E, 2014) environment, except for the K-mean classification process performed in SAGA 6.3.0.

3. Critical aspect (Acr): This layer is used as a way to categorize the surface in relation to the direction of storms. Thus, it is an index that expresses the most vulnerable regions due to their direct exposure to heavy rain events. For the various directions, six classes are determined in the classification approach, and, as this is a discrete attribute, it also takes discrete values in the scale [0, 1] in the standardization approach (also see Table 1).

4. Horizontal overland flow distance (HOFD): HOFD expresses the actual movement of water from cell to cell and not the Euclidean distance. This criterion is the product of the stream network of the area or, more generally, of the DEM (Olaya, 2004). The smaller the flow path from the cell to the riverbed, the more flood-vulnerable the cell is; therefore, the criterion is minimized (Equation 3.b).

5. Vertical distance of channel network (VDCN): It expresses vertical distance between cell elevations and the elevations calculated for the channel network in that

| Criterion | Tool | Software | Values before standardisation/classification | Standardised values | Centroids K-means |
|-----------|------|----------|---------------------------------------------|---------------------|-------------------|
| 6. msTPI  | Multi-scale topographic position index | SAGA | [−90.2, 90.0] | [0, 1] | 1 42.48 |
|           |      |          |                                             |                     | 2 0.61            |
|           |      |          |                                             |                     | 3 −0.01           |
|           |      |          |                                             |                     | 4 −0.88           |
|           |      |          |                                             |                     | 5 −16.79          |
| 7. sWI    | Saga wetness index | SAGA | [−6.5, 14.4] | [0, 1] | 1 2.32 |
|           |      |          |                                             |                     | 2 3.64            |
|           |      |          |                                             |                     | 3 5.58            |
|           |      |          |                                             |                     | 4 7.95            |
|           |      |          |                                             |                     | 5 11.41           |
| 8. CNcomp | Raster calculator | ArcMap | [77, 99] | [0, 1] | 1 77.00 |
|           |      |          |                                             |                     | 2 78.46           |
|           |      |          |                                             |                     | 3 80.29           |
|           |      |          |                                             |                     | 4 89.4            |
|           |      |          |                                             |                     | 5 97.75           |
| 9. dMFI   | Kriging | ArcMap | [66.2, 106.8] | [0, 1] | 1 73.35 |
|           |      |          |                                             |                     | 2 79.17           |
|           |      |          |                                             |                     | 3 83.06           |
|           |      |          |                                             |                     | 4 89.12           |
|           |      |          |                                             |                     | 5 95.90           |
cell. Generally, the cells which are out of the stream network will be assigned a value that represents the elevation difference between those cells and the channel that flows through them, in case it existed. The smaller the distance, the more vulnerable the flood area; thus, the criterion is minimized (Equation (3.b)).

6. (a) Curvature index (CI), (b) curvature classification index (CCI), (c) msTPI: In lieu of the topographic position index (TPI), three indices regarding curvature were compared. This replacement was necessary because, for the calculation of TPI, a control radius is needed, which cannot be the same for the entire study area when applying a MCDA at a RBD level. Thus, (a) index “CI” is calculated using the ArcMap 10.2 Curvature tool, while (b) “CCI,” and (c) “msTPI” factors were obtained with the available tools of SAGA 6.3.0. “C” index considers the curvature of the plane and hills and gives them a value. In case one selects this algorithm, it is illustrated that the classification with K-means leads to a very unequal distribution, as the vast majority of cells are accumulated in one class. The “CCI” index corresponds to the classification of curvature as concave or curved. Thus, nine possible combinations are created (Table 1; criterion 6b) and, therefore, these classes are renumbered between 0 and 1. However, the use of this criterion gives results with similar patterns in its standardized form with those of the “CI” criterion. “CCI” was not used in its classified form for the MCDA, because its representation is of no interest, as its elements accumulate in a class and thus it is not spatially sensitive enough to contribute to FVA. Finally, regarding the interpretation of “msTPI” and given that generally the topographic position of a site may be a hill, a valley, a plane, a ridge, or some other terrain (Tagil & Jenness, 2008), the factor represents the location (i.e., ridges, slopes/planes, top slopes, or bottom of valleys) considering a control radius. This index is calculated based on the elevation difference between the cell and the average altitude of the neighbouring cells within the area the control radius specifies. When “TPI” is negative, the position is more flood-prone, and, as the lower the value, the more vulnerable the area, the criterion is standardized according to Equation (3.a). In this study, the “msTPI” is calculated through the corresponding SAGA tool, as an index of the same philosophy, except that there is no need to introduce a control radius and this function serves the scope of present analysis.

7. SAGA wetness index (sWI) (Olaya & Conrad, 2009): The topographic wetness index (TWI) is a physical attribute of flood-inundation areas, derived from DEMs (Kirkby, 1975) and indicates whether or not a site can create runoff. The SAGA TWI (Böhner et al., 2001) is used, which predicts for cells sited in valley floors with a small vertical distance to a channel. Generally, a TWI includes two measurements, one relevant to the hydrographic position of the cell in the basin, and one relevant to the absence or existence of low slope. The sWI is based on a modified calculation of catchment areas, which does not treat the flow as a thin film. Higher values of soil moisture mean that more water is converted into direct runoff, which is relative to flood occurrence and, thus, the criterion is maximized (Equation (3.a)).

8. Composite curve number (CNcomp): Curve number (SCS, 1986), an empirical parameter used in hydrology to estimate infiltration, is calculated according to the hydrologic soil group, the land cover type and the soil moisture conditions of a catchment. In this study, the distributed CN values are estimated for average soil moisture conditions and are based on the CORINE Land Cover (2012) dataset. However, as a significant part of the region is urban, the information on the percentage of imperviousness (HRL-Imp., 2012) is also considered for this criterion, as it captures the percentage of soil sealing, and it allows definition of more detailed values of CN inside urban polygons of CORINE. Thus, CNcomp is a modified version of the CN layer and it is calculated according to the equation:

\[
CN_{\text{comp}} = \frac{\text{Imperviousness}}{100} \cdot (C_N + [99 - C_N])
\]  

This criterion is also maximized according to Equation 3.a.

9. Daily-modified Fournier index (dMFI). Rainfall, one of the most important parameters when studying flood occurrence, is a time-dependent parameter, which cannot be represented by a constant layer. Inspired by the MFI methodology followed by Papaioannou et al. (2015), the dMFI is used for mapping the maximum daily rainfall, as a factor which represents the rainfall intensity of an area, according to the following equation:

\[
dMFI = \sum_{i=1}^{d} \frac{p_i^2}{P}
\]

where \( p \) the maximum daily precipitation of the month, \( P \) the corresponding monthly precipitation depth and \( d \) the number of days in a month. This layer is created by applying the Kriging method (Oliver & Webster, 1990) to the point feature of dMFI that was calculated for each rain gauge. It is noted that the month of maximum dMFI may differ for each station, to express the maximum amount. Additionally, in case it is required to incorporate probability in FVA, this criterion can be properly modified after considering the
intensity duration frequency curve (IDF curve) of each station to estimate the amount of rainfall for a standard return period (T). This index is proportional to flood vulnerability and it also follows Equation (3.a).

Table 1 summarizes the criteria that were produced and their value range of relevant importance by category, as they emerged in their analysis.

### 3.2 Standardization and classification of MCDA criteria

Initially, two approaches are adopted in order to convert all criteria into a common scale: (a) normalization (i.e., standardization of values in the scale of 0–1) and (b) classification (i.e., five constant values are attributed to five clusters of the factor values). Regarding normalization, each criterion \( R \) is normalized according to the following equations:

\[
X_i = \frac{(R_i - R_{\text{min}})}{(R_{\text{max}} - R_{\text{min}})} \cdot \text{SR} \quad (3a)
\]

\[
X_i = \frac{(R_i - R_{\text{min}})}{(R_{\text{max}} - R_{\text{min}})} \cdot \text{SR} \quad (3b)
\]

where, \( X_i \) the normalized values of a criterion \( R \), \( R_i \) its real values; \( R_{\text{max}}, R_{\text{min}} \) its maximum and minimum values, respectively; \( \text{SR} \) is the range of normalized values (here it is equal to 1). Equation (3.a) is used for criterion standardization in case the flood vulnerability increases when the criterion value also increased (e.g., soil sealing) and Equation (3.b) is used when the two parameters are conversely dependent (e.g., slope), as mentioned for each criterion above.

The second approach corresponds to the classification of each criterion. Generally, classification can be performed with various methods, for example, Jenks Natural Breaks (Jenks, 1967), K-means (MacQueen, 1967), Fuzzy C-Means (Bezdek, 1981; Dunn, 1973) and Clustering Large Applications (Kaufman & Rousseeuw, 1990). For this study, K-means clustering is used for the classification of each criterion value in \( k \) clusters (here, \( k = 5 \)), instead of simple classification methods that are included in the ArcGIS software (ArcMap 10.2; ESRI E, 2014). It is emphasized that using the second approach, minimum memory to store the criteria, less complexity of calculations and time of processing are required.

The values transformation was performed to each raster cell to prepare all criteria for the weighting linear combination that results in the FVA. Thus, the values of reclassification are assigned to the range between 0 (not flood susceptible) and 1 (flood susceptible) for the first approach of standardization. Proportionally, the values 1, 2, 3, 4 and 5 (for very low, low, moderate, high and very high susceptibility) are attributed when performing the classification approach. Thus, the criterion standardization procedure is made through the Raster Calculator (Map Algebra in ArcGIS Spatial Analyst toolbox; ESRI E, 2014), while the classification into five classes was performed via SAGA 6.3.0 (Conrad et al., 2015) using the K-means algorithm and then their reclassification in 1–5 was performed in ArcMap.

### 3.3 Weighting methods and examined scenarios

For the determination of flood vulnerability maps using the criteria described above, estimation of the criteria weights precedes the weighted linear combination (WLC) performance that is expressed through the equation:

\[
S = \sum w_i x_i, \quad (4)
\]

where \( S \) is the flood vulnerability value for each raster cell, \( w_i \) is the weight of each criterion, \( x_i \).

According to Malczewski (1999), there are four main groups of techniques for weighting the criteria: ranking, rating, trade-off, and pairwise comparison method. Ranking methods, which are the simplest methods for assessing the importance of weights, are based on the general principle that every criterion under consideration is ranked in the order of the decision maker's preferences. Rating methods require the estimation of weights on the basis of predetermined scales and, according to Moore (1975), rated scores provide more information than ranked and are easier to obtain. Trade-off analysis methods use direct trade-off assessments between pairs of alternatives. Indifference trade-off guarantees theoretically valid weights as weights are derived directly from trade-offs of value functions (Hobbs, 1980). Finally, pairwise comparison methods, which are implemented in relevant FVA studies and also in this one, involve pairwise comparison to create a ratio matrix (Saaty, 1977). Saaty's technique derives the weights of criteria by taking the principal eigenvector of a square reciprocal matrix of pairwise comparisons between the criteria. The comparisons are based on the relative importance of the two criteria involved in determining suitability for the stated objective. The main feature of this approach is the ability to capture both subjective and objective aspects of a decision. According to Saaty (1977), pairwise comparison numerical values are provided on a nine-point continuous scale (1–9). Particularly for this study, two methods of pairwise comparison are used for the estimation of the relative weight importance: the Analytical Hierarchy Process “AHP” (Saaty, 1977, 1980), as well as, its Fuzzy version “FAHP” (Chang, 1996) that, despite requiring tedious computations when complicated decision-making problems are analysed (as the one presented), is very adept at capturing a human's judgment of uncertainty (Erensal, Öncan, & Demircan, 2006).
This method uses triangular fuzzy set of numbers, matching them to Saaty’s crisp set of numbers and linguistic scale. Here the transformed linguistic scale of significance is used in triangular fuzzy numbers (TFN), as shown in Table 2a and b. The correspondence of Tables 2a and b is directly used, converting the crisp set of Pairwise Comparison Tables produced in the AHP process into TFN ones.

Regarding the hierarchy among criteria, in order to define the influence of these natural factors on flood vulnerability, various relevant implementations were considered (e.g., Kandilioti & Makropoulos, 2012; Kostadinov & Mitrovic, 1994; Mazzorana, Comiti, & Fuchs, 2013; Mazzorana, Hübl, & Fuchs, 2009; Meyer, Scheuer, & Haase, 2009; Papiaiannou et al., 2015; Stefanidis & Stathis, 2013) and finally two main scenarios were created, as well as, their combination. The first scenario (“S.1”) focuses on rainfall intensity and general land morphology, which means that assigns higher importance on these criteria. The second scenario (“S.2”) mainly focuses on the stream network attributes, that is, DEM-derived factors. Finally, the combination of these two scenarios is the third one (“S.3” scenario), which is assumed as the average one. For each one of the three aforementioned scenarios, weights are determined using the AHP and the FAHP method both for the standardization and the classification approaches. Regarding the fuzzy approach in the scenario, acronym “FAHP-1.” means that weighting results from values of Table 2a and “FAHP-2.” from Table 2(b), respectively. The acronym of each scenario, as a combination of the scenario regarding factors hierarchy (S.1, S.2, and S.3) and the weights determination procedure (AHP, FAHP-1., and FAHP-2.), is summarized in Figure 3 (the index “(K)” denotes K-means clustering). These eight scenarios are then applied using (a) the standardized criteria and (b) the classified criteria to obtain the flood vulnerability maps.

### RESULTS AND DISCUSSION

The implementation of the WLC resulted in 16 FVM (eight scenarios, for standardized and classified criteria). The resulting maps present values between the criteria values range (0–1 or 1–5 according to the method of transformation). To express these values as classes of flood vulnerability, K-means algorithm is also adopted to define the margins of the five classes. As each scenario leads to a different result, the classification will also result in different classes for each FVM. However, for demonstration purposes, the class values are kept constant, based on the FVM classification for the FAHP.3 K scenario. By comparing the resulting maps of Figure 4, a significant alteration in flood vulnerability classes is shown. Additionally, for FVM using AHP and normalized criteria, it appears that S.1 lacks altitude information, compared to the FVM of S.2 scenario; both scenarios attribute low weights to the altitude criterion for the AHP method, while for the FAHP method the altitude criterion is assigned zero weight. One can assume that this is not a limitation, as other criteria (VDCN, sWI, HOFD) give clear indications of flood-prone areas. In addition, the criteria investigation revealed that VDCN appears to express altitude characteristics, for instance compared to flow direction, while sWI encloses features relevant to slope and position regarding upstream/downstream. Finally, the HOFD criterion gives information about the horizontal component of the flow. A limitation of this case study concerns the distribution of dMFI, which does not yield satisfactory results, as the available climatological data were limited and a denser

| Linguistic scale          | (a) TFN scale | TFN reciprocal scale | (b) TFN scale | TFN reciprocal scale |
|---------------------------|---------------|----------------------|---------------|----------------------|
| Equally important         | (1,1,1)       | (1, 1, 1)            | (1,1,1)       | (1, 1, 1)            |
| Intermediate [1]          | (1,2,3)       | (1/3, 1/2,1)         | (1,1,3)       | (1/3, 1,1)           |
| Moderately important      | (2,3,4)       | (1/4, 1/3, 1/2)      | (1,3,5)       | (1/5, 1/3, 1)        |
| Intermediate [2]          | (3,4,5)       | (1/5, 1/4, 1/3)      | (1,3,5)       | (1/5, 1/3, 1/5)      |
| Important                 | (4,5,6)       | (1/6, 1/5, 1/4)      | (3,5,7)       | (1/7, 1/5, 1/3)      |
| Intermediate [3]          | (5,6,7)       | (1/7, 1/6, 1/5)      | (3,5,7)       | (1/7, 1/5, 1/3)      |
| Very important            | (6,7,8)       | (1/8, 1/7, 1/6)      | (5,7,9)       | (1/9, 1/5, 1/7)      |
| Intermediate [4]          | (7,8,9)       | (1/9, 1/8, 1/7)      | (7,9,9)       | (1/9, 1/9, 1/7)      |
| Absolutely important      | (9,9,9)       | (1/9, 1/9, 1/9)      | (9,9,9)       | (1/9, 1/9, 1/9)      |

Data adopted by Zhou (2012) Data adopted by Junior, Osiro, and Carpinetti (2014), after modifications

Abbreviations: TFN, triangular fuzzy numbers.
### Scenario of criteria hierarchy

| S.1 | Procedure of weights determination | Acronym of flood vulnerability scenario |
|-----|-----------------------------------|----------------------------------------|
|     | **AHP**                           | **AHP & AHP.1K**                      |
|     | **FAHP-1**                        | **FAHP-1.1 & FAHP-1.1K**              |
|     | **FAHP-2**                        | **FAHP-2.1 & FAHP-2.1K**              |

| S.2 | Procedure of weights determination | Acronym of flood vulnerability scenario |
|-----|-----------------------------------|----------------------------------------|
|     | **AHP**                           | **AHP2 & AHP.2K**                      |
|     | **FAHP-1**                        | **FAHP-1.2 & FAHP-1.2K**               |
|     | **FAHP-2**                        | **FAHP-2.2 & FAHP-2.2K**               |

| S.3 | Procedure of weights determination | Acronym of flood vulnerability scenario |
|-----|-----------------------------------|----------------------------------------|
|     | **AHP**                           | **AHP3 & AHP.3K**                      |
|     | **FAHP**                          | **FAHP.3 & FAHP.3K**                   |

#### FIGURE 3
Examined scenarios: S.1 emphasises the criteria of rainfall intensity and land morphology, S.2 the stream network attributes and S.3 keeps balance among criteria; the index (K) in the end of the scenarios’ acronyms corresponds to the approach following K-means clustering.

#### FIGURE 4
Flood vulnerability maps according to the eight main scenarios (a–h) and also the one resulting from S.3 scenario and fuzzy analytical hierarchy process (FAHP) using the clustered values of criteria (i).
network of stations is needed; this problem is mainly addressed in Western Attica, where there is a shortage of rain gauge stations. The comparison between AHP and FAHP approach indicates that results for each scenario appear to be quite similar, regardless of the weighting method used. This is attributed to the fact that a large number of similarly weighted criteria are assumed for the determination of flood vulnerability. However, one can notice that the FAHP approach for weighting adapts the concept of uncertainty in weighting and thus is preferable and that, as it results in some zero weights (Table 3), it also reduces the total processing time for FVM. Between the two approaches of FAHP, the second one (Table 2b, “FAHP.2.”) yields results closer to the outputs of the AHP process, than those produced by the “FAHP-1.” process.

According to the methodology described above, the selection of the most appropriate factor describing each criterion precedes the MCDA implementation. In this analysis, this investigation mainly concerns the selection of an index in relation to the surface curvature. It was observed that the CI and CCI criteria are graphical representations of the same size, except that the first is of constant value, while the second one is a sub-classification of the first and it also has discrete values. This means that after performing normalization of this criterion, the resulting layers appear to follow the same general pattern, while CCI as a criterion seems to give better precision. The index generates high noise in the final results, as shown in Figure 4(f) for “FAHP.3,” that is scenario S.3 assuming the standardized version of the criteria. However, the results of Figure 4i appear to be better grouped, compared to Figure 4f. The flood vulnerability map in the latter figure results from the classified criteria and, as the entire procedure is less time-consuming when using classified criteria, the criterion was expressed through the msTPI, which calculation, however, is more time-consuming compared to the advantage acquired through the adoption of a K-means approach regarding the total processing time. Determination of the final criteria (nine in number) allows the implementation of the AHP and FAHP criteria weighting methods. Based on the three examined scenarios, different sets of weights resulted and are used for the spatial MCDA FVA. The resulting weights for each scenario are summarized in Table 3.

Regarding the most reliable scenarios, the evaluation was performed by determining which scenario(s) defines successfully areas of high and very high vulnerability, when historic flood incidents are mainly inside these areas and, simultaneously, areas of low and very low vulnerability, when flood incidents inside these areas present very low frequency. Figure 5 provides an example regarding the comparison between the resulting map of “FAHP.3 K” and the dataset of Fire Service operations in flooded properties (black points). As the evaluation of each scenario is based on the dataset of flooded properties, by classifying the resulting FVM into five classes, each point takes an integer value between “1” (very low) and “5” (very high), depending on the corresponding result of each scenario. These classified values are extracted for all examined scenarios in the same range (i.e., 1–5). According to Figure 6, which shows the corresponding FVM performance expressed as the number of incidents in each class, one can see that the majority of points (more than 80%) are concentrated in the two classes of higher flood vulnerability for two scenarios; these are the FAHP-1.2 and the FAHP.3K. Even if the first seems to be more accurate for high vulnerability, it slightly overestimates the areas of low vulnerability and also it is not sensitive inside the urban fabric, due to the higher weight for the curve number. On the other hand, FVM using the FAHP.3K scenario provides a better grouping among classes (shown in different colors in Figure 4) and also the entire procedure is less time-consuming for an almost equal result, taking into consideration that this one

### Table 3 Criteria weights per scenario

| Scenario   | DEM | Sl | Acr | HOFD | VDCN | msTPI | sWI | CNcomp | dMFI |
|------------|-----|----|-----|------|------|-------|-----|--------|------|
| AHP.1(K)   | 0.02| 0.03| 0.04| 0.08 | 0.08 | 0.18  | 0.16| 0.18   | 0.23 |
| AHP.2(K)   | 0.03| 0.08| 0.02| 0.05 | 0.17 | 0.14  | 0.36| 0.11   | 0.04 |
| AHP.3(K)   | 0.02| 0.04| 0.07| 0.06 | 0.11 | 0.16  | 0.23| 0.16   | 0.15 |
| FAHP-1.1(K)| 0.00| 0.00| 0.00| 0.00 | 0.00 | 0.24  | 0.18| 0.25   | 0.33 |
| FAHP-2.1(K)| 0.00| 0.00| 0.00| 0.00 | 0.10 | 0.00  | 0.50| 0.39   | 0.00 |
| FAHP-1.2(K)| 0.00| 0.00| 0.00| 0.01 | 0.01 | 0.25  | 0.18| 0.25   | 0.30 |
| FAHP-2.2(K)| 0.00| 0.02| 0.00| 0.00 | 0.20 | 0.17  | 0.46| 0.15   | 0.00 |
| FAHP-3(K)  | 0.00| 0.07| 0.00| 0.05 | 0.14 | 0.17  | 0.22| 0.18   | 0.16 |

Abbreviations: Acr, Critical aspect; AHP, analytical hierarchy process; CNcomp, composite version of curve number; DEM, digital elevation model; dMFI, daily-modified Fournier Index; FAHP, fuzzy analytical hierarchy process; HOFD, Horizontal overland flow distance; msTPI, multi-scale topographic position index; Sl, Slope; sWI, SAGA wetness index; VDCN, vertical distance to channel network.
expresses the average scenario and also considers the criterion of slopes that is generally significant for flood generation.

Taking into account the abovementioned facts and after evaluating each scenario, it seems that the resulting map considering the “FAHP.3K” scenario can be suggested as the proper one for FVM. This suggestion is based on the fact that “FAHP.3K” is derived from the combination of two main scenarios and a fuzzy logic-based weighting process. Moreover, it is less a time-consuming process compared to the other scenarios that lead to satisfactory results. Regarding the Attica region, the potentially flood-prone areas are concentrated in the Attica basin and in the lowlands of Western and Eastern Attica.

5 | SUMMARY AND CONCLUSIONS

In this work, a GIS-based MCDA was developed and implemented in order to better estimate flood vulnerability in Attica, by investigating various scenarios regarding criteria standardization, hierarchy and factors’ weighting estimation. Each scenario was evaluated using a dataset of point features that correspond to the position of flood-affected properties recorded within the period 2005–2016. The purpose of this study was to identify potentially flood-prone areas by adopting the least subjective and most reliable approach, as a framework that can be applied to other ungauged catchments, toward an integrated flood risk assessment and management. More specifically, findings derived from this research work are concentrated as follows:

- Two different approaches, the standardization and classification of its criterion, were applied for the conversion of all criteria to a common scale. It was found that, when applying the classification approach using the K-means clustering method, the resulting map more clearly gives the classes of flood vulnerability. It is emphasized that using classification methods directly to the criteria instead of the standardization approach, the entire procedure requires comparatively minimum memory to display, process and store the criteria for each grid cell, a fact that leads to less complexity of calculation and, consequently, to both minimization of the required processing time.
(reduced by half) and hardware requirements to export FVM.

- Three different approaches (AHP, FAHP-1., and FAHP-2.) were followed as weighting methods. As a high number of criteria are used, these different weighting methods lead to similar results when slightly altering hierarchy among the nine criteria; however, the fuzzy approach leads to a better evaluation. Generally, using FAHP it seems that the entire analysis is simplified, since the weighting method results in some zero criteria weights; therefore, the necessary processing time for the overall procedure is reduced.

Regarding future research, evaluation results indicate two approaches that reflect high validation score, and this strengthens the opinion that the proposed framework is suitable for FVA, allowing further applications regarding a wider spatial scale, other ungauged catchments or areas of complex land cover. A sensitivity analysis for each criterion weight is proposed in order to define the significance. Additionally, this framework is suggested for small catchments, where it is practically feasible to generate DEM through unmanned aerial vehicle photogrammetry data, in order to quantify the impact of DEM resolution in FVM. Finally, regarding the evaluation process, apart from the point data used in this analysis, any available satellite data of historic floods may be a legitimate datum for results evaluation, especially in semi-urbanised or rural catchments and when assuming a rainfall-related criterion that corresponds to an event of a specific return period.

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ENDNOTE

1 The key milestones are available at: http://ec.europa.eu/environment/water/flood_risk/implem.htm

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