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Multi-Criteria Analysis Framework for Potential Flood Prone Areas Mapping

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Abstract A fundamental component of the European natural disaster management policy is the detection of potential flood-prone areas, which is directly connected to the European Directive (2007/60). This study presents a framework for mapping potential flooding areas incorporating geographic information systems (GIS), fuzzy logic and clustering techniques, and multi-criteria evaluation methods. Factors are divided in different groups which do not have the same level of trade off. These groups are related to geophysical, morphological, climatological/meteorological and hydrological characteristics of the basin as well as to anthropogenic land use. GIS and numerical simulation are used for geographic data acquisition and processing. The selected factor maps are considered in order to estimate the spatial distribution of the potential flood prone areas. Using these maps, the study area is classified into five categories of flood vulnerable areas. The Multi-Criteria Analysis (MCA) techniques consist of the crisp and fuzzy analytical hierarchy processes (AHP) and are enhanced with different standardization methods. The classification is based on different clustering techniques and it is applied in two approaches. In the first approach, all criteria are normalized before the MCA process and then, the clustering techniques are applied to derive the final flood prone area maps. In the second approach, the criteria are clustered before and after the MCA process for the potential flood prone area mapping. The methodology is demonstrated in Xerias River watershed, Thessaly region, Greece. Xerias River floodplain was repeatedly flooded in the last few years. These floods had major impacts on agricultural areas, transportation networks and infrastructure. Historical flood inundation data has been used for the validation of the methodology. Results show that multiple MCA techniques should be taken into account in initial low-cost detection surveys of flood-prone areas and/or in preliminary analysis of flood hazard mapping.

Keywords AHP · Flood prone areas · GIS · Fuzzy Analytical Hierarchy Process (FAHP) · Clustering techniques

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1 Introduction

The occurrence of extreme flooding has always been a threat to human society. Floods are having an important role among natural hazards due to the increasing number of inundation events with their associated social and economic damage. As an example, the annual average flood damage in Europe in the last two decades is about € 4 billion per year, and in the period 1998–2009, Europe experienced more than 200 major floods resulting in approximately 1,126 fatalities (EEA 2010; AghaKouchak et al. 2013). Flood risk management mitigation strategies and planning should be based on the estimation of the flood hazard in terms of its magnitude, frequency, and intensity as well as its consequences. Flood hazard and risk analyses are usually performed using advanced hydrologic and hydraulic-hydrodynamic models to estimate flood peaks and volumes and the propagation in time and space of the flood wave into the river banks and over the floodplains. However, these procedures in engineering practice are typically performed at small scales (river segments) which are important to assess flood risk damage at the existing structures (i.e. buildings) and not at the watershed scale due to data availability constraints. For these reasons, a complete mapping of flood-risk areas at watershed scale is still a difficult task, even in developed countries (de Moel et al. 2009).

The requirement for a complete flood risk management approach at watershed level has been documented by the European natural disaster management policy with the Flood Directive 2007/60/EC. This directive requires all member states to design flood risk management plans by the end of year 2015. Hence, flood mapping is a fundamental step for EU member states in the implementation of the Flood Directive. The detection of potential flood prone areas is a basic component of the flood mapping, directly connected to water resources management with the EU-FD. The last three decades have been worldwide observed a significant increase in the number of flood events. In Europe, overall losses as a consequence of floods have been increased over the last few decades. However, the numbers of mortalities in these phenomena have been reduced since the year 2000 due to national flood mitigation practices despite the substantial increase in the number of floods (Parker et al. 2007). Digital Elevation models (DEMs) and the DEM-derived geomorphological and hydrological attributes (i.e. slope, streams, drainage and catchment areas) has become a standard tool used for flood-prone areas identification (Noman et al. 2001). In this study, flood-prone areas mapping is based on the integration of the DEMs and DEM-derived attributes with multi-criteria analysis methods.

Complex decision problems can be examined through a framework that combines GIS and multi-criteria analysis methods in order to organize the elements into a hierarchical structure. It also examines the relationships among the components of the problem in order to take the proper decision for the primary goal of the investigation (Boroushaki and Malczewski 2010; Chen et al. 2011). The last years many surveys have been widely applied referring to the GIS-based multi-criteria decision analysis (GIS-MCDA) (Malczewski 2006). Analytical Hierarchy Process (AHP) is one of the multi-criteria analysis (MCA) methods that structuring the factors into a hierarchical framework. The decision-makers can evaluate the relative importance of various elements by the use of pairwise comparison tables. The AHP can calculate the score of each alternative with the transformation of the evaluations to numerical values (weights or priorities) (Saaty 1980). Over the last decades, several fuzzy logic methods or theories have been combined with AHP (van Laarhoven and Pedrycz 1983; Buckley 1985; Chang 1996; Mikhailov 2003). Conventional AHP may not totally reflect the human way of thinking, despite the varied range of its applications. Despite that fuzzy AHP (FAHP) requires tedious computations, when complicated decision making problems are analyzed it is skillful of capturing a human's judgment of uncertainty (Erensal et al. 2006).

Integration of AHP into GIS applications has been demonstrated to different scientific disciplines for: a) land use suitability, assessment, classification and planning, b) urban development, suitability and renewal (Chandio et al. 2013 and references therein), c) eco-environmental quality (Huang et al. 2010), d) landslides mapping (Yalcin and Bulut 2007; Feizizadeh and Blaschke 2013) e) earthquakes (Pal et al. 2008), f) health (Jeefoo and Tripathi 2011), g) droughts (Babaei et al. 2013) h) floods (Pawattana and Tripathi 2008; Madhuri et al. 2013) i) water resources management (Machiwal et al. 2011; Anane et al. 2012; Chowdary et al. 2013) and j) pollution (Negi and Jain 2008). Several studies have implemented AHP, FAHP or GIS modeling techniques for the estimation of flood prone areas, flood risk, flood hazard and other natural disasters (Chen et al. 2011; Kourgialas and Karatzas 2011; Park et al. 2013; Zou et al. 2013; Manfreda et al. 2011; Meyer et al. 2009; Stefanidis and Stathis 2013; Tehrany et al. 2013). A respective number of the above mentioned studies are using the Jenks natural breaks classification method (Jenks 1967) and/or predefined subjective tables for classification of the DEM-derived geomorphological and hydrological attributes into thematic maps (criteria maps) and the target variable of interest. For example, Kourgialas and Karatzas (2011) have classified their selected criteria using fixed classes before the implementation of the MCA method. However, using other criteria classification method will affect the final exported flood hazard areas. To this direction, Chen et al. (2011) have classified their criteria with some specific rules to overcome the limitations of predefined subjective tables to increase the subjectivity of the MCA framework for generalized applications.

This study develops an objective GIS-based spatial multi-criteria evaluation framework at catchment scale for the identification of potential flood prone areas at ungauged watersheds. Potential flood prone areas are identified using GIS data and techniques such as clustering/classification procedures and two MCDA methods the AHP and the FAHP. Two different approaches have been implemented and compared in order to investigate the sensitivity of the proposed framework in the identification of the flood prone areas at ungauged watersheds. The first approach is the process where all the criteria (DEM-derived geomorphological and hydrological attributes which are related to the flood generation process) are normalized before the MCA method and then, several clustering and classification techniques are applied to derive the final potential flood-prone areas. The second approach is the method where all the criteria are clustered before and after the MCA process for the production of the potential flooded area maps. The derived flood prone maps in the two approaches have been classified with five different clustering techniques. The methodology is demonstrated to Xerias River watershed, Thessaly region, Greece. Historical flood inundation data (flash flood event of 2006 that flooded sub-urban and urban areas of Volos city) and simulated flooded area derived from hydrologic - hydraulic modeling of the flood event have been used to validate the methodology. The proposed framework is developed for decision makers to identify potential flood prone areas caused from flash and fluvial floods with minimum subjectivity in order to be applied at larger spatial scales for gauged and ungauged catchments. The employed framework could be applied in flood hazard estimation and mapping at areas with limited available information, and/or in areas where preliminary flood hazard evaluation is required for flood mapping purposes using typical hydrologic and hydraulic methods at ungauged watersheds.

2 Study Area

The study area is the watershed of Xerias river located in the region of Thessaly and in the prefecture of Mangesia, Greece (Fig. 1). The watershed area of the Xerias river is about 120 km^2. Elevation ranges from 0 to 1,600 m with mean elevation 458 m. Mean annual

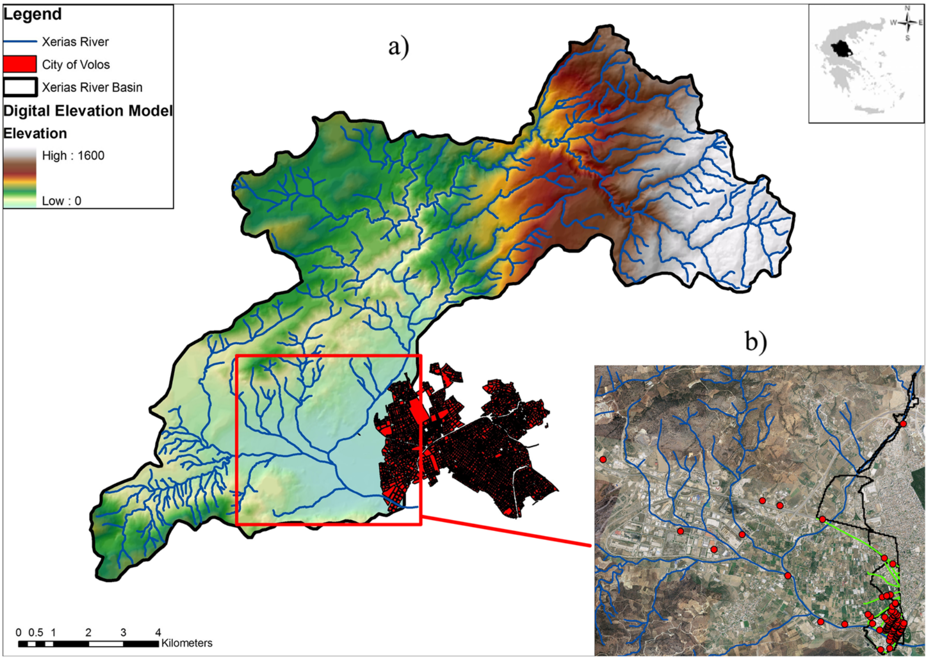

Fig. 1 The study watershed **a** Xerias river basin and **b** historical flood inundation areas used for validation of the framework

precipitation is approximately 700 mm. Xerias river drains through the City of Volos and has experienced frequent flood episodes due to intense storms. In this study, the flood episode on 9th October 2006 is used, which is one of the prefecture's worst recorded floods. This flood had major impacts on agricultural areas, transportation networks and other technical infrastructures at the study watershed (Papaioannou et al. 2011). A railroad bridge connecting Volos and Larissa cities collapsed from severe debris flow and almost one fifth of the Volos City faced extreme mudslides. On that day, a low-pressure system of 1,008 mbar, centered over the Aegean Sea and associated with a cold front, affected the study watershed (Yair et al. 2010). The surface system was associated with a 500 hPa cutoff low over the Ionian Sea that which was moving very slowly southeastward without further deepening. Consequently, a convective storm with extreme rainfall, caused flooding in Volos, where 232 mm rainfall was recorded from 06:00 to 18:00 UTC on 9 October 2006 (Harats et al. 2010). Based on prior Intensity-Duration-Frequency analysis at the greater area the return period of this event is estimated approximately at 100 years.

Historical flood inundation data and flooded area derived from hydrologic reconstruction of the event and hydraulic modeling of the flood have been used to validate the methodology. Specifically, historical flood recordings have been collected by several authorities, newspapers, local interviews and testimonies of flood victims and have been digitized through GIS. The final dataset includes points, polygons and polylines digitized by the following records: 1) Houses that were refunded for electrical machines damages, 2) Companies that were compensated for flood damage, 3) Buildings that were refunded for structural damages, 4) Flooded streets recorded by the Fire Department of the City of Volos, and 5) Estimated area by newspaper articles and human testimonies of flood victims. The modelled flooded area using hydraulic modeling has been estimated with a digital elevation model that created by terrestrial laser scanner data (vertical accuracy of 25 cm) and the use of Clark's instantaneous unit hydrograph applied for the rainfall data of the flood event. The estimated flooded area of Xerias river floodplain was 1.58 km^2 based on historical data and records (i.e. data collected from several authorities, newspapers, local interviews and testimonies of flood victims, 91 % of the total validation area) and hydraulic modeling (9 % of the total validation area). This flood had major impacts on agricultural areas, transportation networks and other technical infrastructures at the study watershed (Papaioannou et al. 2011).

3 Methodology

In this study, an objective GIS-based spatial multi-criteria analysis and evaluation framework has been developed and implemented at catchment scale for the identification of potential flood prone areas. Figure 2 presents the flowchart of AHP, FAHP and GIS processes of the applied method. The methodology is separated in two different approaches. In the first approach, all criteria are normalized, with min-max methodology, in order to perform Boolean algebra through GIS analysis. In the second approach, the criteria are classified at the start of the process using all used clustering techniques and then, they are applied for flood-prone areas mapping using Boolean algebra through GIS. It should be mentioned that all procedural steps have been designed to minimize subjectivity which is an important constraint in the application of multi-criteria evaluation methods. The proposed framework, described in the next paragraphs, is developed for decision makers to identify potential flood prone areas with minimum subjectivity in order to be applied at larger spatial scales.

3.1 Multi-Criteria Analysis Methods

Multi-Criteria Analysis (MCA) is used to analyze a series of alternatives or objectives with a view to ranking them from the most preferable to the least preferable using a structured approach. The final results of MCA are often a set of weights linked to the various objectives. Two MCA methods have been applied and compared for the estimation of the relative weight importance. These methods are the Analytical Hierarchy Process (AHP) and the Fuzzy Analytical Hierarchy Process (FAHP). AHP is a multi-criteria decision method that uses hierarchical structures to represent a problem and, then, develop priorities for alternatives based on the judgment of the user (Saaty 1980). The AHP procedure involves six essential steps (Lee et al. 2008): definition of the unstructured problem, development of the AHP hierarchy, creation of the pairwise comparison table, estimation of the relative weights, consistency evaluation and overall rating of the method. AHP method has been used to weight the criteria. Finally potential flood prone area maps were created with Boolean algebra through GIS. The second method is the FAHP. Last decades have been developed many methodologies of FAHP. In this study, the Chang (1996) extent analysis method of FAHP has been applied. The method is using triangular fuzzy numbers in the pair-wise comparison that are defined by three real numbers expressed as a triple (l, m, u) where $l \leq m \leq u$ for describing a fuzzy event. Different sets of linguistic scales to fuzzy numbers transformations have been tested (Bulut et al. 2012; Lee 2010). The transformed linguistic scales of importance to fuzzy triangular scale numbers with the lowest consistency ratio (lower than 10 %) finally are used, as proposed by Zhou 2012. Table 1 show the crisp numbers of AHP that were used (Saaty and Vargas 1991) and the transformed with the help of the linguistics scales of importance fuzzy triangular scale numbers (Zhou 2012). Weighting coefficients were obtained from FAHP.

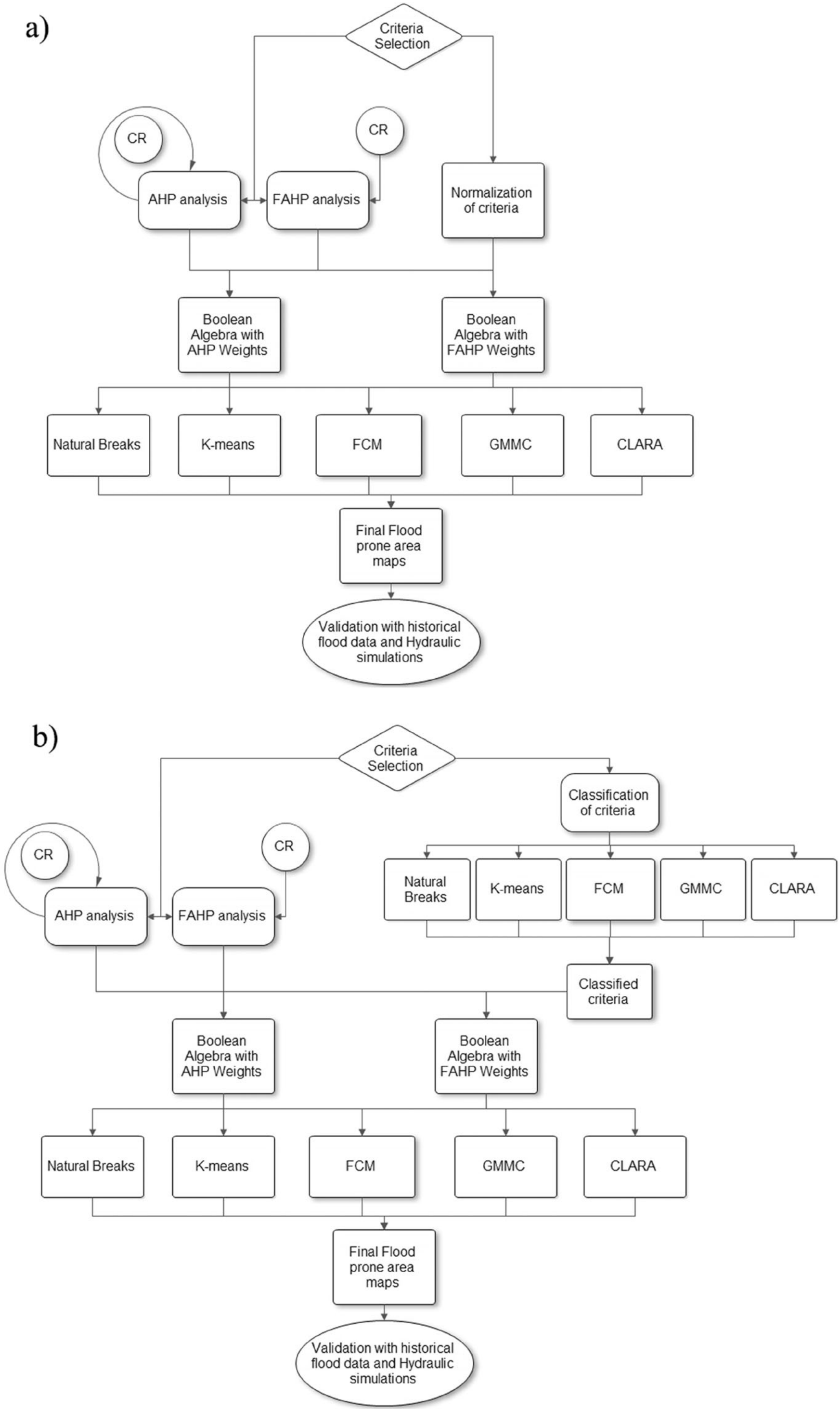

Fig. 2 Flowchart of the applied methodology. **a** 1st Approach **b** 2nd Approach

Table 1 AHP and FAHP linguistic scales for relative importance

	AHP		FAHP	
Linguistic scale for importance	Intensity of imprortance	Values for reciprocal scale	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Equally important	1	1	(1, 1, 1)	(1, 1, 1)
Intermediate 1	2	1/2	(1, 2, 3)	(1/3, 1/2, 1)
Moderately important	3	1/3	(2, 3, 4)	(1/4, 1/3, 1/2)
Intermediate2	4	1/4	(3, 4, 5)	(1/5, 1/4, 1/3)
Important	5	1/5	(4, 5, 6)	(1/6, 1/5, 1/4)
Intermediate 3	6	1/6	(5, 6, 7)	(1/7, 1/6, 1/5)
Very important	7	1/7	(6, 7, 8)	(1/8, 1/7, 1/6)
Intermediate 4	8	1/8	(7, 8, 9)	(1/9, 1/8, 1/7)
Absolutely important	9	1/9	(9, 9, 9)	(1/9, 1/9, 1/9)

3.2 Clustering-Classification Techniques

Clustering algorithms are categorized based on their cluster model. In this study, the following methods have been used and examined: Natural Breaks classification method (Jenks), K-mean clustering method, Fuzzy c-mean (centroid-based clustering methods), Gaussian Mixture Model Clustering (distribution-based clustering methods), Clustering Large Applications method (CLARA). All the above-mentioned methods belong to partitioning methods because they construct k partitions of the data, and were applied with k equal to five in order to create five vulnerability classes of flood prone areas. Due to the variety of the different selected criteria and the different spatial distribution of the values in each criterion, five (5) hazard classes were defined to represent the spatial distribution of the hazard areas and to decrease the calculation time of the classification techniques. This assumption of setting a priori the number of hazard classes is also followed in similar studies for the identification of the flood prone areas (eg. Kourgialas and Karatzas 2011; Stefanidis and Stathis 2013; Zou et al. 2013). As mentioned before, two approaches have been applied: in the first approach, all clustering techniques were applied only at the end of the framework in order to classify the final potential flooded areas, and in the second approach the clustering techniques were applied directly to the criteria (at the beginning of the framework) and after the MCA application for the creation of flood-prone areas and their associated flood hazard degree. These clustering classification techniques are briefly described in the next paragraphs.

1. Natural Breaks: Jenks natural breaks is a data classification method for the determination of the optimum arrangement of values into separate classes so that they can be displayed on a chloropleth map (Jenks 1967). Jenks Optimization method is trying to reduce the variance within classes and to maximize the variance between classes. Natural breaks is one of the most common classification methods that is used in GIS and especially for flood risk areas classification. It is a data classification technique that divides data into classes based on natural groups in the data distribution. In data distribution the class breaks are defined in gaps between clusters of values. The method can locate grouping and patterns inherited in the data, reducing the differences within a class and accentuates the differences between the created classes.

2. K-mean: K-mean clustering method uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. The algorithm moves objects between clusters until the optimization of sum. The most common distance method that is used in k-mean function is the 'sqEuclidean' (i.e. the Squared Euclidean distance) method where each centroid is the mean of the points in that cluster. Another distance method is the 'cityblock' (i.e. the Sum of absolute differences) where each centroid is the component-wise median of the points in that cluster (Mathworks 2013). These two variances of K-means cluster method were employed and examined. In order to avoid local minima the method has been applied iteratively 1,000 times, for both distance methods, with a new set of initial cluster centroid positions each time.
3. Fuzzy C-mean: Fuzzy C-Means (FCM) proposed by Bezdek (Bezdec 1981), is a data clustering technique where an element can belong to two or more clusters with different membership value. This method is frequently used in pattern recognition. The algorithm works iteratively until the production of an optimal C partition by minimizing the weighted within group sum of squared error objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \|x_i - c_j\|^2 \tag{1}$$

where m is any real number greater than 1 and it is set to 2.00 by Bezdek; u_{ij} is the degree of membership of x_i in the cluster j; x_i is the ith of d-dimensional measured data; c_j is the d-dimension center of the cluster and ||*|| is an equation that define the similarity between any measured data and the center (Alata et al. 2008). After the application of FCM clustering method, the defuzzification process of maximum membership procedure was applied in order to convert the fuzzy partition matrix U to a crisp partition. The procedure assigns object k to the class C with the highest membership (Yang and Huang 2007):

$$C_k = arg_i\{max(u_{ik})\}, i = 1, 2, \ldots..c \tag{2}$$

With this procedure, the fuzzy values were converted to crisp values and made possible the visualization of the results.
4. Gaussian Mixture Model: Gaussian Mixture Model (GMM) is a method of mixture models that is widely used in clustering (Bishop 2007). The parameters are usually estimated using maximum likelihood procedures and especially the Expectation-Maximization algorithm (Dempster et al. 1977; Nock and Nielsen 2006). The algorithm assigns posterior probabilities to each component density with respect to each observation. Then, the clusters allocated by selecting the component that maximizes the posterior probability. Gaussian Mixture Model clustering (GMMC) uses an iterative algorithm that converges to a local optimum (like k-means clustering). GMMC is a soft clustering method in most of the studies. The posterior probabilities for each point indicate that each data point has some probability of belonging to each cluster (Mathworks 2013). The method is applied iteratively 1,000 times.
5. CLARA: Kaufman and Rousseeuw (1986) introduced the method CLARA which does not store the entire dissimilarity matrix. This method is also based on the k-medoid approach and in comparison to other partitioning methods, can deal with much larger datasets. Handling with large datasets is achieved by considering sub-datasets of fixed size (sample size) such that the time and storage requirements become linear in dataset size rather than quadratic. Each sub-dataset is partitioned into k clusters using the same

algorithm as in Partitioning Around Medoids (PAM) method (Kaufman and Rousseeuw 1990). The method is applied iteratively 1,000 times with one percent sample size (3,000 points) of the total size of the data set. More information of iterative unsupervised clustering algorithms could be found in the study of Nock and Nielsen (2006).

4 Estimation of Flood-Prone Areas in the Xerias River Basin

The methodology for the identification of flood-prone areas at catchment scale is applied at Xerias river basin, Greece (Fig. 1). The employed multi-criteria analysis methods and clustering-classification techniques are used to derive relationships between the selected criteria, which are quantitative geomorphological and hydrometeorological features derived mainly from digital elevation models, and the flood hazard mapping as depicted from flood-prone areas maps. The application procedure is described in the next paragraphs.

4.1 Criteria Identification

An important aspect in the identification of potential flood prone areas using geomorphologic indices is the selection of the appropriate features. The successful application of MCA methods in detecting potential flood-exposed areas and their flood hazard degree is that the indices should be connected with the physical process of the flood generation mechanism. Furthermore, these features or attributes must be measured or quickly calculated for the whole study area and to have simple interpretability. For these reasons, preliminary analysis using linear correlation of 32 candidate flood-related geomorphological attributes identified 10 important criteria (Papaioannou et al. 2011). The selected criteria were: 1) Digital Elevation Model (DEM), 2) Slope, 3) Aspect, 4) Flow Accumulation (Flow Ac.), 5) Horizontal Overland Flow Distance (HOFD), 6) Vertical Overland Flow Distance (VOFD), 7) Topographic Position Index (TPI), 8) Wetness Index (WI), 9) Curve Number (CN, SCS method), 10) Modified Fournier Index (MFI). All derived features have the same spatial resolution (20 m cell size) and were calculated as normalized indices to increase objectivity and general application of the method in other watersheds. Figure 3 presents the ten selected geomorphologic indices and their normalized spatial distribution used for the detection of potential flood-prone areas. Typical techniques were used for DEM, Slope and Flow Accumulation criteria estimation. The directions of storms were included in the Aspect factor based on historical extreme meteorological events at the study area. Figure 4 shows the final allocation of the Aspect criterion including its flood-prone area classes that emphasizes south bound storm systems, identified in the study area as the most critical aspect for the flood generation combined to severe storm directions. Horizontal overland flow distance is taking into account the real movement of water from cell to cell. For that reason the flow routing algorithms that have been used is the Multiple Flow Direction (Quinn et al. 1991). The distance is expressed in the same units as the heights and cells size value from the DEM grid. Vertical Overland Flow Distance is based on vertical distance between cell elevations and the elevations calculated for the channel network in that cell. Generally, non-channel cells will be assigned a value which represents the elevation difference between those cells and the channel that flows through them, in case it existed. The distance is expressed in the same units as the heights and cells size value from the DEM grid (Olaya 2004). Topographic Position Index (TPI) is an index of displaying the locations in the area of interest. Hence, in relative terms, the topographic position of a location may be hilltops, valley bottoms, or a slope, or an exposed ridge, or a flat plain, or other features

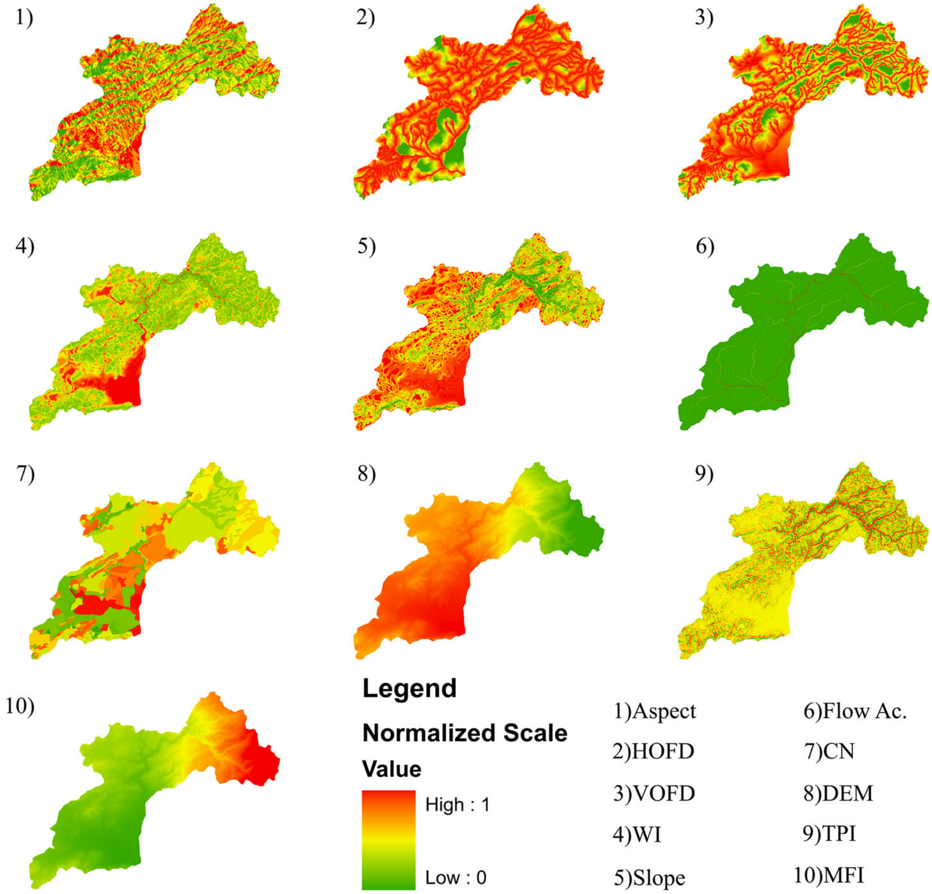

Fig. 3 Selected geomorphologic indices and their normalized spatial distribution

(Tagil and Jenness 2008). TPI was calculated with radius 5 cell size (100 m). The Topographic Wetness Index (TWI) is a physical attribute of flood-inundation areas from DEMs (Kirkby 1975). It includes two representative measurements one related to the hydrographic position of the grid cell in the basin, the drainage area per unit contour length, and one to the presence or absence of flat land. In this study the SAGA Wetness Index (WI) (Boehner et al. 2002) is used, which is similar to the TWI, but it is based on a modified catchment area calculation, which does not treat the flow as a thin film as done in the calculation of catchment areas in conventional algorithms. Hence, WI predicts for cells situated in valley floors with a small vertical distance to a channel a more realistic, higher potential soil moisture and iteratively modifies the catchment area of each grid cell in dependence of neighboring maximum values using a slope-dependent equation unless the results remain unchanged by additional iterations (Boehner et al. 2002). The Curve Number (CN) was developed by the USDA Natural Resources Conservation Service and is an empirical parameter used in hydrology for predicting direct runoff or infiltration from rainfall excess. The runoff CN is based on the area's hydrologic soil group, land use and soil moisture conditions. Because it is a function of the soil and land use of a drainage basin, estimation of a curve number requires mapping of the soil and land use within the drainage basin boundaries, and specification of unique soil types

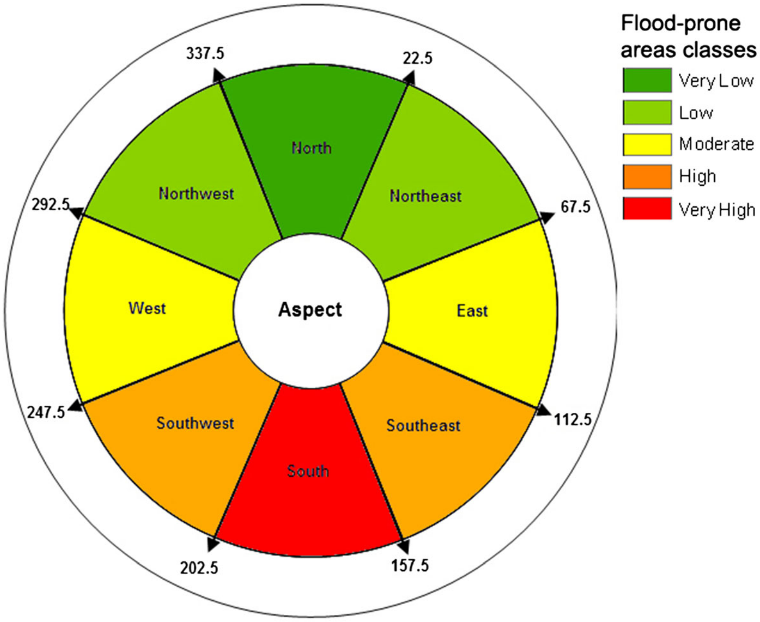

Fig. 4 Final allocation of the Aspect criterion including its flood-prone area classes that emphasizes south bound storm systems

and unique land use categories. CN estimation involves area-weighting land use and soil types. Curve Number values for the study watershed were based on the integration of hydrologic soil group categories and CORINE Land cover classification data as proposed by Miliani et al. 2011. In order to determine the rainfall intensity, monthly precipitation data for the period 1960–2002 were used from four meteorological stations located near Xerias watershed. In this study rainfall is an important parameter of the flood process and was included in the analysis as an extreme precipitation calculated based on the MFI criterion. The rainfall intensity map was created by using the Modified Fournier Index methodology (Morgan 2005):

$$MFI = \sum_{1}^{12} \frac{p^2}{P} \tag{3}$$

where MFI: Modified Fournier Index, Σ: the 12-month summation, p: the average monthly rainfall, and P: the average annual rainfall. For the estimation of MFI map has been used a combinational method regression with elevation and a Spline interpolation of the residuals. Table 2 presents the Pearson correlation of the employed criteria which shows that only MFI is correlated to the DEM as it was expected since MFI is calculated based on DEM using a linear precipitation gradient.

4.2 Pairwise Comparison Tables—Expert Survey

The pairwise comparison is the fundamental component of the AHP process. This step process reduces the conceptual problem complexity because it uses two components only at any given time. Experts provide their judgment of the relative intensity of importance of one evaluation factor (objective and criterion) against another. The pairwise comparison tables were

Table 2 Pearson correlation coefficient matrix of the employed criteria

	DEM	Slope	Aspect	Flow Ac.	HOFD	VOFD	TPI	WI	CN	MFI
DEM	1.00									
Slope	0.37	1.00								
Aspect	0.08	0.00	1.00							
Flow Ac.	0.05	0.05	−0.01	1.00						
HOFD	−0.23	−0.25	−0.14	0.05	1.00					
VOFD	0.29	0.26	0.05	0.06	0.35	1.00				
TPI	0.05	−0.03	0.01	0.10	0.11	0.39	1.00			
WI	0.44	0.69	0.01	0.14	−0.19	0.46	0.28	1.00		
CN	−0.03	−0.08	0.07	−0.05	−0.13	−0.13	−0.03	−0.22	1.00	
MFI	−1.00	−0.37	−0.08	−0.05	0.23	−0.29	−0.05	−0.45	0.03	1.00

completed by nine (9) experts in the field of hydrology. Their results were normalized and examined with the Consistency Ratio approach (CR). For the application of FAHP the estimation of CR was calculated with the simple centroid method (Chang and Wang 2009). In this study, the acceptable CR limit based on the 10 selected indices should be less than 10 %. In AHP method the experts modified their pairwise comparison tables until their CR is lower than the acceptable CR limit. Consistency ratio of FAHP was also smaller than 10 % for the final selected tables. An example of AHP pairwise comparison table can be found in Table 3. The final selected weights stem from one pairwise comparison table of an expert and named as "Expert Knowledge" and the median of all the pairwise comparison matrices referred as "Group of Experts".

4.3 Criteria Classification

The six clustering/classification techniques considered in this study are the following: 1) Natural Breaks, 2) K-mean with Euclidean distance method, 3) K-mean with Cityblock distance method, 4) FCM, 5) GMMC and 6) CLARA with Euclidean distance calculation. In the first approach all the criteria were normalized, with min-max methodology, in order to perform the Boolean algebra through GIS analysis. In the second approach the

Table 3 Example of AHP pairwise comparison table

	DEM	Slope	Aspect	Flow Ac.	HOFD	VOFD	TPI	WI	CN	MFI
DEM	1	1/6	2	1/7	1/3	1/5	1/3	1/9	1/6	1
Slope	6	1	4	1/5	2	1/5	1/2	1/7	1/2	4
Aspect	1/2	1/4	1	1/7	1/2	1/6	1/5	1/8	1/5	1/3
Flow Ac.	7	5	7	1	4	2	3	1/2	2	5
HOFD	3	1/2	2	1/4	1	1/3	1/3	1/7	1/5	2
VOFD	5	5	6	1/2	3	1	2	1/4	2	4
TPI	3	2	5	1/3	3	1/2	1	1/3	3	5
WI	9	7	8	2	7	4	3	1	5	9
CN	6	2	5	1/2	5	1/2	1/3	1/5	1	3
MFI	1	1/4	3	1/5	1/2	1/4	1/5	1/9	1/3	1

criteria were classified at the beginning with all clustering techniques and then were applied through GIS with Boolean algebra. In both approaches, potential flood prone areas were derived from the summation of the criteria multiplied by the respective relative weights (AHP, FAHP) using Boolean algebra. Then, the criteria were classified with all the above mentioned clustering methods. In the second approach the clustering techniques were applied only with the respective clustering technique (i.e. FCM with FCM in Fig. 2).

The majority of the studies that combine AHP-FAHP and GIS are using simple classification methods that are included in the GIS software's. In this study different clustering techniques have been applied in order to: 1) explore the dependency of the output on input parameters, 2) identify the most sensitive criteria in clustering techniques, 3) show the impacts of using different clustering methods on the mapping results. After the application of the AHP and FAHP, the final criteria were classified with the above six clustering techniques in five potential flood prone classes: 1) Very Low—value 1, 2) Low—value 2, 3) Moderate—value 3, 4) High—value 4, 5) Very high—value 5.

5 Results - Discussion

Pairwise comparison application and analysis produced the relative weights of the study factors. Table 4 presents these weights for both MCA methods (AHP and FAHP, respectively) and shows that the most important factors are the Wetness Index followed by the Curve Number (CN). Hence flood prone areas identification depends mainly on these two factors. An important finding revealed from Table 4 is that in AHP all criteria contribute in the estimation process whereas in FAHP some criteria with minor weights are eliminated from the process. Consistency ratio of the pairwise comparison is 4.3 and 6.8 % for AHP and FAHP, respectively. An example of the spatial distribution of the applied clustering methods in MCA is presented in Fig. 5. This figure shows the final maps of AHP Group of Experts (1st approach), whereas Fig. 6 shows the same approach for FAHP application. The majority of the clustering techniques are giving a similar spatially distributed pattern in the classes of potential flooded areas with an exception at lowlands for the first approach and with differences in GMMC method for the second approach. Figures of the second approach are not shown do to paper length limitations and their similar spatial distribution with Figs. 5 and 6. The choice of experts (group of experts or expert knowledge) seems to be insensitive to the MCA methods in both approaches. The distribution of the classes of the derived flood prone maps is presented in Table 5 for the two approaches and MCA methods using Expert knowledge. The classes for all classification methods in the first approach are ranging between 3.13 and 18.16 % and in the second are ranging from 5.17 to 24.53 % (Table 5).

Table 4 AHP and FAHP relative weights of the criteria and their consistency ratios

	DEM	Slope	Aspect	Flow Ac.	HOFD	VOFD	TPI	WI	CN	MFI	CR
AHP expert knowledge	0.03	0.09	0.02	0.14	0.13	0.05	0.07	0.25	0.20	0.02	4.3 %
AHP group of experts	0.03	0.11	0.02	0.15	0.08	0.07	0.08	0.26	0.17	0.03	4.3 %
FAHP expert knowledge	0.00	0.09	0.00	0.18	0.14	0.00	0.02	0.31	0.26	0.00	6.7 %
FAHP group of experts	0.00	0.13	0.00	0.19	0.05	0.03	0.06	0.32	0.22	0.00	6.8 %

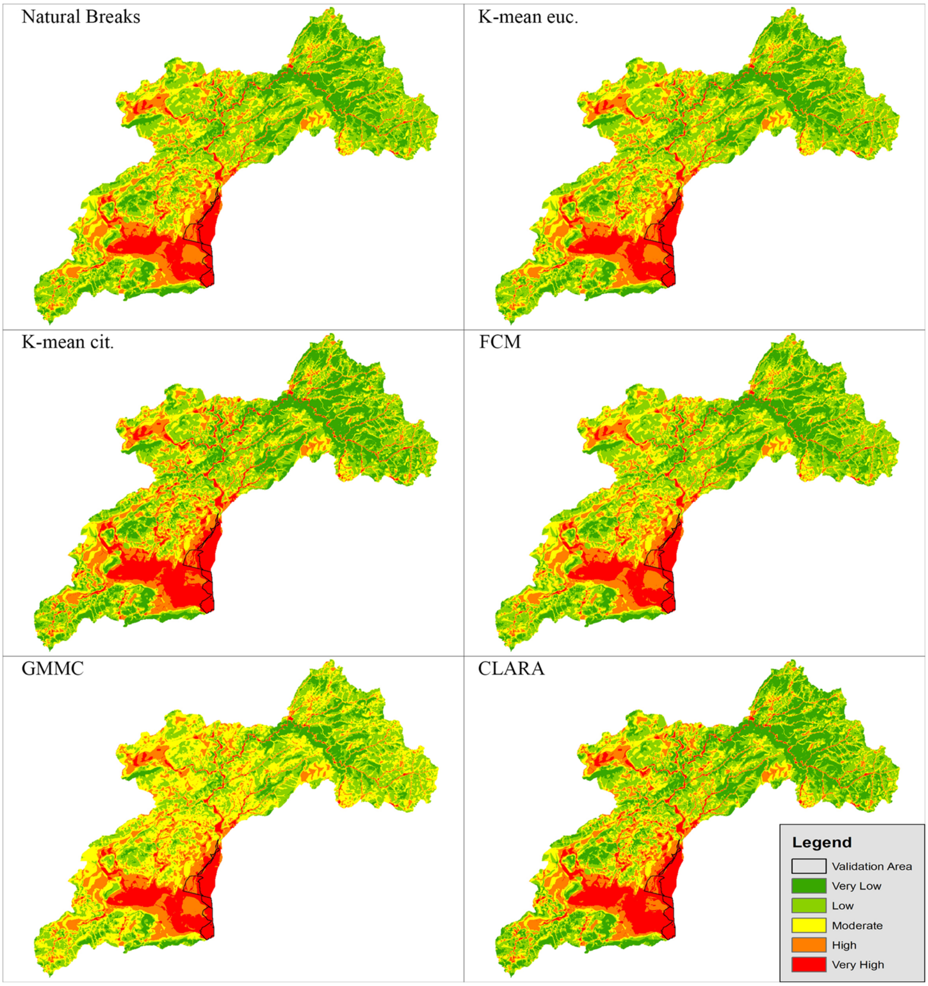

Fig. 5 Final maps of AHP Group of Experts, 1st approach

The historical flood inundation data and flooded area derived from hydrologic and hydraulic modeling (Papaioannou et al. 2011) of the flood episode occurred in October 9th, 2006 are used to validate the produced potential flood prone areas. Figure 7 presents the comparison of all clustering methods for both approaches and shows the contribution of each class on the validation flooded areas only. Flood hazard degree based on the derived flood prone areas mapping shows that only three hazard classes are presented in the validation area. Furthermore, it is observed that K-means cit. and CLARA techniques have the largest contribution in the Very High class in the first approach (Fig. 7). In the 2nd approach no one method is consistently outperformed the other study methods. A general remark is that AHP has larger agreements than FAHP in Very High hazard class (Fig. 7) and the choice of the selected pairwise comparison tables (Expert knowledge or Group of experts) is insensitive on the MCA methods. This finding demonstrates the general application of the procedure and the minimization of subjectivity of MCA methods. In the first approach all classification methods show similar patterns in the estimation of flood prone areas. However, K-means cit. and CLARA

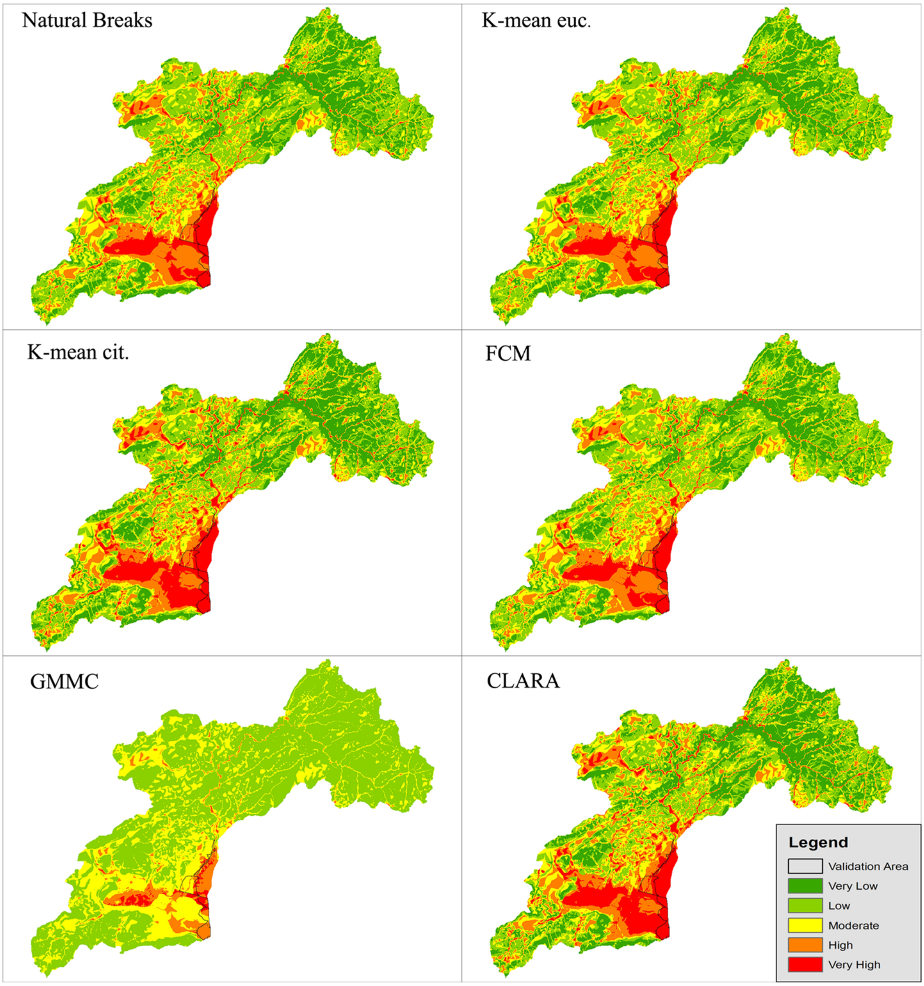

Fig. 6 Final maps of FAHP Group of Experts, 1st approach

have the highest contribution percentage in Very High class (i.e. for AHP Expert knowledge 77.9 % and 78 %, respectively). Finally it is observed that in one case (first approach), the GMMC technique for FAHP group of experts has larger differences in the classes distribution. This is probably due to the convergence algorithm of GMMC method which gave different distribution patterns. In general GMMC technique was the most unstable method for our case study and in some cases failed to create the desired number of classes. The comparisons between the two different approaches showed in that using normalized data (criteria) before the MCA application have better response to the framework than the clustering application. In general at watershed scale the two approaches present approximately 25 % discordant classes. At the validation flooded area better response is observed with the first approach. Finally, in the majority of the cases, Natural Breaks (Jenks) method had the smallest contribution percentage in Very High class. Hence, caution and comparison with other clustering techniques is recommended on its application for mapping purposes.

Table 5 Percentage of flood prone areas classes of AHP and FAHP "Expert Knowledge" for both approaches

1st approach						
Flood prone areas classes	Natural breaks	K-means euc.	K-means cit.	FCM	GMMC	CLARA
AHP expert knowledge						
Very low	17.31	17.29	20.53	17.10	8.22	20.26
Low	33.25	32.24	27.48	31.88	25.18	27.43
Moderate	25.99	25.93	24.13	26.05	36.11	24.30
High	16.86	17.41	17.19	17.66	20.13	17.32
Very high	6.60	7.13	10.66	7.30	10.35	10.69
FAHP expert knowledge						
Very low	20.76	20.45	22.44	19.80	19.31	22.21
Low	34.05	32.19	27.47	32.07	15.89	27.19
Moderate	24.02	24.70	24.05	25.18	37.72	24.44
High	15.63	16.67	16.47	16.94	20.92	16.58
Very high	5.54	5.99	9.56	6.01	6.16	9.57
2nd approach						
Flood prone areas classes	Natural breaks – Natural breaks	K-means euc. – K-means euc.	K-means cit. – K-means cit.	FCM – FCM	GMMC – GMMC	CLARA–CLARA
AHP expert knowledge						
Very low	19.54	18.60	19.87	16.36	14.70	18.81
Low	28.28	27.45	24.94	25.69	15.31	23.00
Moderate	23.62	23.79	22.42	25.98	46.27	21.74
High	20.76	22.18	21.34	22.07	0.00	21.16
Very high	7.80	7.99	11.44	9.90	23.73	15.29
FAHP expert knowledge						
Very low	21.09	23.08	21.77	21.10	14.53	29.46
Low	30.75	30.78	27.18	27.70	25.06	28.14
Moderate	25.93	25.23	24.23	25.59	36.63	22.54
High	15.18	14.27	18.19	16.15	9.79	12.33
Very high	7.05	6.64	8.64	9.46	13.99	7.53

6 Concluding Remarks

An objective GIS-based spatial multi-criteria evaluation framework has been applied at catchment scale and could be used in decision making for flood prone area assessment. The methodology is based on limited data and information with minimum subjectivity in multi-criteria analysis. Furthermore, it incorporates expert opinion and knowledge on the criteria and their weights, and provides a framework for helping the decision maker through multi-criteria combination problems. The overlay results obtained from the methodology against historical flood events and flood inundation modeling verified the credibility of the method.

In the two study approaches AHP have better response than FAHP and their which is independent on the choice of the selected pairwise comparison tables (Expert knowledge or Group of experts) is insensitive on the MCA methods. The majority of the clustering techniques are giving a similar spatially distributed pattern in the classes of potential flooded areas with an exception at lowlands where two clustering techniques have better response (K-

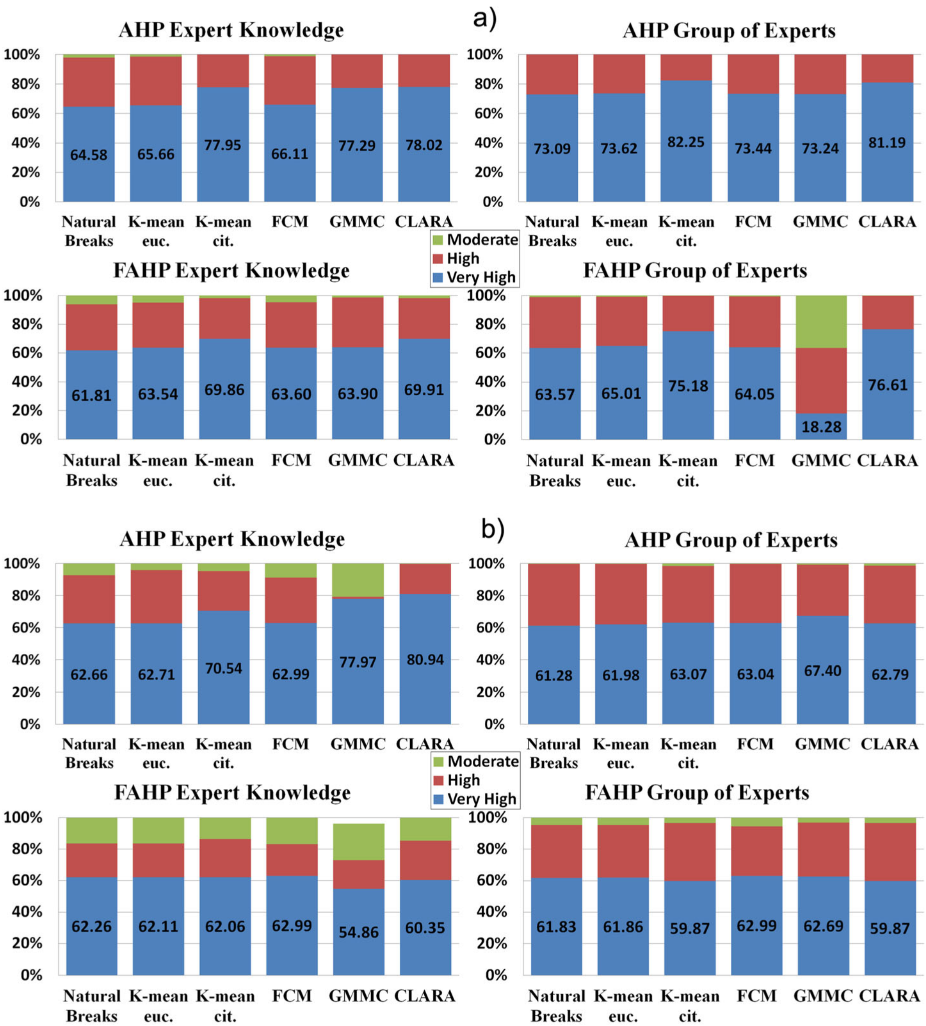

Fig. 7 Classes participation percentage on validation areas for all the examined cases. a) first approach, b) second approach

means cit. and CLARA) (Figs. 5, 6 and 7). The results indicate the general application of the procedure and the minimization of subjectivity of MCA methods. Finally a general remark is that Natural Breaks (Jenks) method had the smallest contribution percentage in Very High class.

Application of the proposed framework in Xerias river basin showed that multiple MCA techniques should be taken into account in initial low-cost detection surveys of flood-prone areas. Furthermore, the use of multiple clustering techniques is necessary in preliminary analysis of flood risk mapping where observed flood inundation areas have been estimated in order to not only simulate the flood-prone areas but also to evaluate their associated flood hazard degree. The integration of spatial data and application of GIS-based multi-criteria evaluation procedures could provide a superior database and guide map for decision makers in order to produce potential flood prone areas mapping. The employed framework could be applied in flood hazard estimation at areas with limited available information, and/or in areas where preliminary flood hazard evaluation is required for flood mapping purposes using hydrologic and hydraulic modeling.

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