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Enhancement of Socioeconomic Criteria for the Assessment of the Vulnerability to Flood Events with the Use of Multicriteria Analysis †

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Abstract: The aim of the research is the re-assessment of the flood risk when the sensitivity criteria used to evaluate the vulnerability are enhanced with adaptive-recovery capacity criteria and the exposure. Hence, in the proposed methodology, the vulnerability to flooding is addressed as a synthesis between the adaptive-recovery capacity, the exposure, and the sensitivity. To do so, a multicriteria ranking is proposed. The multicriteria ranking is based on the fuzziness in order to interpret the multicriteria synthesis of the widely-used multicriteria technique for order preference by similarity to ideal solution (TOPSIS) method. The case study areas are the Greek parts of the Nestos and Strymonas transboundary river basins.

Keywords: flood risk; vulnerability to flooding; multicriteria analysis; TOPSIS; fuzzy pattern recognition; fuzzy sets

1. Introduction

Floods are among the most destructive water-related hazards and are considered responsible for the loss of human lives, infrastructure damages, and economic losses [1]. In 2007, the European Union ratified the Flood Directive (FD) as its response to the protection of citizens, properties, environment, and cultural heritage against flood events. The final implementation instruments of the FD are the flood risk management plans. These plans demonstrate for the areas that have been identified as prone flood areas under three different scenarios, i.e., a low probability, a medium probability and a high probability scenario, the potential population, economic activities, and the environment at potential risk from flooding, while proposing appropriate measures and actions to manage these risks. However, in order to take advantage of the proximity to water resources, either for water supply or irrigation purposes, urbanization and construction of built-up environments on natural drainages, flood plains, and riverbeds is an old but continuous and current practice [2]. The increased population, together with increased socio-economic activities within flood vulnerable areas, amplifies the flood risk.

Flood risk and vulnerability can be viewed as multidimensional and complicated issues. A modern approach for interpreting the anthropogenic and natural pressures on the environment is through the vulnerability assessment, i.e., a problem identification process (hazard), the problem's quantification (exposure), and the impact rate assessment [3]. According to Intergovernmental Panel on Climate Change IPCC [4], vulnerability is the degree to which a system is susceptible to the adverse effects of environmental changes, while vulnerability may also be attributed as the extent to which changes could harm a system, or by which a community can be affected by the impact of a hazard [5]. Various methods have been proposed for the vulnerability assessment, such as index-based methods, indicator-based approach, and GIS-based decision support systems [6]. In addition, multicriteria decision analysis (MCDA) is considered an important tool for the assessment of the vulnerability [7] since it performs a spatial ranking of the identified hazards, namely sensitivity, the preparedness facilities and capabilities, namely adaptive capacity, and the exposure, which, in case of floods, is related to the hydrometeorological conditions.

Therefore, based mainly on Reference [5], a fuzzified multicriteria method is developed and applied for assessing the vulnerability to flood with respect to the sensitivity, adaptive capacity, and the exposure. These three aspects are seen as criteria, which are evaluated based on several sub-criteria. The selected method is a fuzzy modification of the widely used TOPSIS method (TOPSIS: Technique for Order Preference by Similarity to Ideal Solution) since it is an understandable method in the engineering practices.

2. Materials and Methods

2.1. Case Study Areas

The proposed methodology is applied to the Greek parts of the Nestos and Strymonas transboundary river basins. The Nestos river basin is shared between Bulgaria, which is an upstream country, and Greece, which is a downstream country. The basin is characterized as a mountainous basin with forested or natural grassland areas to cover 75.41% of the basin and almost 69.2% of its 2834 km^2, shown in Table 1 [8], which has an elevation above 100 m a.s.l. The waters before discharging into the North Aegean Sea cross a deltaic area of 550 km^2, which is extensively being used for irrigated agriculture, with the majority of the basin's inhabitants engaged in the primary sector. According to the relevant National Flood Risk Plan (NFRP) [9], the inundated areas in case of 50-year return period floods are concentrated in the deltaic area and cover 85.5 km^2 (Figure 1).

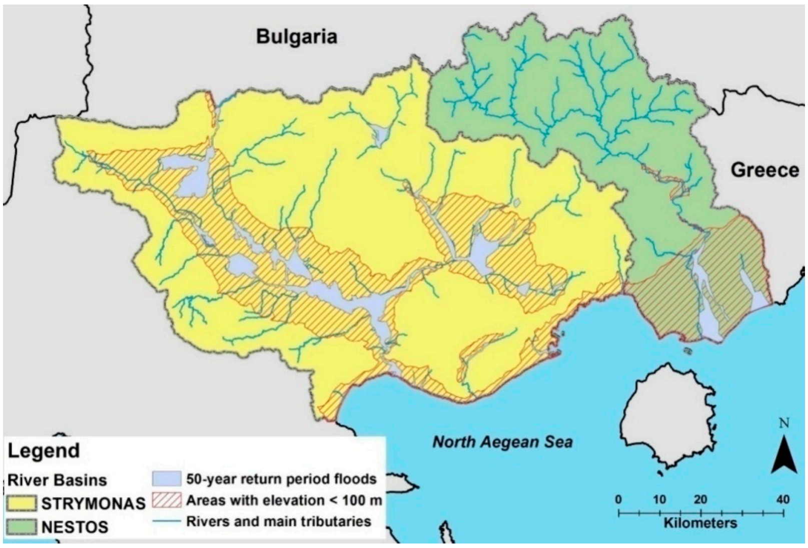

Figure 1. Illustration of the case study areas and the subdivision of the areas to the elevation threshold of 100 m.

The Strymonas river basin is also a transboundary river basin with Bulgaria, North Macedonia, and Greece to be the riparian countries. Almost half of the basin, i.e., 47.2%, is located under 100 m a.s.l, and constitutes a significant plain for irrigated agriculture (Figure 1). By taking into consideration the elevation at the Greek-Bulgarian borders, i.e., the entrance point of the river in Greece, is lower than 100 ma.s.l. and the river's length until the estuaries is 110 km (Table 1), it can been concluded that, due to the longitudinal incline of $9 \times 10^{-3}\%$, the downstream part of the basin is a flood-prone area. Based on data from the relevant NFRP [10] for 50-year return period floods, the inundated areas cover 431.4 km^2.

Table 1. Nestos and Strymonas river basins hydrological characteristics.

River	Extend (km^2)	Mean Elevation (m)	River Length (km)	Annual Precipitation (mm)	Annual Discharge ($\times 10^6 m^3$)
Nestos	2834	606	130	678	687
Strymonas	7282	430	110	675	1514

For the implementation process, both basins are divided to the lowland areas, which are considered financially robust areas due to irrigated agriculture but also flood prone areas, and the mountainous areas, which present less inundations but have decreased incomes (Figure 1). With the proposed division, four areas with two for each basin are designated. In particular, Areas 1 and 2 belong to the Nestos basin and correspond to areas with lower and upper elevation by 100 m, respectively. Accordingly, Areas 3 and 4 belong to the Strymonas basin and correspond to areas with lower and upper elevations by 100 m, respectively.

2.2. TOPSIS Method Based on a Fuzzy Pattern Recognition

Let us generally consider either a ranking problem or a classification problem with N data points in which each of them has an M dimension. Let us also consider the ideal and the anti-ideal solution [11,12], which are fictitious alternatives (points) (more general for K clusters). The ideal and the anti–ideal alternatives are points with an M dimension [13,14]. When the fuzzy ranking is applied in multicriteria problems, the data points are the examined alternatives (here, the selected areas) and the dimension of the data points is identical with the number of the examined criteria. In this article, three criteria examined the sensitivity, adaptive capacity, and the exposure criteria.

Let us consider as **R** the matrix, which contains the normalized score of the criteria with respect to each alternative (here, the areas).

$$\mathbf{R} = \begin{bmatrix} r_{11} & \cdots & r_{1M} \\ \cdots & r_{im} & \cdots \\ r_{N1} & \cdots & r_{NM} \end{bmatrix} \tag{1}$$

Furthermore, in order to determine the total contribution/score (r') of each criterion m, more often the weight (w_m) of each criterion is combined with the score (r) of each alternative i, as follows (weighted normalized score) [13].

$$r_{im}' = w_m \cdot r_{im} \tag{2}$$

As can be seen, even if the data are crisp numbers, the fuzziness is used to achieve the final membership function indicating to which degree the examined alternative belongs to the ideal point by taking into account all the distances from both the ideal and the anti-ideal points [12].

The most widely used measure of distance between the alternative i and the ideal and the anti-ideal points are:

$$d_i^{+} = \left[\sum_{m=1}^{M} \left[\left(r_{i,m}' - v_m^{+} \right) \right]^2 \right]^{1/2} \tag{3a}$$

$$d_i^{-} = \left[\sum_{m=1}^{M} \left[\left(r_{i,m}' - v_m^{-} \right) \right]^2 \right]^{1/2} \tag{3b}$$

A common choice is to select as:

$$A^{+} = \{1,1,..,1\} \left(v_m^{+} = 1, \forall m = 1,..,M \right),\ A^{-} = \{0,0,..,0\} \left(v_m^{-} = 0, \forall m = 1,..,M \right)$$

regarding the ideal and the anti-ideal points. However, the monotony can be different as in case of the adaptive capacity criterion.

The next critical concept is the membership degree μ, which indicates the relative membership degree of alternative i belonging to either the ideal (μ_i^+) or the anti-ideal solution (μ_i^-). The membership degree μ_i^+ takes into account the distance of each area (alternative i) compared with all categories. Hence, the ideal membership degree μ_i^+ is not identical with the distance with the ideal alternative. A basic property that must be verified in the fuzzy pattern recognition is that the sum of the membership values for each alternative under the ideal and the anti-ideal solution is equal to one [15].

$$\mu_i^+ + \mu_i^- = 1 \tag{4}$$

In general, the methodology of fuzzy sets comprises a mapping from a general set X to the closed interval [0,1], which is described by its membership function [16]. Therefore, the above constraint can be easily achieved since the membership function takes values between zero and one.

Lastly, the membership degree is selected by aiming to minimize the following objective function, which expresses the sum of the relative distances of the alternatives from the patterns.

$$\min\left(F = \sum_{i=1}^{N} f\left(r_i''\right)\right),\ f\left(r_i\right) = \left(\mu_i^+ \cdot d_i\left(A^+, r_i'\right)\right)^2 + \left(\mu_i^- \cdot d_i\left(A^-, r_i'\right)\right)^2 \tag{5}$$

By using the Lagrange theory of optimization (because of the equality constraint of Equation (4)), it is easy to see that the membership degree of belonging of the alternative i at the ideal point is equal to Reference [14].

$$\mu_i^+ = \frac{1}{\frac{\left(d_i^+\right)^2}{\left(d_i^+\right)^2} + \frac{\left(d_i^+\right)^2}{\left(d_i^-\right)^2}} = \frac{1}{1 + \frac{\left(d_i^+\right)^2}{\left(d_i^-\right)^2}} = \frac{\left(d_i^-\right)^2}{\left(d_i^+\right)^2 + \left(d_i^-\right)^2} \tag{6}$$

At this point, it must be noted that the TOPSIS can be justified based on a fuzzy pattern recognition. As previously mentioned, TOPSIS is a multicriteria technique was developed in Reference [11]. According to the conventional TOPSIS, the closeness to the ideal solution, C_i^* is determined as follows.

$$C_i^* = \frac{\left(d_i^-\right)}{\left(d_i^+\right) + \left(d_i^-\right)} \tag{7}$$

Since the above measure is achieved rather empirically without any mathematical justification, Equation (6) could be preferred when compared to Equation (7) since its mathematical background is based on the optimization.

In addition, according to Equation (6), the degree according to which the alternative i belongs to the anti-ideal—point is the complement with the degree, according to which the same alternative belongs to the ideal—point. However, the majority of the multicriteria application with the fuzzified version of TOPSIS uses Equation (7) for the final evaluation, while the fuzziness is used to express the evaluation of the criteria. In this case, the fuzziness is used only to achieve the membership function, which expresses the degree according to which each alternative belongs to the ideal solution in a rational and understandable way.

As can be found in Reference [12], the above methodology can be used not only for two categories (ideal and anti-ideal points) but in order to classify to several categories. Each category is described by each centre. In the case of the widely-used fuzzy classification (or fuzzy clustering), the centres of the categories are determined through an iterative progress. However, in cases of multicriteria applications, the pre-defined centres used are to be selected a priori while the centers of the categories are often located at the edges of the decision space (e.g., ideal and anti-ideal points).

2.3. Proxy Variables and Input Data

In the research, 11 proxy variables, or indexes, are used to quantify the flood vulnerability using the concept of sensitivity-adaptive capacity-exposure. Desirable proxy variables are those indicators that quantify, measure, and communicate relevant information [5]. At the same time, the indicators should simplify or represent a number of important properties, rather than focus on isolated characteristics of a system [5]. The multiplier relation among these three components and the application of the previously mentioned concept in case of natural hazards is proposed in the literature [17]. Furthermore, in Reference [18], adaptive capacity, exposure, and sensitivity are considered as an additive model, i.e., a simple value function with equal weights. This is an approach adopted in the specific research.

The variables and the given weights per criteria are depicted in Table 2. The weighting of the main criteria as well as the weights of the indicators was conducted according to Reference [5] after some adaptations based on regional factors. Particularly, in Reference [5], the weights are produced by using the Delphi method with a systematic way. Delphi is routinely being applied in the conventional multicriteria analysis as a subjective weighting method [19]. In comparison to Reference [5], some indicators have no physical meaning in Greece, such as monsoons duration and intensity. Thus, these indicators were not considered. At any case, the sum of the indicators must be equal with the total weight of the corresponding criterion. This can be achieved after a simple adaption based on the initial weights, which are provided in Reference [5]. An interesting point is that the weights of the criteria (sensitivity, adaptive capacity, and exposure) are similar to those proposed in case of the simple additive model [18].

Sensitivity is attributed by seven proxy variables that are related with qualitative, e.g., the population density, and quantitative characteristics, e.g., areas with an elevation lower than 100 m (and not 10 m, as proposed in Reference [5]), of the areas under investigation. Three proxy variables of adaptive capacity are selected in two opposite ways: (1) indirect adaptive capacity such as the financial independence and the number of civil servants per population and (2) direct adaptive capacity, such as the number of civil servants related to water management. Lastly, since floods are directly related with the hydrometeorological characteristics (rainfalls and runoffs), one proxy variable related is selected for describing the exposure.

Table 2. Description and weights of utilized proxy variables.

Vulnerability Components	Weights [5]	Criterion	Criterion Description	Individual Weights [5]	Source of Data
Sensitivity	0.37	C1	Areas with elevation < 100m	0.31	GTOPO30 Digital elevation Model & GIS Analysis
		C2	Settlements located in areas with elevation < 100 m	0.23	National statistics & GIS Analysis
		C3	Flooded areas for T = 50 years	0.19	National Flood Risk Plans
		C4	Population density (persons/km^2)	0.16	National statistics & GIS Analysis
		C5	Total population	0.11	National statistics
		C6	Regional average slope (°)	0.10	GIS Analysis
		C7	Percentage of road area (%)	0.10	Egnatia Street Observatory
Adaptive capacity	0.30	C8	Financial independence (%)	0.10	National statistics
		C9	Number of civil servants per population	0.11	National statistics

			(persons/10^3 people)		
		C10	Number of civil servants related to water	0.16	National statistics
Exposure	0.33	C11	Surface runoff (mm/day)		National Flood Risk Plans

3. Results and Discussion

The normalization is based on the comparative values, which is a process that is the rational approach in case of the ranking process. The values of the criteria for each alternative (examined areas) are presented in Table 3 (pay-off matrix). During the first synthesis, that is the synthesis of the proxy variables, a simple weighted value function is used. In the final synthesis of the criteria (sensitivity, adaptive capacity, exposure), the fuzzified TOSPSIS method is used (Equation (6)). The final results are presented in Table 4.

Table 3. Pay-off matrix of the examined areas.

Criteria	Area 1	Area 2	Area 3	Area 4
(+) sensitivity×0.37	0.092	0.066	0.240	0.217
(−) adaptive capacity×0.30	0.159	0.006	0.157	0.060
(+) exposure×0.33	0.245	0.030	0.330	0.000

According to the achieved values (Table 4), the areas that are most vulnerable to flooding are categorized as $A_3>A_1>A_4>A_2$. It must be clarified that, in Table 4, the first two rows express the distances from the ideal and the anti-idea points while the final selection is based on the third row, which expresses the membership degree of belonging of each area at the "ideal" solution. If only the distances from the ideal points are considered, the results should be very different. As previously mentioned, the μ_i^+ takes into account the distance of each area (alternative *i*) compared to all categories that are the ideal and the anti-ideal points and not only to an examined category.

Table 4. Membership degree of belonging of each area at the "ideal" solution (high vulnerability).

Scores	Area 1	Area 2	Area 3	Area 4
(−) distance from ideal solution d_i^+	0.332	0.427	0.204	0.369
(+) distance from anti-ideal solution d_i^-	0.297	0.303	0.432	0.324
(+) membership degree (ideal solution) (μ_i^+)	*0.445*	*0.335*	*0.818*	*0.435*

An important output issue in the fuzzified TOPSIS is that the ranking is the same either following the maximum membership degree of belonging of each area at the "ideal" solution (μ_i^+) or following the minimum membership degree of belonging at the "anti-ideal" solution (μ_i^-) since its addition is equal to one (Equation (4)). It should be mentioned that this does not generally stand in case of the widely used TOPSIS [20].

An interesting point is that although Area 2 has lower sensitivity and exposure than Area 1 (where Area 1 and Area 2 are the upstream and the lowland parts of the Nestos basin, respectively), Area 2 will be selected as more vulnerable to flooding than Area 1 due to its low adaptive capacity in case that the maximum distance from the anti-ideal solution is adopted to characterize the vulnerability $\left(d_i^-\right)$.

However, in contrast with the droughts the vulnerability is not sufficient to characterize the risk of the floods. Since the flood is a significantly more local phenomenon than the drought, the risk assessment should take into account the flooded areas as well as the velocity and the depth of the flooded areas (components of the hazards). In this work the exposure is included within the vulnerability as an additional criterion which considers indirectly that fact. Without the criterion of exposure the Area 2 will be more vulnerable than Area 1 because of low adaptive capacity.

An additional intersecting point is that the majority of the articles, which combine the fuzziness (or more advanced theories as the intuitionistic fuzzy numbers, e.g., [13,21]) with the TOPSIS method, use Equation (7) instead of the theoretical method founded in Equation (6). In this article, the use of Equation (6) is suggested, as it is compatible with the fuzzy pattern recognition that Reference [5] have already used. Furthermore, the proposed methodology can be extended to include the case of fuzziness (or intuitionistic fuzzy numbers) in the evaluation of both the criteria and the weights. With the use of distances between fuzzy numbers, the fuzziness can be incorporated in the decision leading simultaneously to a crisp decision [12].

4. Conclusions

The research investigates the vulnerability of flood prone areas when socio-economic criteria are inserted into the equation. For this purpose, the fuzzified multicriteria method of TOPSIS based on fuzzy pattern recognition is utilized for components that cover the sensitivity, the adaptive capacity, and the exposure of areas to flood risk. The proposed methodology takes the advantage of the fuzzy version of TOPSIS, which is the simultaneous consideration of the distance from both the ideal and the anti-ideal solution and, moreover, it uses a type of a membership function interpretable and compatible with that of the fuzzy pattern recognition, which is based on optimization.

In the research, the socio-economic factors are attributed to the regional characteristics of the areas under investigation, i.e., the economically poor regions coincide with low adaptive-recovery capacity, since the impacts on the environment due to flood events require additional funds for the rehabilitation of the damages as well as for preparedness measures for potential future inundations. Regarding the exposure, a very interesting issue that is proposed to be integrated in the proposed methodology as future research is the impact of climate change. By quantifying the outputs of climate models as hydrometeorological criteria, a significant overview of the vulnerability under climate change will be produced.

Since the flood is a significantly more local phenomenon than the drought, the risk assessment should take into account the flooded areas as well as the velocity and the depth of the flooded areas with a more robust way.

To sum up, it is believed that the measures for flood mitigation, preparedness, and response proposed in the National Flood Risk Management Plans of the Flood Directive implementation process should be evaluated under the concept of the proposed methodology. The outputs could offer a hierarchization of the proposed measures, which will be based not only on economic criteria but also on the socioeconomic vulnerability of the flood prone areas.

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