Expert Systems with Applications 41 (2014) 644–654

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Robust spatial flood vulnerability assessment for Han River using fuzzy TOPSIS with α-cut level set

Gyumin Lee [a], Kyung Soo Jun [a], Eun-Sung Chung [b,*]

[a] Graduate School of Water Resources, Sungkyunkwan University, Suwon 440-746, Republic of Korea
[b] School of Civil Engineering, Seoul National University of Science and Technology, Seoul 139-743, Republic of Korea

ARTICLE INFO

Keywords:
Fuzzy TOPSIS
Han River
α-cut level set
Spatial flood vulnerability

ABSTRACT

This study aims to improve the general flood vulnerability approach using fuzzy TOPSIS based on α-cut level sets which can reduce the uncertainty inherent in even fuzzy multi-criteria decision making process. Since fuzzy TOPSIS leads to a crisp closeness for each alternative, it is frequently argued that fuzzy weights and fuzzy ratings should be in fuzzy relative closeness. Therefore, this study used a modified α-cut level set based fuzzy TOPSIS to develop a spatial flood vulnerability approach for Han River in Korea, considering various uncertainties in weights derivation and crisp data aggregation. Two results from fuzzy TOPSIS and modified fuzzy TOPSIS were compared. Some regions which showed no or small ranking changes have their centro-symmetric distributions, while other regions whose rankings varied dynamically, have biased (anti-symmetric) distributions. It can be concluded that α-cut level set based fuzzy TOPSIS produce more robust prioritization since more uncertainties can be considered. This method can be applied to robust spatial vulnerability or decision making in water resources management.

1. Introduction

River, coastal and flash floods can claim human lives, destroy properties, damage economies, make fertile land unusable and damage the environment. The development of techniques, measures and assessment methodologies to increase understanding of flood risk or vulnerability can assist decision makers greatly in reducing damage and fatalities. Different methods to assess risk and vulnerability of areas to flooding have been developed over the last few decades.

However, the term "risk" in relation to flood hazards was introduced by Knight (1921), and is used in diverse different contexts and topics showing how adaptive any definition can be (Sayers et al., 2011). Smith (2004) considered risk as the product of two components, i.e., probability and consequence. This concept of flood risk is strictly related to the probability that a high flow event of a given magnitude occurs, which results in consequences which span environmental, economic and social losses caused by that event. This deterministic approach use physically based modeling methods to estimate flood hazard/probability of particular event, coupled with damage assessment models which estimate economic consequence to provide an assessment of flood risk in an area (Balica, Popescu, Beevers, & Wright, 2013).

On the other hand, after many discussions and disputes, the term "vulnerability" can be commonly understood that vulnerability is the degree to which a system is susceptible to, or unable to cope with the adverse effects of environmental changes (IPCC, 2001). In relation to hazards and disasters, vulnerability is a concept that links the relationship that people have with their environment to social forces and institutions, as well as the cultural values that sustain and contest them. The concept of vulnerability expresses the multidimensionality of disasters by focusing attention on the totality of relationships in a given social situation. These relationships, together with environmental forces, are capable of producing a disaster prevention plan (Frerks, Bankoff, & Hilhorst, 2004). Vulnerability also refers to the extent to which changes could harm a system, or to which a community can be affected by the impact of a hazard. Therefore, this parametric approach aims to use readily available data of information to build a picture of the vulnerability of an area (Balica, Popescu, Beevers, & Wright, 2013).

Although each of these approaches has advantages and disadvantages for decision makers, this study used the parametric vulnerability which has been increasingly accepted since it is coupled with climate change approach to disaster in recent years.

Parametric vulnerability research generally consists of various sub-topics such as indicator selection, weight determination and assessment methodology (Moel, Alphen, & Aerts, 2009; RPA, 2004; Akter & Simonovic, 2005; Thinh & Vogel, 2006; Meyer, Scheuer, & Haase, 2009; Chung & Lee, 2009; Sebald, 2010; Chung,

* Corresponding author. Tel.: +82 2 970 9017; fax: +82 2 948 0043.
E-mail address: eschung@seoultech.ac.kr (E.-S. Chung).

0957-4174/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2013.07.089

Hong, Lee, & Burian, 2011; Jun, Chung, Kim, & Kim, 2011, 2012). That is, parametric vulnerability approach is quite similar to the general multi-criteria decision-making (MCDM) method.

However, although MCDM is suitable for decision-making in flood vulnerability, MCDM is very difficult to exactly be applied since the data for flood vulnerability closely related to social, economic and environmental circumstances have high uncertainty. Therefore, the flood vulnerability assessment should consider lots of uncertainties, such as the uncertainty of weights and proxy variables' crisp data. Thus, Simonovic and Niruoama (2005) combined MCDM method and fuzzy set theory to address various uncertainties in water resources management. Fuzzy MCDM methods to reduce the uncertainty of parametric approach inherent in the processes of weights determination and derivation of crisp input data have used in the various fields such as reservoir operation (Fu, 2008; Afshar, Mariño, Saadatpour, & Afsahr, 2011), groundwater vulnerability (Zhou, Wang, & Yang, 1999), group decision making (Shih, Shyur, & Lee, 2007), airline industry (Torlak, Sevkli, Sanal, & Zaim, 2011), tourism (Tsaur, Chang, & Yen, 2002), plant location selection (Chu, 2002), water resources vulnerability (Kim & Chung, 2013) and flood vulnerability (Sebald, 2010; Lee, Jun, & Chung, 2013).

Even fuzzy MCDM approaches, however, lead to a crisp relative closeness for each alternative. Thus, it is continuously, argued fuzzy weights and fuzzy ratings should result in fuzzy relative closeness. Crisp relative closeness provides only one possible solution to a fuzzy MCDM problem, but cannot reflect the whole picture of its all possible solutions. In spite of the fact that fuzzy TOPSIS (technique for order preference by similarity to an ideal solution; Hwang & Yoon, 1981) offers a fuzzy relative closeness for each alternative (Triantaphyllou & Lin; 1996; Kang, Lee, Chung, Kim, & Kim, 2013), the closeness is badly distorted and over exaggerated because of the reason of fuzzy arithmetic operations. Therefore, Wang and Elhag (2006) developed a fuzzy TOPSIS method based on α level sets and the fuzzy extension principle, which turns out to be a nonlinear programming problem. This also used an α-level set based fuzzy TOPSIS to develop a flood vulnerability approach for Han River in Korea, considering various uncertainties in the fuzzy MCDM process.

2. Methodology

2.1. Fuzzy set theory with α level sets

A fuzzy set theory is a powerful mathematical tool for handling uncertainty in decision making. A fuzzy set is a general form of a crisp set. A fuzzy number takes on values in the closed interval 0 and 1, in which 1 represents full membership and 0 represents non-membership. In contrast, crisp sets only allow values of 0 or 1. There are different types of fuzzy numbers that can be utilized, depending on the situation. It is often convenient to work with TFNs because they are relatively simple to compute and are useful for representing and processing information in a fuzzy environment.

(1) Triangular fuzzy numbers (TFNs)
A fuzzy number, $\widetilde{A}$, on R can be a TFN if its membership function, $\mu\widetilde{A}(x): R \to [0,1]$, can be defined as follows:

$$\mu_{\widetilde{A}} = \begin{cases} 0, & x \leqslant a \\ \frac{x-a}{b-a}, & a \leqslant x \leq b \\ \frac{c-x}{c-b}, & b \leqslant x \leq c \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

(2) Multiplication of TFNs
Suppose that we have two TFNs $\widetilde{A}$ and $\widetilde{B}$ such that $\widetilde{A} = (a_1, a_2, a_3)$ and $\widetilde{B} = (b_1, b_2, b_3)$ then, the multiplication of the fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$ is defined as follows:

$$\widetilde{A} \oplus \widetilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{2}$$

$$\widetilde{A} \ominus \widetilde{B} = (a_1 - b_1, a_2 - b_2, a_3 - b_3) \tag{3}$$

$$\widetilde{A} \odot \widetilde{B} = (a_1 b_1, a_2 b_2, a_3 b_3) \tag{4}$$

Let $\widetilde{A} = (a_1, a_2, a_3)$ and $\widetilde{B} = (b_1, b_2, b_3)$ be two TFNs, then the distance between them using vertex method is defined as (Chen, 2000)

$$d(\widetilde{A}, \widetilde{B}) = \sqrt{\frac{1}{3}\left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]} \tag{4}$$

(3) α-cut level set
The α-cut of fuzzy number A can be defined as (Kaufmann & Gupta, 1991):

$$(\widetilde{A})_\alpha = \{x | f_a(x) \geq \alpha\} \tag{5}$$

where $x \in R, a \in [0,1]$.

$(\widetilde{A})_\alpha$ is a non-empty bounded closed interval contained in R and it can be denoted by $(\widetilde{A})_\alpha = [(a)_{\alpha^L}, (a)_\alpha^U]$, where $(a)_\alpha^L$ and $(a)_\alpha^U$ are the lower and upper bounds of the closed interval, respectively.

For example, if a TFN $\widetilde{A} = (1, m, n)$, then the α-cut of A can be expressed as:

$$(\widetilde{A})_\alpha = [(a)_\alpha^L, (a)_\alpha^U)] = [(m - l)\alpha + l, -(u - m)\alpha + u]. \tag{6}$$

Given fuzzy numbers A and B, $A, B \in R^+$, the α-cuts of A and B are $(A) = [(a)_\alpha^L, (a)_\alpha^U]$ and $(A) = [(b)_\alpha^L, (b)_\alpha^U]$, respectively. By interval arithmetic, some main operations of A and B can be expressed as follows:

$$(A \oplus B)_\alpha = [(a)_\alpha^L + (b)_\alpha^L, (a)_\alpha^U + (b)_\alpha^U)] \tag{7}$$

$$(A \ominus B)_\alpha = [(a)_\alpha^L - (b)_\alpha^L, (a)_\alpha^U - (b)_\alpha^U)] \tag{8}$$

$$(A \otimes B)_\alpha = [(a)_\alpha^L (b)_\alpha^L, (a)_\alpha^U (b)_\alpha^U)] \tag{9}$$

2.2. TOPSIS method

TOPSIS, known as one of the most classical MCDM methods, is based on the idea, that the chosen alternative should have the shortest distance from the positive ideal solution and on the other side the farthest distance of the negative ideal solution (Hwang & Yoon, 1981: Lai, Liu, & Hwang, 1994). The technique is based on the concept that the ideal alternative has the best level for all attributes, whereas the negative ideal is the alternative with all of the worst attribute values. A TOPSIS solution is defined as the alternative that is simultaneously farthest from the negative ideal and closest to the ideal alternative (Chu, 2002). According to Kim, Park, and Yoon (1997) and Shih, Shyur and Lee (2007), there are four advantages of using TOPSIS: (1) a sound logic that represents the rationale of human choice; (2) a scalar value that accounts for both the best and worst alternatives simultaneously; (3) a simple computation process that can be easily programmed; and (4) for any two dimensions, the performance measures for all alternatives can be visualized on a polyhedron.

The procedure of TOPSIS can be expressed in a series of steps: