Climatic Change (2013) 121:301–315
DOI 10.1007/s10584-013-0879-0

Assessing climate change vulnerability with group multi-criteria decision making approaches

Yeonjoo Kim · Eun-Sung Chung

Received: 6 October 2012 / Accepted: 18 August 2013 / Published online: 14 September 2013

Abstract This study developed an approach to assess the vulnerability to climate change and variability using various group multi-criteria decision-making (MCDM) methods and identified the sources of uncertainty in assessments. MCDM methods include the weighted sum method, one of the most common MCDM methods, the technique for order preference by similarity to ideal solution (TOPSIS), fuzzy-based TOPSIS, TOPSIS in a group-decision environment, and TOPSIS combined with the voting methods (Borda count and Copeland's methods). The approach was applied to a water-resource system in South Korea, and the assessment was performed at the province level by categorizing water resources into water supply and conservation, flood control and water-quality sectors according to their management objectives. Key indicators for each category were profiled with the Delphi surveys, a series of questionnaires interspersed with controlled opinion feedback. The sectoral vulnerability scores were further aggregated into one composite score for water-resource vulnerability. Rankings among different MCDM methods varied in different degrees, but noticeable differences in the rankings from the fuzzy- and non-fuzzy-based methods suggested that the uncertainty with crisp data, rather widely used, should be acknowledged in vulnerability assessment. Also rankings from the voting-based methods did not differ much from those from non-voting-based (i.e., average-based) methods. Vulnerability rankings varied significantly among the different sectors of the water-resource systems, highlighting the need to assess the vulnerability of water-resource systems according to objectives, even though one composite index is often used for simplicity.

1 Introduction

Assessing vital systems' impacts on and vulnerability to climate change is of great interest for people who need to better cope with hazards and threats to those systems. Emphasis is being

Electronic supplementary material The online version of this article (doi:10.1007/s10584-013-0879-0) contains supplementary material, which is available to authorized users.

Y. Kim
Korea Environment Institute, Seoul, South Korea

E.-S. Chung (✉)
Department of Civil Engineering, Seoul National University of Science and Technology,
Seoul, South Korea
e-mail: eschung@seoultech.ac.kr

shifted from an impact-led approach to a vulnerability-led approach to assessment. An impact-led approach to climate change focuses on the climate hazards to which people are exposed, while a vulnerability-led approach concentrates on the social, economic and institutional factors that influence how people respond to climate hazards (Adger et al. 2004). The need for adapting to climate change is growing, and assessments of the adaptive capacity and resulting vulnerability of human systems are focused on developing adaptation polices and strategies.

Vulnerability has been used in many different ways in various research communities. Vulnerability is often found in risk and disaster management analysis and is conceptualized as the dose–response relationship between an exogenous hazard to a system and its adverse effects. In political economy and human geography, vulnerability is an a priori condition of a community that is determined by socio-economic and political factors (Fussel and Klein 2006). The Intergovernmental Panel on Climate Change (IPCC) combined these concepts, and defined vulnerability as "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate changes, including climate variability and extremes. Vulnerability is a function of the character, magnitude, rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity" (McCarthy et al. 2001). Here, the concept of climate-change vulnerability integrates the external dimension such as the 'exposure' of a system to climate hazards, with the internal socio-economic dimension such as its 'sensitivity' and 'adaptive capacity' to climate stressors (Fussel and Klein 2006). While the IPCC suggested that vulnerability is a function of exposure, sensitivity and adaptive capacity, various frameworks of climate-change vulnerability have also been suggested (e.g., Moss et al. 2002; Brooks et al. 2005). Moss et al. (2002) developed a vulnerability-resilience indicator (VRI) prototype model, defining vulnerability as the sensitivity and adaptability of a system to climate change, and defined the difference between the sensitivity and adaptive capacity as the VRI.

To assess vulnerability in a quantitative manner, key indicators must be selected to represent vulnerability, and multiple indicators are often aggregated to a composite index (Adger et al. 2004), which is often used to assess human and environmental security and vulnerability to various hazards, as observed in various well-known national-level indices such as the Human Development Index (Moss et al. 2002). Climate-change vulnerability assessments have been performed in various spatial scales and sectors (e.g., Moss et al. 2002; O'Brien et al. 2004). Moss et al. (2002) estimated national-level VRI scores for 38 countries under both current and potential future conditions, based on forecasts by an integrated assessment model. The VRI aggregates various sectors, including infrastructure, food security, ecosystem, human health, water resources, economics, human resources and environmental capacity.

For water-resources management, indicator-based vulnerability assessments have been widely performed as well. For example, Gleick (1990) evaluated climate-change vulnerability within the 18 water-resource regions of the US using an index, which is composed of five indicators of regional vulnerability: storage ratio, demand ratio, hydropower use, ground-water overdraft and streamflow variability. Additionally, he established warning thresholds for the each of the indicators.

Vulnerability in association with decision-making problems has been the focus of few studies. Rankings of vulnerability scores can be translated into prioritizing climate-change adaptation plans as a decision-making process involves the selection of the preferred alternatives among a number of alternatives to achieve certain objectives. Decision-making processes are often complicated, with multiple conflicting criteria, and multi-criteria decision making (MCDM) methods have been successfully employed to identify desired policy alternatives. Most climate-change vulnerability scores are aggregated by the weighted averages of measures in key indicators, a weighted sum method (WSM), which is a classic MCDM approach. Several recent studies used various MCDM methods to assess vulnerability (e.g., Chung and Lee 2009; Jun et al. 2011; Lee et al. 2013). Jun et al. (2011)

developed a framework to quantify the flood with a technique for order preference by similarity to ideal solution (TOPSIS) method, one of MCDM methods.

In this study, we developed an approach to assess the variability to climate change and variability using various group MCDM methods and identified the sources of uncertainty in assessments. We focused on group MCDM methods as many decision-making problems are solved with a collaborative effort and, thus, MCDM problems for a group decision environment are not uncommon. We used WSM, TOPSIS, fuzzy TOPSIS, TOPSIS in a group decision environment, as well as TOPSIS combined with voting methods, and assessed for a water-resources system in South Korea, including water supply and conservation (WS), flood control (FC) and water quality (WQ) sectors. These group MCDM methods were applied to a sub-national (province) level of South Korea (Fig. 1).

2 Methods

Climate-change vulnerability was assessed using various group MCDM methods as the steps in the approach follows: (1) determine the key indicators (proxies) of IPCC-based

Fig. 1 Map of study area. South Korea includes 16 provinces of Seoul (A01), Busan (A02), Daegu (A03), Incheon (A04), Gwangju (A05), Daejeon (A06), Ulsan (A07), Gyeonggi-do (A08), Gangwon-do (A09), Chungcheongbuk-do (A10), Chungcheongnam-do (A11), Jeollabuk-do (A12), Jeollanam-do (A13), Gyeongsangbuk-do (A14), Gyeongsangnam-do (A15) and Jeju-do (A16)

vulnerability for each sector with a survey of expert groups, which is the first step of the Delphi process; (2) as part of the Delphi process, determine the weights of key indicators based on surveys of expert groups, then, collect data for the key indicators for all regions and standardize the data; (3) quantify and rank vulnerability using the various group MCDM techniques such as the WSM, TOPSIS, fuzzy-based TOPSIS, TOPSIS in a group decision environment, and TOPSIS combined with the voting methods (Borda count and Copeland's methods); (4) analyze the resulting rankings with the Spearman rank correlation. See the electronic supplementary material (ESM) for the details on the methods, including the Delphi process, fuzzy set theory, MCDM techniques and Spearman rank correlation (see Eqs. A1–A4, respectively; ESM).

2.1 Climate-change vulnerability framework and indicators

In this study, we used the IPCC-based vulnerability framework among various conceptual frameworks. The vulnerability of any system at any scale reflects the exposure and sensitivity of that system to hazardous conditions and the ability, capacity, or resilience of the system to cope, adapt, or recover from the effects of those conditions. Climate exposure (*E*) refers to a vast variety of climate-related stimuli such as a rise in sea level, temperature changes, precipitation changes, heat waves, heavy rainstorms, and climatic droughts. Sensitivity (*S*) is the degree to which a system is modified or affected by perturbations. Adaptive capacity (AC) is the ability of a system to evolve to accommodate environmental hazards or policy changes and to expand the range of variability with which it can cope (Adger 2006). Mathematically, we defined vulnerability (*V*) as follows:

$$V = \alpha \times E + \beta \times S - \gamma \times AC \tag{1}$$

where α, β, and γ ($\alpha + \beta + \gamma = 1$) are the weights for *E*, *S* and AC, respectively.

To assess *E*, *S* and AC of a system, key indicators or proxy variables that quantify, measure, and communicate relevant information must be identified for use in the assessment or model (Hamouda et al. 2009). These indicators should simplify or summarize a number of important properties rather than focus on isolated characteristics of the system. Indicators must be measurable, or at least observable, and the methodology used to construct them should be transparent and understandable (Seager 2001).

2.2 Multi-criteria decision making

Decision-making problem is the process of finding the best option from all of feasible alternatives. In most cases, criteria for judging the alternatives are multiple, leading to a MCDM problem. MCDM problems can be expressed with a decision (or performance) matrix *D* with x_{ij}, indicating the performance rating of each alternative i (i=1, …, m) and each criterion j (j=1, …, n); and a weighting vector W with w_j, indicating the weight for each criterion j. Also, the data for the decision matrix *D* come from different sources, so it is necessary to normalize it to a dimensionless matrix. The normalized performance matrix $R=(r_{ij})_{mxn}$ was used to assess vulnerability with different MCDM methods (see Eq. A3.1 in the ESM).

MCDM problems involve various uncertainties such as uncertain weighting values for proxy variables when there are influential stakeholders with different interests, and uncertain crisp input data due to transformations of rough data into numerical values. The random or fuzzy nature of the available information is attributed to the inclusion of human judgments and preferences in a problem formulation. After Bellman and Zadeh (1970) first introduced the theory of fuzzy sets to the problem of MCDM as an effective approach to treat vagueness, lack of knowledge and ambiguity inherent in the human decision, fuzzy set theory has been applied extensively in MCDM processes (e.g., Zhou et al. 1999; Fu 2008). Among various types of fuzzy representations, this study uses a triangular fuzzy number (TFN), for which a fuzzy number is defined by three numbers $a_1 < a_2 < a_3$ where the base of the triangle is in the interval between a_1 and a_3 and the vertex is at a_2. It is written as $\widetilde{a} = (a_1, a_2, a_3)$ (see Eq. A2 in the ESM).

Furthermore, many decision-making problems are solved with a collaborative effort and thus MCDM problems for a group-decision environment are not uncommon. In this study, we assessed climate-change vulnerability based on surveys from a group of people to quantify the relative importance of criteria for vulnerability. Among many different approaches to solve the MCDM problem, we chose to use six different MCDM methods, including the WSM, the most commonly used MCDM, and various TOPSIS methods with multiple decision makers (DMs; Table 1).

2.2.1 TOPSIS

The TOPSIS method was developed to solve MCDM problems in which preference information is not articulated (Hwang and Yoon 1981). The technique is based on the concept that the positive ideal solution (PIS) has the best values for all attributes, whereas the negative ideal solution (NIS) is the alternative with all of the worst attribute values. A TOPSIS solution is defined as the alternative that is simultaneously farthest from the NIS and closest to the PIS (Chu 2002). Then the relative closeness (RC) based on the distances to PIS and NIS is used to determine the preference for alternatives.

Mathematically, the TOPSIS procedure (see Eq. A3.2 in the ESM) can be summarized as in the following. First, the weighted normalized value v_{ij} is determined with the product of

Table 1 Different MCDM methods used in this study

	Method	Description	Crisp/fuzzy?	Average/voting?
M1	WSM	The weighted sum is estimated using the averaged weight from individual DMs and the averaged performance value	Crisp	Average
M2	TOPSIS	The relative preference defined by TOPSIS is estimated using the averaged weight from individual DMs and the averaged performance value	Crisp	Average
M3	Fuzzy TOPSIS	The relative preference is estimated using the fuzzified weights from individual DMs and the fuzzified performance value	Fuzzy	Average
M4	Group TOPSIS	The relative preference is estimated with internally integrating weights from individual DMs	Crisp	Average
M5	TOPSIS-Borda	Borda counts are estimated after applying TOPSIS for individual DMs (multiple TOPSIS with the weights from individual DM)	Crisp	Voting
M6	TOPSIS-Copeland	Copeland's counts are estimated after applying TOPSIS for individual DMs	Crisp	Voting

multiplying the normalized performance value by the weighting value ($v_{ij}=w_j \times r_{ij}$). Next, PIS (A^+) and NIS (A^-) are determined in that:

$$\begin{array}{cccccccc} A^+ & = & \left(v_1^+, v_2^+, \ldots, v_n^+\right) & \& & A^- & = & \left(v_1^-, v_2^-, \ldots, v_n^-\right) \\ v_1^+ & = & \max\limits_i & v_{ij} & \& & v_j^- & = & \min\limits_i \quad v_{ij} \end{array} \tag{2}$$

where using Euclidean distances of each alternative from PIS and NIS (d_i^+ and d_i^-, respectively), RC for each alternative (RC_i) is then calculated as follows:

$$RC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{3}$$

Extended from TOPSIS, fuzzy TOPSIS (see Eq. A3.3 in the ESM) solves problems of decision making with uncertain data. Considering the fuzziness in the decision data, linguistic variables are used to assess the weights of all criteria and normalized performance ratings of each alternative with respect to each criterion.

Group TOPSIS (see Eq. A3.4 in the ESM), devised by Shih et al. (2007), extends TOPSIS to a group-decision environment by internally aggregating individual DM's preferences, so that multiple preferences of more than one DM are integrated. TOPSIS procedure is repeated for each DM, and then the geometric mean of distances to PIS and NIS for each DM are taken.

2.2.2 TOPSIS with Borda count and Copeland methods

Group TOPSIS is intuitive and does not consider either preference levels or preference priorities among alternatives for individual decision makers. With voting methods, the TOPSIS procedure is repeated for individual DMs, and the consequent preferences (i.e., rankings) from individual DMs are aggregated for a collective decision-making environment based on the voting methods, Borda count and Copeland methods. Similarly, Shih et al. (2004) developed the group-decision support system, aggregating the DMs' preferences based on TOPSIS with Borda count method.

Borda count method is a technique that allows a voter to rank a set of candidates (alternatives) by assigning different preferences to each alternative (Saari 1995). In a vote with *m* alternatives, a score of *m*-1 will be assigned to the most favored candidate, a score of *m*-2 to the second most favored candidate, and so on, with the least favored candidate receiving a score of zero. These scores from DMs are summed up for each alternative, and then the sum is ordered for a collective decision among DMs. In Copeland's method, all possible alternatives were paired for each DM and the number of pairwise victories and defeats are summed up, respectively. Then their difference for each alternative is estimated and ordered for a decision among DMs.

3 Case study of water resources in South Korea

3.1 Study domain

The vulnerability assessment methodology was applied to the water-resources system in South Korea (Fig. 1), covering an area of 48,877 km^2 with a population of almost 50 million. South Korea consists of 16 provincial-level divisions (see Table B1 in the ESM). The capital of South Korea, Seoul (A01), has a population of about 10 million with the highest population density and gross regional domestic product (GRDP) of the 16 provinces. The province with the lowest population and GRDP is Jeju-do (A16), which is an island and Korea's southernmost province. In this study, the water-resource system is divided into three sectors of (1) WS, (2) FC and (3) WQ based on the management purpose. By employing multiple group MCDM methods, we evaluated the climate-change vulnerability scores for these three sectors separately and then aggregated them into one integrated vulnerability score.

Note that NIER (2011) performed the vulnerability assessment of Korea for different sectors including water resources (WS, FC and WQ), agriculture, health and so on with WSM based on the climate and environmental data for present and future times (see Eq. A5 in the ESM for data description). Following NIER (2011), Jun et al. (2013) performed the flood vulnerability assessment with the fuzzy TOPSIS method, and Kim and Chung (2013) showed the advantage of the fuzzy VIKOR, one of recent MCDM approach for evaluating the climate-change vulnerability, using the water supply in Korea as an example. Building from those studies, this study attempts to assess the vulnerability of three sectors with the multiple group MCDM methods and integrate the vulnerability of the three sectors into one. Differently from the previous studies, this study shows only the present time vulnerability without the future vulnerability using the climate-change scenarios, which will be published in a separate paper later.

3.2 Vulnerability assessments

3.2.1 Identification of key indicators

This step is to identify key indicators of three water-resource sectors under the IPCC vulnerability concept. After a series of discussions with researchers and governmental officials, 24 key indicators for WS, FC and WQ were identified to quantify the vulnerability. Because these variables were not determined objectively, they were screened by experts (DMs for MCDM); the group of 11 experts, including hydrologists, water-resource managers, and climate-change experts participated in this step regarding WS and FC, and the other group of 11 experts, including environmental engineers, water-resource managers and climate-change experts, participated in regards to WQ. If proxy variables were rejected by at least two respondents, they were removed and consequently 24, 21, and 22 key indicators were determined for WS, FC and WQ, respectively. This screening process is the first step of the Delphi technique. Note that we followed the indicators of NIER (2011) for WS and FC, but the indicators for WQ were newly determined in this study to better represent the climate-change vulnerability in regard to water quality.

For WS (Table 2), the 24 proxy variables were included. For climate exposure, variables representing seasonal variations in water availability such as precipitation and evapotranspiration in winter and spring (dry season in South Korea), were selected. Lower precipitation or higher evaportranspiration in winter and spring suggest increased exposure to drought risks. Also the maximum of continuous non-rainy days was chosen as it clearly represents the possibility of drought, and the underground outflow was selected as it refers to water resources available during the dry season. For sensitivity, proxy variables that influenced the probability of drought damages were chosen, and for adaptive capacity, proxy variables representing socio-economic capacity to cope with drought damages were selected. Proxy variables such

Table 2 List of vulnerability components and key indicators for WS. In the third column (Relation to vulnerability), the positive (negative) signs mean that the higher the indicator, the higher (lower) the vulnerability

Vulnerability components (VC) or key indicators			
Names [units]	Labels	Relation to vulnerability	Average weights
Climate exposure	E	+	0.35
The maximum of continuous non-rainy days [days]	Cl	+	0.22
Winter (Dec, Jan and Feb; DJF) precipitation [mm]	C2	−	0.18
Spring (Mar, Apr and May; MAM) precipitation [mm]	C3	−	0.21
Winter (DJF) evapotranspiration [mm]	C4	+	0.10
Spring (MAM) evapotranspiration [mm]	C5	+	0.13
Underground outflow [mm]	C6	−	0.15
Sensitivity	S	+	0.29
Population density [persons/km^2]	C7	+	0.11
Total population [persons]	C8	+	0.10
Water supply [liter/person/day]	C9	+	0.07
Grain production per area [ton/km^2]	C10	+	0.07
Livestock production per area [km^2]	C11	+	0.06
Groundwater usage [m^3/year]	C12	+	0.08
River usage [m^3/year]	C13	+	0.09
Household water consumption [l0^3 m^3/year]	C14	+	0.15
Industrial water usage [10^3 m^3/year]	C15	+	0.14
Agriculture water usage [10^3 m3/year]	C16	+	0.13
Adaptive capacity	AC	−	0.36
Financial independence of local government from the national government [%]	C17	−	0.12
Civil servants per population [persons/10^4 people]	C18	−	0.05
GRDP [10^6 Korean Won]	C19	−	0.09
Number of civil servants related to water [persons]	C20	−	0.09
Percent of populations accessible to water-supply system [%]	C21	−	0.15
Groundwater capacity [10^3 m^3/year]	C22	−	0.14
Reservoir for water supply capacity per area[10^3 m^3]	C23	−	0.21
Recycled water usage per area [10^3 ton/year]	C24	−	0.15

as financial independence of local government from the national government, civil servants per population, GRDP and number of civil servants related to water represent the adaptive capacity of the water-resource systems and they were chosen for all three including WS, FC and WQ.

For FC (Table 3), 21 out of 24 proxy variables were finally considered, and the 3 variables that were dropped after the first step of Delphi survey include average rainy days, hourly maximum precipitation and precipitation frequency for climate exposure. The dropped variables were considered to be irrelevant to flood risks or redundant given other proxy variables. The proxy variables for climate exposure include variables related to precipitation intensity, including daily maximum precipitation and days with heavy precipitation, as they directly influence flood occurrence. For sensitivity, the proxy variables were

Table 3 The same with Table 2 but for FC

Vulnerability components (VC) or key indicators Names [units]	Labels	Relation to vulnerability	Average weights
Climate exposure	E	+	0.39
Daily maximum precipitation [mm]	C1	−	0.31
Days with heavy rainfall (over 80 mm/day) [day]	C2	+	0.23
Maximum rainfall of 5 days period [mm/5 days]	C3	+	0.19
Surface runoff [mm/day]	C4	+	0.16
Summer (i.e., June, July, August and September; JJAS) Precipitation [nm]	C5	+	0.11
Sensitivity	S	+	0.27
Population density [persons/km^2]	C6	+	0.10
Total population [persons]	C7	+	0.10
Low-lying area of less than 10 m [km^2]	C8	+	0.07
Low-lying household of less than 10 m [# of households]	C9	+	0.12
Area ratio of the riverbanks [%]	C10	−	0.10
Regional average slope [degree]	C11	+	0.11
Percent of road area per total area [%]	C12	+	0.07
Flood damage cost (last three years) [10^3 Korean Won]	C13	+	0.16
Flood damage population (last three years) [10^3 Korean Won]	C14	+	0.15
Adaptive Capacity	AC	−	0.34
Financial Independence of local government from the national government [%]	C15	−	0.13
Civil servants per population [persons/10^4 people]	C16	−	0.07
GRDP [10^6 Korean Won]	C17	−	0.11
Number of civil servants related to water [persons]	C18	−	0.13
River improvement rate [%]	C19	−	0.14
Capacity of drainage facilities [m^3/mm]	C20	−	0.21
Flood control ability of reservoirs [10^6 m^3]	C21	−	0.21

related to the probability of flood damage. Increases in low-lying areas and households significantly tend to increase the flood risk, while decreases in the areal ratio with the riverbanks tend to decrease the risk. The socio-economic aspects for coping with flood damage were selected for adaptive capacity.

For WQ (Table 4), 22 proxy variables were included. Maximum of continuous rainy days for climate exposure and length of road per area for sensitivity were dropped as similar proxy variables were selected. For climate exposure, variables related to both temperature and precipitation intensity were chosen as many environmental phenomena such as heat waves, droughts and floods could potentially cause water-quality problems. For sensitivity, the proxy variables were related to the probability of water-quality deterioration, mainly including variables representing the pollutant sources and transports. Except for forest area ratio, all proxies for sensitivity were positively related to vulnerability. The forested area tends to minimize surface runoff, soil erosion and, thus, sediment transport, tending to lead the system in resilience to climate change and variability. For adaptive capacity, the proxy variables include variables related to the socio-economic aspects for coping with water-quality problems such as the sewerage distribution ratio.

Table 4 The same with Table 2 but for WQ

Vulnerability components (VC) or key indicators			
Names [units]	Labels	Relation to vulnerability	Average weights
Climate exposure	E	+	0.32
Maximum temperature [°C]	Cl	+	0.14
Daily maximum precipitation [mm]	C2	+	0.13
Days with heavy precipitation (over 80 mm/day) [day]	C3	+	0.14
The maximum of continuous non-rainy days [day]	C4	+	0.32
The number of days above 33°C of daily maximum temperature [#]	C5	+	0.15
The number of days above 25°C of daily minimum temperature [#]	C6	+	0.12
Sensitivity	S	+	0.34
Population density [persons/km^2]	C7	+	0.07
Regional average slope [degree]	C8	+	0.07
Percentage of road area [%]	C9	+	0.11
Population engaged in livestock [persons]	C10	+	0.08
Livestock production status [heads/km^2]	C11	+	0.13
Fertilizer usage per cultivated area [ton/ha]	C12	+	0.14
Distribution of major animal species [# of species]	C13	+	0.07
Distribution of major plant species [# of species]	C14	+	0.08
Forest area ratio [%]	C15	−	0.12
Percentage of land managed [%]	C16	+	0.12
Adaptive capacity	AC	−	0.35
Financial independence of local government from the national government [%]	C17	−	0.13
Civil servants per population [persons/10^4 people]	C18	−	0.13
GRDP [10^6 Korean Won]	C19	−	0.16
Number of civil servants related to water [persons]	C20	−	0.14
Sewerage distribution ratio [%]	C21	−	0.29
River improvement rate [%]	C22	−	0.15

3.2.2 Construction of performance matrix

To construct the performance matrix (see Eq. A5 in the ESM), data for the key indicators were obtained from NIER, Statistics Korea, the National Institute of Disaster Management Institute and GIS analyses at the district level for the 232 districts in the 16 provinces, as detailed in the ESM (see Eq. A5 therein).

All of the key indicators' performance values for the 232 districts were normalized after log-transformation, if necessary, and then either averaged or fuzzified. Here log-transformation was performed for the variables whose raw data include the extreme value far from the rest of data. For each indicator in each province, the values for a_1 and a_3 in the TFN (see Eqs. A1 and A2 in the ESM) were determined by the minimum and maximum values from the districts belonging to the province, respectively; the value of a_2 in the TFN was determined by the representative value of the bin, showing the highest probability in the 3-bin histogram based on district-level values. If a province had the same value for all of the districts for a certain indicator, one value was used for the TFN, meaning that a_1, a_2 and a_3 were the same. In this way, geographic heterogeneity within the province is represented with the TFN as in Fig. C1a in the ESM with the example of population density. While the averaged number (blue line) represent one value, the TFN (red lines) represent a wide range of possible values of the indicator.

3.2.3 Determination of weights

Like the 2nd and 3rd steps of the Delphi technique, the weighting factors for key indicators and vulnerability components (i.e., E, S and AC in Eq. 1) were determined through two individual surveys, which were conducted to reduce the variability of the weighting values determined by the expert group (NIER 2011). Tables B2, B3, and B4 of the ESM show the resulting weighting factors from 11 experts and their minimum, maximum and average for each indicator. Distributions of weights for each indicator (figures not shown) show variable patterns; in many cases, weights tend to distribute around the mode as we intended, but in other cases weights tend to split into two extremes.

The weights from the 11 experts were averaged, fuzzified or used as is, according to the group MCDM methods. TFNs can represent different opinions regarding the relative importance of different components. For weights for the criteria, the values for a_1 and a_3 in the TFN (see Eq. A1 in the ESM) were determined by the minimum and maximum values of weights from different experts, respectively. TFNs of weights for WS, FC and WQ are presented in Table B6 of the ESM, and the TFNs of weights for population density (C7) in WS are presented, for example, in Figure C1b in the ESM.

Furthermore, we conducted an additional survey with 9 experts, including water-resource managers, environmental scientists and climate-change scientists, to determine the relative weights among WS, FC and WQ and aggregate the three vulnerability scores (see Table B5 in the ESM). Note that this survey could also have been a part of the afore-mentioned Delphi processes, but the survey was only designed after the earlier surveys determining the key indicators and their weights (NIER 2011). Then, the weights from the nine experts were averaged to aggregate the vulnerability scores from the three different sectors using the WSM.

3.2.4 Application of different group MCDM methods

Using six different MCDM methods, we estimated and ordered vulnerability scores for sixteen provinces (Table 4). The sectoral vulnerability scores for WS, FC and WQ were then integrated into one composite score and ranking using WSM. In the following, the MCDM procedure is explained along with the example of fuzzy TOPSIS for WS (Method 3).

After normalizing the fuzzy performance matrix, the fuzzy weights were multiplied to derive the weighted normalized performance matrix (step 1 of Eq. A3.3 in the ESM), which allows us to determine the FPIS and FNIS (step 2). As the size of the normalized fuzzy performance matrix is 16 by 72, the normalized fuzzy performance only for the criteria of population density (C7 for water supply) is provided in (a) of Table B7 in the ESM. Its weighted version as well as FPIS and FNIS for population density are shown in (b) of Table B7 in the ESM. Then, the Euclidean distances from FPIS and FNIS of all criteria were calculated and then summed up for each province (step 3, (c) of Table B7 in the ESM). Finally the relative closeness with respect to FPIS (i.e., separation measure) was derived for each province and ranked (step 4 in Table B8 of the ESM).

For the voting-based approaches, the TOPSIS procedure is repeated for each DM before applying the voting methods (see Table B9 in the ESM). For Borda count, a score of 16 was assigned to the most vulnerable province, a score of 15 to the second most vulnerable province, and so on, and then scores for each province are summed up in Table B10 of the ESM. In Copeland's method, each province was matched against every other province in a series of imaginary one-on-one contests. In each pairing, wins and losses for each DM were counted. These pairwise wins and losses were summed up and their differences were calculated for the final ranking as in Table B11 of the ESM.

3.3 Results analysis

3.3.1 Comparison among MCDM methods

We examined how largely vulnerability depended on different group MCDM methods, aiming to understand uncertainties associated with the methods. Vulnerability rankings with different MCDM methods were associated with each other in different degrees with rank correlations averaged along different sectors, ranging from 0.61 to 0.99 (see Table B12 of the ESM). In particular, the fuzzy TOPSIS showed relatively low correlations with other non-fuzzy MCDM methods, which are all based on averaging or voting. As shown in Figure C1 of the ESM1, the fuzzy representation lent significantly different weights and performance values to the MCDM approaches. Voting-based TOPSIS presented good rank correlations with averaged-based (non-voting based TOPSIS) methods.

According to the final rankings of provinces, the provinces ranked as the top to the third were considered the vulnerable group and the provinces ranked as the bottom to the third from the bottom (i.e., 14th, 15th and 16th) were considered the resilient group. As shown in Table 5, rankings with the different MCDM methods show a relatively good agreement for the vulnerable and resilient groups, which are important to be identified for prioritizing adaptation practices, and a relatively poor agreement for the mid-ranking provinces (Table 5).

For WS, the vulnerable group identified by the different MCDM methods is quite consistent except for A14 (Gyeongsangbuk-do). While A14 belongs to the vulnerable group based on fuzzy TOPSIS, all other methods suggest it as the resilient group. For FC, the vulnerable group and the specific rankings of provinces in the group are consistent along the different MCDM methods. For WQ, the vulnerable group is identified a little differently according to the different methods but all methods point out A01 (Seoul) as belonging to the vulnerable group.

In general, rankings among the different MCDM methods varied from one to another by different degrees. Results from the rank correlations showed relatively poor associations between rankings from fuzzy-based and non-fuzzy-based methods, which suggested that the uncertainty with crisp data should be acknowledged in vulnerability assessment, but relatively good associations exist between rankings from voting-based and average-based methods. One province identified as one of the most vulnerable provinces, requiring urgent adaptation policies, with one MCDM method could be ignored with the other methods, but mostly top-ranked and bottom-ranked provinces were very similar with all MCDM methods.

3.3.2 Comparison among sectors and integrated vulnerability

Vulnerability rankings varied with the sectors of the water-resource system, but sectoral vulnerability scores were further integrated into one single score because policy makers often require simple information and water resources that could be viewed as a whole

Table 5 Vulnerability rankings among 16 provinces according to each sector and each MCDM. The numbers inside the parentheses below the title of sectors indicate the weights among the three sectoral vulnerability scores to estimate the integrated vulnerability

Sector	Method	A01	A02	A03	A04	A05	A06	A07	A08	A09	A10	Al11	A12	A13	A14	A15	A16
WS (0.27)	WSM	6	1^a	5	2^a	3^a	7	4	9	10	11	8	13	16^b	15^b	12	14^b
	TOPSIS	6	1^a	5	3^a	2^a	7	4	12	10	11	8	14^b	16^b	15^b	13	9
	Fuzzy TOPSIS	9	2^a	5	1^a	11	14^b	8	7	10	13	4	15^b	12	3	6	16^b
	Group TOPSIS	8	3^a	4^b	2^a	1^a	6	5	12	9	10	7	11	16^b	14^b	15^b	13
	TOPSIS-Borda	6	1^a	5	3^a	2^a	8	4	12	9	10	7	15^b	14^b	16^b	13	11
	TOPSIS-Copeland	6	1^a	5	2^a	3^a	7	4	12	10	11	8	14^b	15^b	16^b	13	9
FC (0.49)	WSM	16^b	3^a	10	8	5	7	2^a	14^b	13	12	15^b	11	4	9	6	1^a
	TOPSIS	16^b	3^a	13	9	4	7	2^a	15^b	12	10	14	11	5	8	6	1^a
	Fuzzy TOPSIS	16^b	3^a	14^b	6	8	12	2^a	9	11	13	15	10	4	7	5	1^a
	Group TOPSIS	16^b	3^a	10	5	4	5	6	2	14^b	13	11	15^b	12	7	9	8
	TOPSIS-Borda	16^b	3^a	13	9	5	7	2^a	15^b	12	10	14^b	11	4	8	6	1^a
	TOPSIS-Copeland	16^b	3^a	12	9	5	7	2^a	15^b	13	10	14^b	11	4	8	6	1^a
WQ (0.24)	WSM	1^b	2^a	3	8	4	6	10	11	16^b	15^b	5	13	9	14^b	12	7
	TOPSIS	3	6	8	7	9	12	14^b	11	16^b	15^b	1	10	2^a	5	13	4
	FuzzyTOPSIS	1	2^a	7	6	8	11	12	4	16^b	15^b	5	13	3^a	14^b	9	10
	Group TOPSIS	1	2^a	4	6	7	8	11	10	16^b	15^b	3	13	9	12	14^b	5
	TOPSIS-Borda	2	4	8	6	9	12	14^b	10	16^b	15^b	1	11	3^a	7	13	5
	TOPSIS-Copeland	2	4	8	7	9	10	13	11	16^b	15^b	1	12	3^a	6	14^b	5
Integrated	WSM	10	2^a	8	5	4	6	3	15^b	16^b	14^b	13	12	7	11	9	1^a
	TOPSIS	15^b	2^a	10	6	4	7	3	16^b	14^b	12	11	13	5	9	8	1^a
	Fuzzy TOPSIS	16^b	1^a	10	5	9	13	2	8	15^b	14^b	11	12	4	7	6	3^a
	Group TOPSIS	14^b	2^a	7	5	4	6^b	3	16^b	15^b	12	13	11	8	10	9	1^a
	TOPSIS-Borda	12	1^a	9	6	4	7	3	16^b	15^b	13	8	14^b	5	10	11	2^a
	TOPSIS-Copeland	12	1^a	8	5	4	7	3	16^b	15^b	13	9	14^b	6	10	11	2^a

[a] The rankings for three most vulnerable districts (1, 2 and 3)

[b] The rankings for three least vulnerable districts (16, 15 and 14)

regardless of management purposes. Rank correlations between different sections range from 0.30 between WQ and WS to 0.03 between WQ and FC (see Table B12 in the ESM), suggesting little associations among different sectors of water-resources system. Also rank correlations between the integrated and sectoral rankings for WS, FC and WQ were 0.43, 0.87 and 0.36, respectively, as expected, based on their weights (0.27 for WS, 0.49 for FC and 0.24 for WQ).

Examining the specific rankings in Table 5, A02 (Busan), A07 (Ulsan) and A16 (Jeju-do) were identified as being in the vulnerable group based on the integrated score, which is the same with FC. Regardless of the MCDM methods, A01 (Seoul) belongs to the resilient group for FC but the vulnerable group for WQ. Based on the integrated score, A01 belongs to the resilient group with the three MCDM methods of TOPSIS, fuzzy TOPSIS and group TOPSIS. Floods are weakly linked to droughts and water quality and thus critical information disappears when aggregating these three aspects. Here we note that floods can cause water-quality problems although major climatic drivers for water-quality problems are high temperature and droughts (Table 4). This finding calls for caution when using a composite index, which is very convenient and provides a simple format of information but often hides specific details.

4 Conclusions and discussions

This study developed an approach to assess climate-change vulnerability using various group MCDM methods and identified the sources of uncertainty in assessments. We used six different group MCDM methods. Assessments were carried out for the South Korean water-resource system, categorized into the sectors of WS, FC and WQ. The sectoral vulnerability scores were further aggregated into one composite score for water-resource vulnerability.

The rank correlations among the different group MCDM methods corresponded to different degrees, but obvious differences in rankings between the fuzzy-based and non-fuzzy-based methods suggested that the uncertainty with crisp data, which are rather widely used, should be acknowledged in vulnerability assessment. However, we also found relatively good associations between rankings from voting-based and average-based methods. Vulnerability rankings varied significantly with the sectors of the water-resource system. From a flood control perspective, Seoul (A01) is the least vulnerable province across all MCDM methods but it is among the most vulnerable in terms of water quality. It highlights the need to assess the vulnerability of water-resource systems according to objectives, although one composite index is often used for simplicity.

This study focused on the uncertainty of vulnerability with different group decision-making approaches with the present time data only. As already pointed out, this study was of the climate-change vulnerability approach for not only the present time but also the future based on the climate-change scenarios generated by any general circulation models and regional climate models. Changes in vulnerability along different time periods and different climate-change scenarios will be explored further in detail.

Eriksen and Kelly (2007) noted that the fundamental scale of vulnerability is local, although processes operating at broader spatial scales contribute to patterns of vulnerability. Indeed, this study focused on vulnerability at the province level, while vulnerability occurs at the local level; therefore, further investigations are necessary regarding the specific causes of vulnerability at the local level in the provinces that are identified as vulnerable.

Acknowledgments This study was supported by grants from the Climate Change Correspondence R&D Program funded by Korea Ministry of Environment (RE201206045) and the Advanced Water Management Research Program funded by Korea Ministry of Land, Infrastructure and Transport (12-TI-C01)

References

Adger WN (2006) Vulnerability. Glob Environ Change-Human Policy Dimens 16(3):268–281

Adger W, Brooks N, Kelly M, Bentham G, Agnew M, Eriksen S (2004) New indicators of vulnerability and adaptive capacity. Technical report 7, Tyndall Centre for Climate Change Research, Univ. of East Anglia, Norwich, UK

Bellman RE, Zadeh LA (1970) Decision-making in a fuzzy environment. Manag Sci 17(4):141–164

Brooks N, Adger WN, Kelly PM (2005) The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. Glob Environ Change-Human Policy Dimens 15(2):151–163

Chu TC (2002) Facility location selection using fuzzy TOPSIS under group decisions. Int J Uncertain Fuzziness Knowledge-Based Syst 10(6):687–701

Chung ES, Lee KS (2009) Identification of spatial ranking of hydrological vulnerability using multi-criteria decision making techniques: case study of Korea. Water Resour Manag 23(12):2395–2416

Eriksen S, Kelly P (2007) Developing credible vulnerability indicators for climate adaptation policy assessment. Mitig Adapt Strateg Glob Chang 12(4):495–524

Fu GT (2008) A fuzzy optimization method for multicriteria decision making: an application to reservoir flood control operation. Expert Syst Appl 34(1):145–149

Fussel HM, Klein RJT (2006) Climate change vulnerability assessments: an evolution of conceptual thinking. Clim Chang 75(3):301–329

Gleick PH (1990) Global climatic changes. Civ Eng Practice 5(1):53–68

Hamouda MA, El-Din MMN, Moursy FI (2009) Vulnerability assessment of water resources systems in the Eastern Nile Basin. Water Resour Manag 23(13):2697–2725

Hwang CL, Yoon K (1981) Multiple attributes decision-making methods and applications. Heidelberg, Springer

Jun KS, Chung ES, Sung JY, Lee KS (2011) Development of spatial water resources vulnerability index considering climate change impacts. Sci Total Environ 409(24):5228–5242

Jun KS, Chung ES, Kim YG, Kim Y (2013) A fuzzy multi-criteria approach to flood risk vulnerability in South Korea by considering climate change impacts. Expert Syst Appl 40(4):1003–1013

Kim Y, Chung ES (2013) Fuzzy VIKOR approach for assessing the vulnerability of the water supply to climate change and variability in South Korea. doi:10.1016/j.apm.2013.04.040

Lee G, Jun KS, Chung ES (2013) Integrated multi-criteria flood vulnerability approach using fuzzy TOPSIS and Delphi technique. Nat Hazards Earth Syst Sci 13:1293–1312

McCarthy JJ, Canziani OF, Leary NA, Dokken DJ, White KS (2001) Climate change 2001: impacts, adaptation and vulnerability. Cambridge University Press, Cambridge

Moss R, Brenkert A, Malone E (2002) Vulnerability to climate change: a quantitative approach. US Department of Energy, Washington, DC

NIER (2011) Sectoral climate change vulnerability map for guiding the development of climate change adaptation action plan at district level. National Institute of Environmental Research, Kyungseo-Dong, Seo-Gu, Incheon, Korea

O'Brien K, Leichenko R, Kelkar U, Venema H, Aandahl G, Tompkins H, Javed A, Bhadwal S, Barg S, Nygaard L, West J (2004) Mapping vulnerability to multiple stressors: climate change and globalization in India. Glob Environ Change-Human Policy Dimens 14(4):303–313

Saari D (1995) Mathematical complexity of simple economics. Not Am Math Soc 42(2):222–230

Seager J (2001) Perspectives and limitations of indicators in water management. Reg Environ Chang 2(2):85–92

Shih HS, Wang CH, Lee ES (2004) A multiattribute GDSS for aiding problem-solving. Math Comput Model 39(11–12):1397–1412

Shih H-S, Shyur H-J, Lee ES (2007) An extension of TOPSIS for group decision making. Math Comput Model 45(7–8):801–813

Zhou HC, Wang GL, Yang Q (1999) A multi-objective fuzzy pattern recognition model for assessing groundwater vulnerability based on the DRASTIC system. Hydrols Sci 44(4):611–618