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Identifying the Contributing Sources of Uncertainties in Urban Flood Vulnerability in South Korea Considering Multiple GCMs, SSPs, Weight Determination Methods, and MCDM Techniques

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Abstract: This study quantified uncertainties involved in assessing the future flood vulnerability in 33 urban areas with population exceeding designated thresholds in South Korea. The driver-pressure-state-impact-response (DPSIR) framework was utilized as the study procedure, integrating social, economic, and environmental factors. In addition, a total of 220 cases of combinations were examined, encompassing twenty general circulation models combined with shared socioeconomic pathway scenarios, five weight determination methods, and three multi-criteria decision-making (MCDM) techniques, as sources of inherent uncertainties in the process. The rankings of urban flood vulnerability (UFV) for the selected cities were comprehensively assessed considering all combinations, followed by an analysis of variance test to investigate contributing sources of uncertainties. As a result, Incheon and Busan were found to be vulnerable to flooding, while Yeongcheon and Andong appeared to be safe cities. Some cities exhibited wide ranges in their rankings, such as Daegu, Yangpyeon, and Jeongeup. The identified contributing sources were weighting (58%), MCDM (27%), and the combination of weighting and MCDM methods together (15%). This study revealed that weight determination methods and MCDM techniques are the primary sources of uncertainties in the assessment of future UFV instead of multiple GCMs and SSPs. This finding underscores the importance for decision-makers and stakeholders to carefully consider these uncertainties for sustainable flood risk management and prevention.

Keywords: urban flood vulnerability; multi-criteria decision making; uncertainty; analysis of variance

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1. Introduction

Flooding is a widespread natural hazard experienced globally, and has considerable impacts on human societies. Climate change and urbanization serves as key factors that exacerbate flood risk (potential for adverse consequences for human or ecological systems) and vulnerability (propensity or predisposition to be adversely affected) to the community [1,2]. Recent studies indicate there is a significant increase in frequency and/or intensity of extreme precipitation, with projections suggesting further intensification in the future due to global warming, consequently increasing the risk of flooding [3–5]. In addition, a study shows that annual maximum daily precipitation has a significant increasing trend in the past decades at a global scale, which can influence flood risk [6]. In addition, most cities are developed near rivers or oceans to secure water resources. The proximity of cities to water, coupled with increasing urban population densities and impervious land areas, has led to increased vulnerability in the system due to fluvial-, pluvial-, and coastal-flood [7,8]. Moreover, rapid urbanization without proper land use planning or management increases the exposure to floods [9,10]. The increased frequency of flooding is exacerbating the deterioration of urban systems, hindering sustainable development, and placing greater strain on social-environmental systems. This potential threat underscores the necessity for attention and contribution to adequately prepare for future flood risks.

Understanding and adapting to future climate risk requires not only assessing the hazard but also quantifying the associated risk. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6) has annotated the core definition of risk as "the potential for adverse consequences" which is an interaction between hazard, vulnerability, and exposure. Uncertainty, the incomplete knowledge, which can result from hazard, vulnerability, and exposure, is recognized as a key component of the concept of risk [11]. These conceptual terminologies provide a more robust basis to decision-makers to manage risk.

Research has been actively conducted in the past with a shared goal to explore the links between climate change vulnerability and urbanization [12]. For example, the shared socio-economic pathways (SSP), an integrated climate change scenario, was developed and applied to future vulnerability assessments, where previous studies revealed that urbanization should be included and specified as vulnerability conditions [13–15]. The relationship of vulnerability factors, such as positive and negative effects of urbanization and vulnerability, is still insufficiently understood [16–18]. The majority of the aforementioned articles suggested that urbanization will contribute to an escalation in climate change vulnerability. Meanwhile, several studies argued that urbanization may have both positive and negative consequences, indicating that it is not always a driver for increased vulnerability. Therefore, urbanization was considered as a pivotal factor influencing both vulnerability and response capacity, as its impact is contingent upon the specific contextual conditions, which may either exacerbate or ameliorate these factors [18,19]. Recent studies have investigated the relationship between flooding and rapid urbanization, both on a global scale and within developing and developed countries or at the city level on regional scales [2,20–22].

Two approaches are commonly used to assess flooding. One is a physical- and numerical-model based approach, in which typical outcomes are inundation and flood hazard maps according to targeting return periods [23,24]. This method offers precise spatial distribution characteristics of flood risk and provides valuable information for flood risk management, mitigation, and prevention. The other approach is a multi-criteria index-based approach considering natural characteristics and socio-economic datasets related to the study area [25]. This method enables the flexible selection of indicators based on data availability and quantification methods to evaluate flood vulnerability and risk. Due to advanced technologies, these approaches are now often integrated with geographic information systems, remote sensing, and deep learning techniques for assessing flooding [26,27].

Various methodologies for carrying out uncertainty and sensitivity analysis on climate change vulnerability have been proposed in regional case studies. The following frameworks combine different components of factors and their associating variables to construct the foundation of each vulnerability assessment approach: driving force-pressure-state-impact-response (DPSIR), social, ecological, and technological systems (SETS), IPCC AR4-based exposure, sensitivity, and adaptive capacity (ESAC), IPCC AR5-based hazard, exposure, and vulnerability (HEV), etc. [2,22,28,29]. Several studies have utilized the technique for order of preference by similarity to ideal solution (TOPSIS), a multi-criteria decision making (MCDM) method, to quantify the climate change vulnerability, to derive the distribution of weights, and to reduce the uncertainty of weights [30,31]. Further implementations and applications on TOPSIS enabled a stronger ability of the model to manage uncertainty in an effective manner based on coupling with Pythagorean fuzzy set, VIKOR, and grey theory [32–35].

A recent study quantified uncertainties and evaluated flood vulnerability for medium-sized cities on a regional scale utilizing the abovementioned MCDM approaches incorporating general circulation models (GCMs) [28]. However, a smaller number of previous studies have explicitly examined what can be the contributing sources of uncertainty to flood vulnerability when considering both the medium and big populated cities in Korea. Therefore, in this study, we present a comparative analysis to investigate the uncertainties that lie in the assessment of future urban flood vulnerability (UFV) process in populated cities in Korea. This study aims to answer the following research questions.

(1) How does flood vulnerability compare when estimated using different weighting, MCDM, and GCMs with climate change scenarios for different sizes of cities?
(2) To what extent does flood vulnerability vary when considering all plausible inputs?
(3) How does the relative sensibility to the various components of flood vulnerability assessment compare (i.e., weights, decision making process, and climate model)?

To answer these questions, this study evaluated the flood vulnerability for cities with populations exceeding a certain threshold utilizing the DPSIR framework, which are integrated with social, economic, and environmental (SEE) factors. Within the process, a composite integrated model incorporating various weighting values for criteria and MCDM scheme and GCMs including future scenarios in South Korea were applied to examine the results of flood vulnerability. This study assessed the urban flood vulnerability utilizing the multi-criteria index-based approach, which derives the rankings of cities vulnerable to flooding according to calculated proxy variables. Then, the analysis of variance (ANOVA) test was utilized to determine disparities among the derived priority rankings of flood vulnerability for each city, considering all plausible components from the designated model. The equal weight, entropy, Delphi, fuzzy, and grey approaches were utilized to derive weighting values, while WSM, VIKOR, and TOPSIS approaches were employed for the MCDM process. Note that the 'vulnerability' in this study includes both the exposure of the system affected (i.e., the population and economic assets located in area potentially affected by flooding) and the vulnerability of the system (i.e., the susceptibility of the exposed elements to flooding).

This paper is organized as follows. Descriptions of the data and cities considered in this study, along with the description of each methodology considered in this study, are explained in Section 2. Section 3 presents the results including the obtained or computed weighting values, derived rankings based on each method, and contributing sources of uncertainties based on a statistic test. Finally, Section 4 summarizes our findings with a conclusion.

2. Methods

2.1. Study Area, GCMs, and SSPs

This study was applied to 33 selected big and medium cities where synoptic weather observation centers exist in South Korea. This study defined a "big city" as one with a population greater than 500,000 and a "medium city" as having a population between 100,000 and 500,000. Although big cities with large populations can affect the vulnerability of medium-sized cities during the normalization process, this study considered both big and medium cities as a whole sample to investigate the characteristics on vulnerability, ignoring the impact of city size. Figure 1 illustrates the location of the big and medium cities considered in this study with different colors. The detail information of the selected 33 cities such as their size, area, location, and population can be found in the Supplementary Material (Table S1).

GCMs are developed based on their own physical climate system processes and mathematical expressions, thereby offering a range of climate projection [36]. These models typically encompass physical processes in the atmosphere, oceans, glaciers, and the Earth's surface. Therefore, they are valuable tools for analyzing climate change topics and estimating future climates resulting from rising concentrations of greenhouse gases. This study selected ten GCMs (CMIP6) under two-SSP scenarios (SSP 2–4.5 and 5–8.5) on the climate change and assessed flood vulnerability using monthly maximum precipitation for the future period (2070–2099). The GCM data, characterized by varying spatial resolutions, were downscaled to a spatial resolution of $0.25^\circ \times 0.25^\circ$ using linear interpolation. Additionally, the inverse distance weighting method was employed as a spatial interpolation technique to simulate point climate data for the study area based on the downscaled GCMs grid data. As part of the process, bias correction was conducted using the quantile mapping method, which is widely employed for this purpose. The 10 GCMs under two-SSP scenarios were employed, and 20 different cases of future monthly precipitation for the future period were applied as the driver component in the environmental factor. The information of ten CMIP6 GCMs selected in this study is described in the Supplementary Material (Table S2).

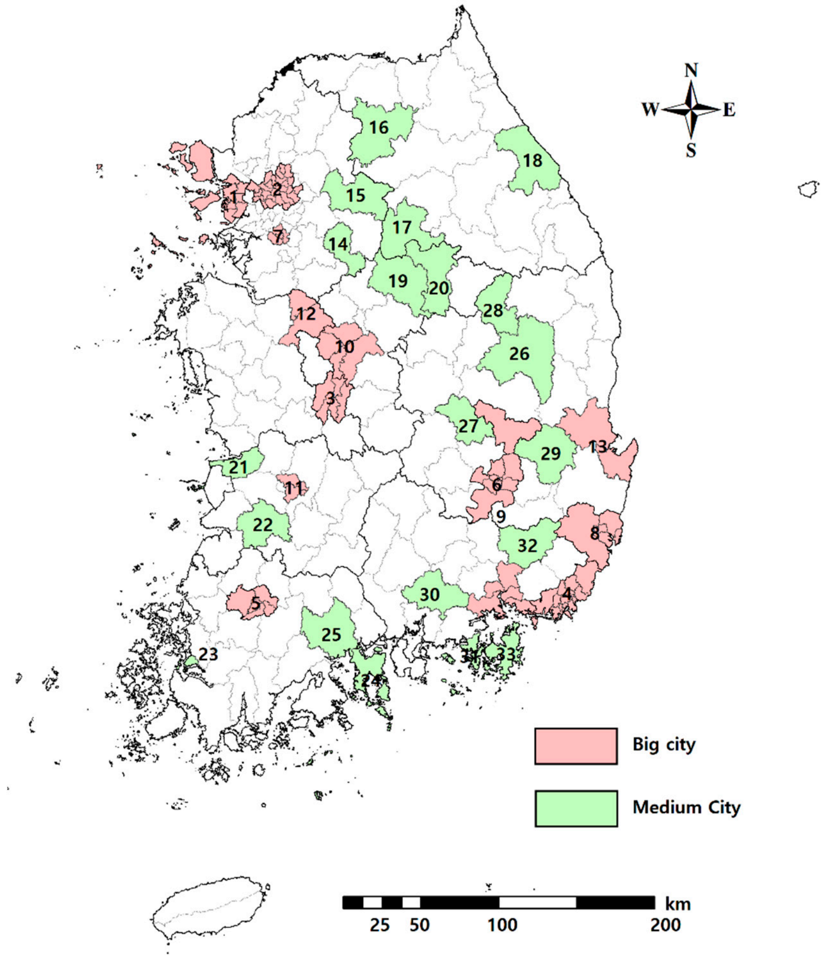

Figure 1. Map of study area over Republic of Korea.

2.2. DPSIR Framework and Social-Economic-Environmental Factors

This study utilized the DPSIR framework, developed by the European Environment Agency in 1999 [37]. The DPSIR framework was improved based on the integration of the PSR (Pressure-State-Response) and DSR (Driver-State-Response) framework presented by the OECD (Organization of Economic Cooperation and Development) in 1993 and the United Nations in 1996, respectively. This framework is widely used and applied globally due to the fact that it addresses the limitations of the PSR framework by incorporating additional components such as 'drivers (or driving forces)' and 'impact' factors alongside the existing PSR structure [38–40].

In this study, indicators for UFV evaluation were selected using the DPSIR framework considering SEE factors. A total of 25 indicators were selected, categorized into SEE factors, which collectively determine flood vulnerability in urbanized cities within the study area. Each factor comprises between six to twelve indicators, all of which were classified into the DPSIR groups based on their relevance to flooding characteristics. These indicators initially stemmed from multiple rounds of surveys conducted among group of experts, and was applied in a study by [28]. This study is a follow-up to the previously mentioned study and focuses on techniques for quantifying uncertainties and identifying the sources that contribute to them. However, some certain aspects were reconstructed in this study by removing unnecessary indicators (i.e., population density, annual maximum precipitation, and daily maximum temperature) and increasing the data length of historical indicators from 2007 to 2022, while the previous historical data length was between 2010 to 2020. The 25 indicators, their belonging factors and DPSIR group, along with their expected benefit and cost impact to flood vulnerability are listed in Table 1. For example, the social factor includes indicators such as population growth, class of population vulnerable to disaster, administrative district area, population, distance to shore, developed area, number of flood events, number of casualties, number of injured people, number of inhabitants per resident, number of hospital beds per thousand people, and number of doctors per thousand people. Most of the indicators for the social factor are related to population and characteristics of the urban area. Indicators relating to cost and economic activity are categorized into the economic factor, while social infrastructures to prevent flooding and climatic data are categorized into the environment factor.

Table 1. Selected indicators for urban flood vulnerability (UFV) in this study.

Factor	DPSIR	Label	Indicators	Benefit vs. Cost	Period and Source of Data Collection
Social	Driver	I01	Population growth	(−)	2007–2022 Statistic Year Book of Natural Disaster (https://kosis.kr/index/index.do (accessed on 5 July 2023))
		I02	Class of population vulnerable to disaster	(−)	
		I03	Administrative district area	(−)	
		I04	Population	(−)	
		I05	Distance to shore	(+)	
	Pressure	I06	Developed area	(−)	
	State	I07	Number of Flood events	(−)	
	Impact	I08	Number of casualties	(−)	
		I09	Number of injured people	(−)	
	Response	I10	Number of inhabitants per resident	(−)	
		I11	Number of hospital beds per thousand people	(+)	
		I12	Number of doctors per thousand people	(+)	
Economic	Driver	I13	Unemployment ratio	(−)	
	Pressure	I14	Financial independence rate	(+)	
		I15	GRDP	(+)	
	State	I16	Developing plan area	(−)	
	Impact	I17	Cost of damage	(−)	
	Response	I18	Cost for recovery	(−)	
		I19	Disaster prevention budget	(+)	
Environmental	Driver	I20	Future monthly precipitation (GCMs)	(−)	2070–2099 GCMs + SSP scenarios
	Pressure	I21	Daily maximum precipitation	(−)	2007–2022 Statistic Year Book of Natural Disaster (https://kosis.kr/index/index.do (accessed on 5 July 2023))
	State	I22	Damage area	(−)	
	Impact	I23	Number of restored households	(−)	
	Response	I24	Length of levee	(+)	
		I25	Number of reservoirs	(+)	

2.3. MCDM Techniques

In order to analyze the uncertainties inherent in the use of decision making process, this study compared three-MCDM methods: weighted sum method (WSM), VIKOR, and TOPSIS. Note that this study combined WSM with equal weight, entropy, and Delphi (3 cases), VIKOR with equal weight, entropy, and Delphi (3 cases), and TOPSIS with equal weight, entropy, Delphi, fuzzy, and grey (5 cases), which in total is 11 cases. These 11 cases are combined with 10 GCMs and 2 SSP scenarios. Therefore, this study conducted the flood vulnerability assessment 220 times.

The WSM integrates all multi-objective functions into a single scalar using the weighted sum. The method of WMS is well described in [41], and the composite objective function, U, can be expressed as follows:

$$U = \sum_{i=1}^{k} w_i F_i(x) \tag{1}$$

where w_i is the weight and $F_i(x)$ is the objective function criterion of the ith criterion or attribution. Minimizing Equation (1) provides a sufficient condition for Pareto optimality [42,43].

The VIKOR method provides rankings, compromise solution, and the intervals of weight stability to assess the preference stability of the compromise solution derived from the initial weights. It derives the multi-criteria ranking index based on the particular measure of 'closeness' to the 'ideal' solution [44]. The VIKOR method and its compromise ranking algorithm is well described in [45] and can be found in the Supplementary Material (Equations (S1)–(S4)).

The TOPSIS method, known as the technique for order preference by similarity to an ideal solution, was introduced by [46], referencing the work of [47]. The principle of this method is that the selected alternative should be closest to the positive-ideal solution while being farthest from the negative-ideal solution. The TOPSIS procedure consists of several steps, which are well described in [45] and can be found in the Supplementary Material (Equations (S5)–(S11)).

2.4. Weight Determination Methods

This study applied five different methods to define the weighting values for UFV criteria and to examine whether the different weighting determination methods cause uncertainties in assessing urban flood vulnerability. Equal weight and entropy methods were selected to represent the objective weighting values, while the Delphi technique was utilized to represent the subjective weighting values. In addition, fuzzy and grey were employed to provide different concentrations and ranges based on subjective weighting values. The weighting values obtained by equal weight, entropy, and Delphi were combined with WSM, VIKOR, and TOPSIS, while fuzzy and grey were combined only with the TOPSIS.

Equal weight assigns the same value to all selected indicators for flood vulnerability. This method does not provide preference based on the indicators and treats each indicator equally in terms of contribution to the decision making process. The weighting value for the jth criterion, w_j, can be expressed as follows:

$$w_j = \frac{1}{n}, \sum_{j=1}^{n} w_j = 1 \;\; (j = 1, 2, \ldots, n) \tag{2}$$

Entropy method, proposed by [48], is widely used in decision-making to obtain the objective weight. Its advantage is the avoidance of the interference of human factors on the weight of indicator. The entropy weight value can be derived by the following three-steps: First, standardization of the value should be done. The standardized value of the ith alternative in the jth criterion can be expressed as follows:

$$s_{ij} = \frac{v_{ij}}{\sum_{i=1}^{m} v_{ij}}. \tag{3}$$

Second, the entropy value E_j of the jth criteria can be expressed as follows:

$$E_j = \frac{\sum_{i=1}^{m} s_{ij} \cdot \ln s_{ij}}{\ln m}. \quad (4)$$

where $s_{ij} \cdot \ln s_{ij}$ is set to 0 when $s_{ij} = 0$ for convenience in the actual evaluation.

Finally, the weight w_j can be defined as follows:

$$w_j = \frac{1 - E_j}{\sum_{i=1}^{m} (1 - E_j)}. \quad (5)$$

This study also utilized the Delphi technique developed by [49] which is a method that can solve complex problems by a series of questionnaires and feedback from a group of experts. In this study, we determined the weighting values for flood vulnerability indicators based on two rounds of surveys from the expert group including hydrologists, water resources engineers, and climate change experts.

The fuzzy-TOPSIS method, proposed by [50], addresses uncertainty in MCDM problems by considering the triangle fuzzy number (TFN) and extends the classical TOPSIS method to accommodate group decision-making scenarios. TFN represents a fuzzy set where elements possess uncertain boundaries, which can be used easily because it can be expressed by three dots. Similarly, the grey systems theory also offers a practical approach for managing uncertainty, particularly in situations involving highly imprecise data [51,52]. 'Grey' denotes information that is partially known, and a grey number represents a value whose exactness is unknown, but a range within which the value falls is known [53]. Detailed procedure of both the fuzzy-TOPSIS and grey-TOPSIS are described in the Supplementary Material (Equations (S12)–(S22)).

2.5. Statistical Test for Flood Vulnerability Results

Analysis of variance (ANOVA), developed by Sir Ronald A. Fisher (1925), is designed to determine if there is a significant difference among the means of two or more groups. Essentially, ANOVA addresses whether all the group means are equal, or the variance between the group means greater than what would be anticipated by chance. Therefore, ANOVA's strength lies in its capacity to not only quantify the uncertainty linked to each individual source but also to assess the uncertainty stemming from the interactions among these sources [54,55]. In this study, the derived rank based on the flood vulnerability assessment was considered instead of the mean value to explore whether the different procedures have an impact on flood vulnerability ranks. The sources of uncertainty considered in this study includes GCMs combined with SSP scenarios, weight determination methods, and MCDM techniques, which make a total of 220 cases. According to the ANOVA theory, the total sum of squares (SST) can be divided into sums of squares due to individual sources. Hence, in this study, the SST can be expressed as follows:

$$SST = SS_{GCM,SSP} + SS_{Weight} + SS_{MCDM} + SS_{GCM,SSP:Weight} + SS_{GCM,SSP:MCDM} + SS_{Weight:MCDM} + SS_{GCM,SSP:Weight:MCDM} \quad (6)$$

where $SS_{GCM,SSP}$, SS_{Weight}, and SS_{MCDM} represents the variance due to individual sources relating to GCM scenarios, weighting, and MCDM methods, and $SS_{GCM,SSP:Weight}$, $SS_{GCM,SSP:MCDM}$, $SS_{Weight:MCDM}$, and $SS_{GCM,SSP:Weight:MCDM}$ represent the variance due to combined sources.

3. Results

3.1. Development of the Decision Matrix

The decision matrix, which is the initial matrix in the evaluation process, was developed considering 24 historical indicators (2007–2022; I01–I19 and I21–I25) and 1 indicator based on future projection (2070–2099; I20). According to the methodology outlined in this study, the future monthly precipitation data from GCMs, along with the two distinct SSP scenarios, are categorized within the 'Driver' subgroup of the 'Environmental' factor. Hence, this study assessed UFV using multiple decision matrices. In order to obtain the decision matrix with alternatives and criteria as the cities and indicators, respectively, the mean value of each indicator was computed in this study. These matrices were applied for the cases using equal weight, entropy, and Delphi. Moreover, the separate decision matrices for fuzzy-TOPSIS and grey-TOPSIS, incorporating the changing indicator (I20), were developed due to their distinct procedures, which take into account the minimum, maximum, and most frequently occurring values. Figure 2 illustrates the distribution of one indicator (I01; population growth) for each city through histograms. The minimum, maximum, and most frequently occurring values are computed based on these histograms to develop the decision matrix for the fuzzy- and grey-TOPSIS methods. Note that Figure 2 represents the histogram for a single indicator. Therefore, there are 43 additional figures similar to this one for indicator I20 and the other indicators.

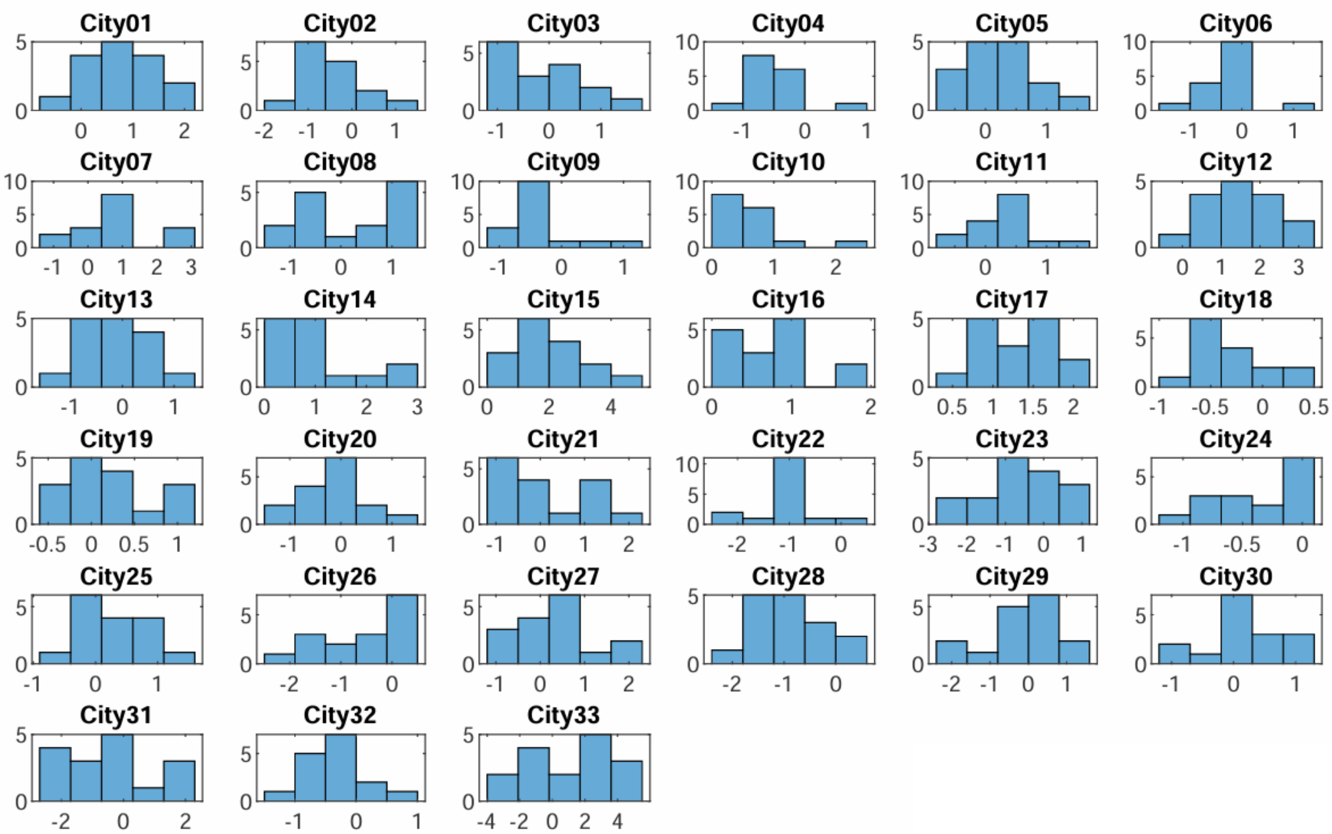

Figure 2. Histogram of indicator I01 (population growth) for each city.

3.2. Evaluation the Urban Flood Vulnerability from Different Methods

3.2.1. Weighting Values from Different Methods

Three different MCDM methods and five different weighting methods, incorporating ten GCMs and two SSP scenarios, were used to evaluate UFV in this study. The weighting values for each indicator were either obtained through surveys (Delphi method) or computed. The weighting values based on the equal weight, Delphi, fuzzy, and grey methods remain constant throughout the whole study procedure. Note that the weighting values for fuzzy and grey were also obtained by the Delphi survey for this study. However, due to the outlined framework of this study, the weighting values for entropy vary for each case. This is because the varying indicator I20 was affecting the weighting values for the DPSIR groups and their corresponding SEE factors.

Figures 3–5 illustrates the chart of the obtained and computed weighting values for the criteria considered in this study. Figure 3 shows the weighting values according to the 25 selected indicators. The sum of the weighting values for the indicators belonging to the DPSIR groups are one. For example, the sum of indicators (I01 to I05), which constitute the driver group in the social factor, is one. Similarly, the weighting values for the indicators that exists solely in the DPSIR groups, such as I06 and I07, are one. For the entropy method, indicator I20 solely composed the driver group in the environment factor. Therefore, the weighting value for each indicator remains the same while indicator I20 varies. However, the weighting values for the DPSIR groups and SEE factors slightly changed due to the variation of the indicator I20 (Figures 4 and 5). Nevertheless, it was found that there were not any significant variations within the weighting values in the DPSIR and SEE level for the entropy method aspect.

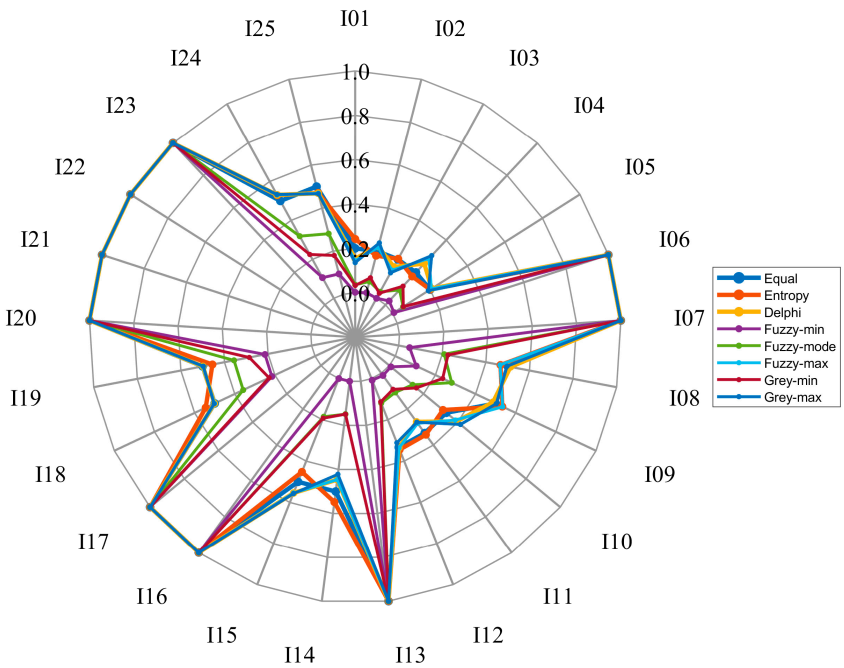

Figure 3. Charts of weighing values for the selected 25 indicators.

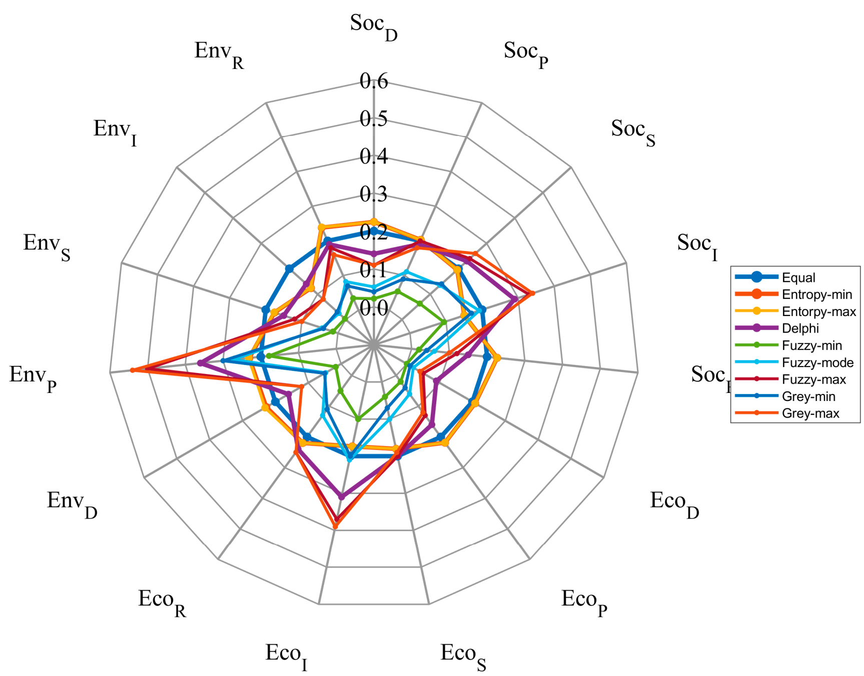

Figure 4. Charts of weighing values for the DPSIR groups.

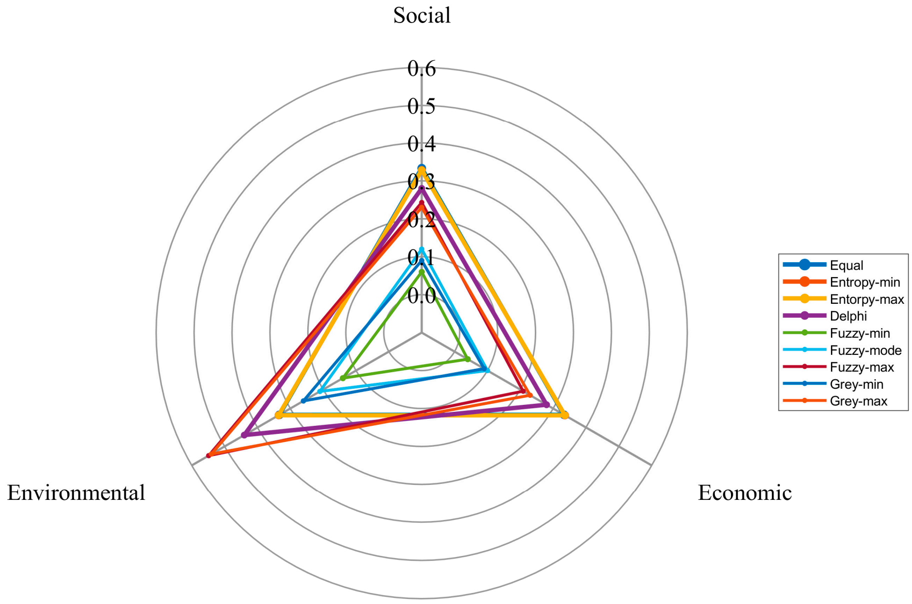

Figure 5. Charts of weighing values for the SEE factors.

The weighting values for equal, entropy, Delphi, Fuzzy-max, and Grey-max were observed to have no considerable difference in the 25 indicators (Figure 3). However, in Figure 4, considerable changes in the weighting values can be observed. The weighting values based on the equal, entropy, and Delphi method for the DR, PD, and DSI groups in the SEE factors, respectively, had greater weights compared to maximum values of the fuzzy and grey approach. The opposite cases, when the maximum weighting values of the fuzzy and grey methods were two or three times greater than the other weighting methods, were observed for the SI, I, and P groups in the SEE factors. At the SEE factor level (Figure 5), the weighting values based on the equal and entropy method exhibited similarities across factors, with the chart's shape resembling an equilateral triangle. The chart representing the other weighting methods resembles an isosceles triangle, indicating that the environmental factor has relatively higher weights compared to the others. The difference in weighting values resulting from various methods are anticipated to cause uncertainties in the UFV assessment, even before entering the decision-making process.

3.2.2. UFV Assessment Based on Different MCDM Techniques

MCDM methods were integrated with the computed weighting values. Based on the developed decision matrix, the weighting values and MCDM methods were applied for all plausible combinations. As per the outlined methodology of this study, the UFV assessment was conducted 220 times, corresponding to the number of combinations of the GCMs and SSP scenarios, weight determination methods, and MCDM techniques. Proxy values were obtained for each city after following all steps of a single MCDM method. The obtained proxy values were utilized to prioritize flood vulnerability for each city. The city with the highest proxy value was ranked as 1st (most vulnerable to urban flooding), while the city with the lowest proxy value was ranked as 33rd (least vulnerable to urban flooding). Figure 6 presents the ranking information using aggregated statistics, which shows representative information such as the highest, the lowest, and the most frequent ranking for each city.

According to Figure 6, cities 1 (Incheon), 2 (Seoul), 4 (Busan), and 13 (Pohang) were observed as cities vulnerable to flooding when considering the most common rank. However, Incheon and Busan showed a narrow range in their rank variation, whereas Seoul and Pohang exhibited relatively greater changes in their ranks. On the other hand, cities ranked below or equal to 28th, such as 20 (Jecheon), 22 (Jeongeup), 23 (Mokpo), 26 (Andong), 27 (Gumi), 28 (Yeongju), and 29 (Yeongcheon), were identified as cities safe from flooding.

The rankings for Andong, Yeongju, and Yeongcheon showed less diversity, indicating that these cities have robust results despite the application of numerous combinations of uncertainty sources.

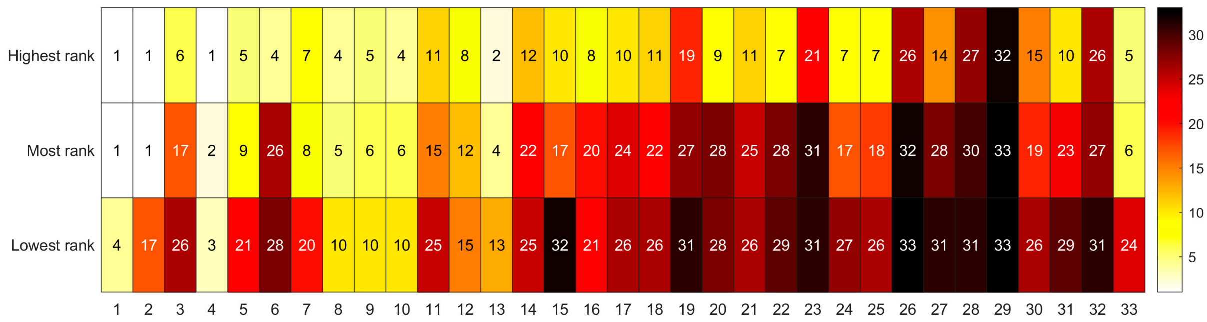

Figure 6. Highest, most common, and lowest rank of flood vulnerability for each city considering all scenarios.

When comparing the size of cities, the majority of the big cities had higher ranks, indicating that most of the big cities are vulnerable to flooding, except for cities 3 (Daejeon), 6 (Daegu), and 11 (Jeonju). In contrast, medium cities were low ranked. However, when considering the highest rank for the medium cities, it was observed that 12 cities were ranked higher than 13th, indicating that medium cities can be more vulnerable to flooding than some of the big cities under specific cases and scenarios.

Figure 7 visualized the maximum difference between the ranking for UFV in each city considering all plausible scenarios. According to this figure, cities that are sensitive and less sensitive to the applied methodology can be easily sorted out. As a result, cities with minimal ranking differences, such as 1 (Incheon), 4 (Busan), 28 (Yeongju), and 29 (Yeongcheon), appeared to be insensitive. In contrast, 3 (Daejeon), 6 (Daegu), 15 (Yangpyeong), 22 (Jeongeup), and 24 (Yeosu) were found with greater ranking differences, indicating that UFVs of these cities are highly influenced by either the GCMs and SSP scenarios, weight determination methods, or MCDM techniques. This suggested that the sensitivity to the applied methodology for flood vulnerability varies from city to city.

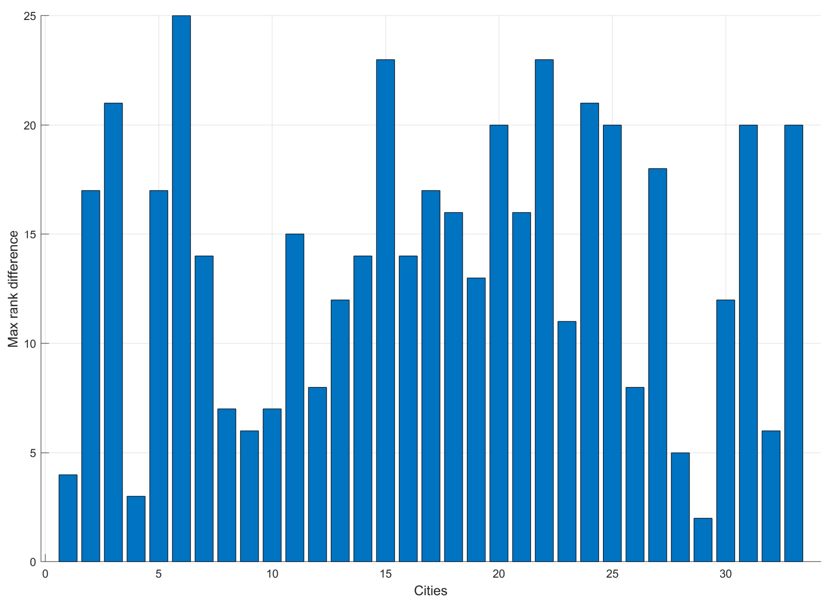

Figure 7. Maximum difference between the flood vulnerability ranks in each city considering all scenarios.

3.3. Statistical Analysis of Urban Flood Vulnerability Rankings

In order to examine the sources of uncertainties that lies in the scenarios and methods in the flood vulnerability assessment in each city, this study utilized the ANOVA test. Figure 8 illustrates the ratio of contributing sources based on the ANOVA test, while Table 2 shows brief statistic information relating to Figure 8. The test was conducted with the ranking resulting from the UFV assessment for each city considering the combination of GCMs, SSP scenarios, weight determination methods, and MCDM techniques. The SST obtained from Equation (6) was converted to 100% for visualization purposes. As a result, the individual weighting and MCDM method and the weighting combined with MCDM methods were greatly involved in causing uncertainties in the UFV. The weighting methods were the most sensitive source, contributing to a broad spectrum of uncertainties in UFV, with a ratio of contribution to the variance in rankings ranging from 35.0% to 92.9% in 19 cities. The MCDM techniques were observed to be the next influential source as their ratios of contribution ranged between 40.7% to 71.4% in nine cities, while the combination of the weight determination and MCDM methods showed a range of 28.4% to 58.6% in five cities.

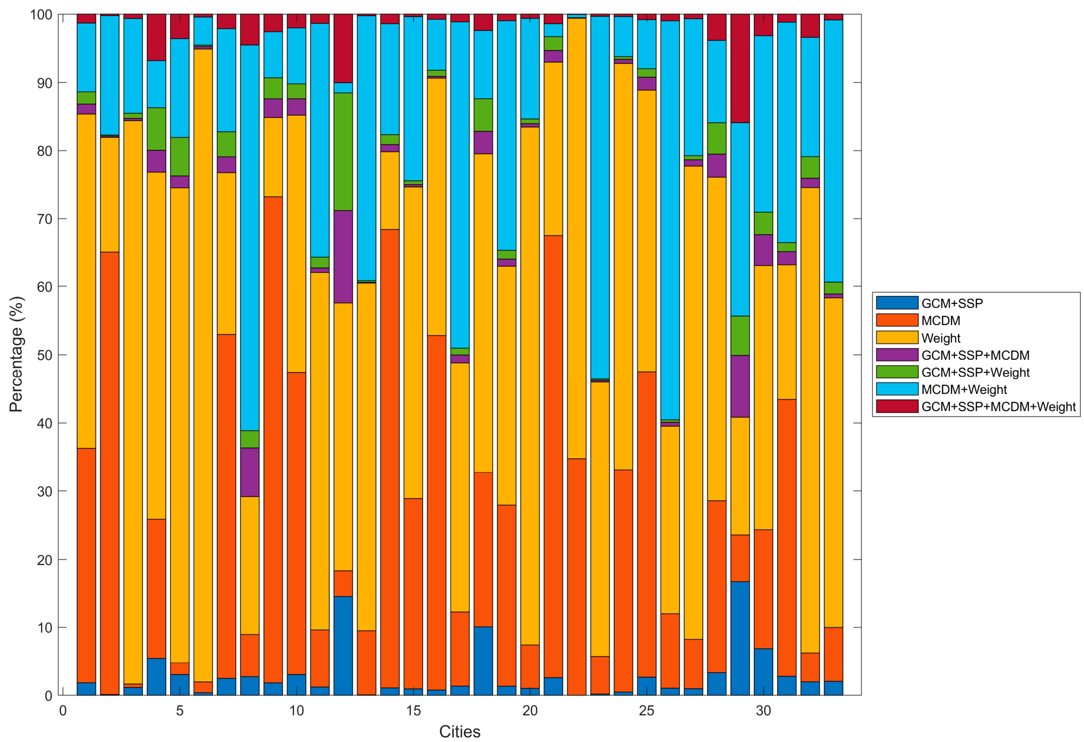

Figure 8. Contributing sources of uncertainty based on ANOVA test for the flood vulnerability ranks in each city.

Table 2. Minimum and maximum of the ratio of contributing sources that causes ranking variation in UFV for all cities and only considering the cities with the sources that contributed the most.

Sources	All Cities		Considering Only the Cities Based on the Most Contributed Sources	
	Min	Max	Min	Max
GCM + SSP	0.01	16.70	-	-
MCDM	0.51	71.37	40.66	71.37
Weight	11.44	92.93	35.06	92.93
GCM + SSP + MCDM	0.02	13.60	-	-
GCM + SSP + Weight	0.06	17.25	-	-
MCDM + Weight	0.46	58.55	28.42	58.55
GCM + SSP + MCDM + Weight	0.07	15.93	-	-

The application of different weight determination methods and MCDM methods influenced the final flood vulnerability rankings. For example, the objective weighing methods, such as equal weight and entropy method, calculated weighting values based on the information content of each criterion, which reduces the reliance on subjective judgements. It can be inferred that the objective weighting values can be used for regions with no background knowledge about the characteristics and environment of the area. On the other hand, the subjecting weighting method (i.e., Delphi technique) reflects experts' opinions by identifying indicators that require particular focus, and can lead to different outcomes based on comprehensive understanding of various factors. Furthermore, the application of different MCDM methods can be crucial in decision making since they can lead to different outcomes. There are chances of obtaining similar results when applying different MCDM methods, especially when considering a smaller number of criteria and alternatives [35]. However, the final outcomes based on different MCDM methods can vary due to the fact that recent studies are comprehensively utilizing numerous climate data, land use data, socio-economic data, and so on. Our findings show that weights and decision-making techniques have to be carefully selected, as they are the primary sources of uncertainty. Recognizing that utilization of different weighting approaches and MCDM methods can yield diverse outcomes can assist policymakers, officials, and planners in sustainable urban management, planning, and flood risk prevention.

4. Conclusions

This study evaluated UFVs considering future climate change in urbanized cities in South Korea. The DPSIR framework integrated with SEE factors were utilized as for the study procedure. Indicators related to urban flooding were selected, and their weighting values were obtained by the equal weight, entropy, Delphi, fuzzy, and grey approaches. The weighting values for each method were then used in three different MCDM methods, which are WSM, VIKOR, and TOPSIS. The UFV assessment was conducted 220 times, which is the number of combinations of the three sources of uncertainties considered in this study: GCMs, SSP scenarios, weight determination methods, and MCMD techniques. The derived rankings for each city were aggregated to investigate the variation of the flood vulnerability ranks based on different methodologies and to explore the ratio of contributing sources causing uncertainty based on the ANOVA test.

This study revealed that weighting values are the most contributing source that cause variation to the UFV ranks, followed by MCDM methods and the combination of weight determination and MCDM methods. Daegu appeared to have the most difference between the maximum and minimum ranks, indicating that this city's rank for flood vulnerability is sensitive to varying weightings and MCDM methodologies. Nevertheless, some cities were found having robust ranking with fewer changes: Incheon and Busan were identified as vulnerable cities, whereas Yeongcheon was depicted as the safest city to flooding. In addition, the majority of the big cities scored high ranks, while medium cities were low-ranked when comparing the city size. The results of this study suggests that weight determination and MCDM methods are the primary components that can cause uncertainty. Therefore, to better understand the uncertainty in the assessment of flood vulnerability and to effectively communicate with decision–makers and stakeholders, it is essential to take all plausible methods into account.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16083450/s1, Table S1: Information of the 33 cities included in this study, Table S2: CMIP6 GCMs used in this study and their resolutions and developers, Equations (S1)–(S11): VIKOR and TOPSIS procedure, Equations (S12)–(S22): Fuzzy- and grey-TOPSIS procedure.

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References

1. Walsh, J.; Wuebbles, D.; Hayhoe, K.; Kossin, J.; Kunkel, K.; Stephens, G.; Thorne, P.; Vose, R.; Wehner, M.; Willis, J.; et al. 2014: Ch. 2: Our Changing Climate. In *Climate Change Impacts in the United States: The Third National Climate Assessment*; U.S. Global Change Research Program: Washington, DC, USA, 2014; pp. 19–67.
2. Chang, H.; Pallathadka, A.; Sauer, J.; Grimm, N.B.; Zimmerman, R.; Cheng, C.; Iwaniec, D.M.; Kim, Y.; Lloyd, R.; McPhearson, T.; et al. Assessment of Urban Flood Vulnerability Using the Social-Ecological-Technological Systems Framework in Six US Cities. *Sustain. Cities Soc.* **2021**, *68*, 102786. [CrossRef]
3. Tabari, H. Climate Change Impact on Flood and Extreme Precipitation Increases with Water Availability. *Sci. Rep.* **2020**, *10*, 13768. [CrossRef] [PubMed]
4. Myhre, G.; Alterskjær, K.; Stjern, C.W.; Hodnebrog, Ø.; Marelle, L.; Samset, B.H.; Sillmann, J.; Schaller, N.; Fischer, E.; Schulz, M.; et al. Frequency of Extreme Precipitation Increases Extensively with Event Rareness under Global Warming. *Sci. Rep.* **2019**, *9*, 16063. [CrossRef]
5. Kharin, V.V.; Zwiers, F.W.; Zhang, X.; Wehner, M. Changes in Temperature and Precipitation Extremes in the CMIP5 Ensemble. *Clim. Change* **2013**, *119*, 345–357. [CrossRef]
6. Westra, S.; Alexander, L.V.; Zwiers, F.W. Global Increasing Trends in Annual Maximum Daily Precipitation. *J. Clim.* **2013**, *26*, 3904–3918. [CrossRef]
7. Wing, O.E.J.; Bates, P.D.; Smith, A.M.; Sampson, C.C.; Johnson, K.A.; Fargione, J.; Morefield, P. Estimates of Present and Future Flood Risk in the Conterminous United States. *Environ. Res. Lett.* **2018**, *13*, 034023. [CrossRef]
8. Hong, C.Y.; Chang, H. Residents' Perception of Flood Risk and Urban Stream Restoration Using Multi-Criteria Decision Analysis. *River Res. Appl.* **2020**, *36*, 2078–2088. [CrossRef]
9. Luino, F.; Turconi, L.; Petrea, C.; Nigrelli, G. Uncorrected Land-Use Planning Highlighted by Flooding: The Alba Case Study (Piedmont, Italy). *Nat. Hazards Earth Syst. Sci.* **2012**, *12*, 2329–2346. [CrossRef]
10. Bae, S.; Chang, H. Urbanization and Floods in the Seoul Metropolitan Area of South Korea: What Old Maps Tell Us. *Int. J. Disaster Risk Reduct.* **2019**, *37*, 101186. [CrossRef]
11. Reisinger, A.; Howden, M.; Vera, C.; Garschagen, M.; Hurlbert, M.; Kreibiehl, S.; Mach, K.J.; Mintenbeck, K.; O'neill, B.; Pathak, M.; et al. *The Concept of Risk in the IPCC Sixth Assessment Report: A Summary of Cross-Working Group Discussions*; Guidance for IPCC Authors; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2020; p. 15.
12. Vörösmarty, C.J.; Green, P.; Salisbury, J.; Lammers, R.B. Global Water Resources: Vulnerability from Climate Change and Population Growth. *Science* **2000**, *289*, 284–288. [CrossRef]
13. Van Vuuren, D.P.; Riahi, K.; Moss, R.; Edmonds, J.; Thomson, A.; Nakicenovic, N.; Kram, T.; Berkhout, F.; Swart, R.; Janetos, A.; et al. A Proposal for a New Scenario Framework to Support Research and Assessment in Different Climate Research Communities. *Glob. Environ. Change* **2012**, *22*, 21–35. [CrossRef]
14. Kriegler, E.; O'Neill, B.C.; Hallegatte, S.; Kram, T.; Lempert, R.J.; Moss, R.H.; Wilbanks, T. The Need for and Use of Socio-Economic Scenarios for Climate Change Analysis: A New Approach Based on Shared Socio-Economic Pathways. *Glob. Environ. Change* **2012**, *22*, 807–822. [CrossRef]

15. O'Neill, B.C.; Kriegler, E.; Riahi, K.; Ebi, K.L.; Hallegatte, S.; Carter, T.R.; Mathur, R.; van Vuuren, D.P. A New Scenario Framework for Climate Change Research: The Concept of Shared Socioeconomic Pathways. *Clim. Change* **2014**, *122*, 387–400. [CrossRef]
16. Pelling, M. *The Vulnerability of Cities: Natural Disasters and Social Resilience*; EARTHSCAN Publications Ltd.: London, UK, 2003.
17. Romero Lankao, P.; Qin, H. Conceptualizing Urban Vulnerability to Global Climate and Environmental Change. *Curr. Opin. Environ. Sustain.* **2011**, *3*, 142–149. [CrossRef]
18. Cardona, O.D.; Van Aalst, M.K.; Birkmann, J.; Fordham, M.; Mc Gregor, G.; Rosa, P.; Pulwarty, R.S.; Schipper, E.L.F.; Sinh, B.T.; Décamps, H.; et al. Determinants of Risk: Exposure and Vulnerability. In *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2012; ISBN 9781139177245.
19. Adger, W.N.; Agrawala, S.; Mirza, M.M.Q.; Conde, C.; O'Brien, K.; Pulhin, J.; Pulwarty, R.; Smit, B.; Takahashi, K. Assessment of Adaptation Practices, Options, Constraints and Capacity. In *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2007; pp. 717–743.
20. Rentschler, J.; Salhab, M.; Jafino, B.A. Flood Exposure and Poverty in 188 Countries. *Nat. Commun.* **2022**, *13*, 3527. [CrossRef] [PubMed]
21. Parvin, F.; Ali, S.A.; Calka, B.; Bielecka, E.; Linh, N.T.T.; Pham, Q.B. Urban Flood Vulnerability Assessment in a Densely Urbanized City Using Multi-Factor Analysis and Machine Learning Algorithms. *Theor. Appl. Climatol.* **2022**, *149*, 639–659. [CrossRef]
22. Tanim, A.H.; Goharian, E.; Moradkhani, H. Integrated Socio-Environmental Vulnerability Assessment of Coastal Hazards Using Data-Driven and Multi-Criteria Analysis Approaches. *Sci. Rep.* **2022**, *12*, 11625. [CrossRef] [PubMed]
23. Gori, A.; Blessing, R.; Juan, A.; Brody, S.; Bedient, P. Characterizing Urbanization Impacts on Floodplain through Integrated Land Use, Hydrologic, and Hydraulic Modeling. *J. Hydrol.* **2019**, *568*, 82–95. [CrossRef]
24. Anees, M.T.; Abdullah, K.; Nawawi, M.N.; Ab Rahman, N.N.; Piah, A.R.; Zakaria, N.A.; Syakir, M.I.; Omar, A.M. Numerical Modeling Techniques for Flood Analysis. *J. Afr. Earth Sci.* **2016**, *124*, 478–486. [CrossRef]
25. De Brito, M.M.; Evers, M. Multi-Criteria Decision-Making for Flood Risk Management: A Survey of the Current State of the Art. *Nat. Hazards Earth Syst. Sci.* **2016**, *16*, 1019–1033. [CrossRef]
26. Wu, L.; Tong, J.; Wang, Z.; Li, J.; Li, M.; Li, H.; Feng, Y. Post-Flood Disaster Damaged Houses Classification Based on Dual-View Image Fusion and Concentration-Based Attention Module. *Sustain. Cities Soc.* **2024**, *103*, 105234. [CrossRef]
27. Zou, Q.; Zhou, J.; Zhou, C.; Song, L.; Guo, J. Comprehensive Flood Risk Assessment Based on Set Pair Analysis-Variable Fuzzy Sets Model and Fuzzy AHP. *Stoch. Environ. Res. Risk Assess.* **2013**, *27*, 525–546. [CrossRef]
28. Kang, H.-Y.; Chae, S.T.; Chung, E.-S. Quantifying Medium-Sized City Flood Vulnerability Due to Climate Change Using Multi-Criteria Decision-Making Techniques: Case of Republic of Korea. *Sustainability* **2023**, *15*, 16061. [CrossRef]
29. Das, S.; Ghosh, A.; Hazra, S.; Ghosh, T.; Safra de Campos, R.; Samanta, S. Linking IPCC AR4 & AR5 Frameworks for Assessing Vulnerability and Risk to Climate Change in the Indian Bengal Delta. *Prog. Disaster Sci.* **2020**, *7*, 100110. [CrossRef]
30. Song, J.Y.; Chung, E.S. Robustness, Uncertainty and Sensitivity Analyses of the TOPSIS Method for Quantitative Climate Change Vulnerability: A Case Study of Flood Damage. *Water Resour. Manag.* **2016**, *30*, 4751–4771. [CrossRef]
31. Hajkowicz, S.; Collins, K. A Review of Multiple Criteria Analysis for Water Resource Planning and Management. *Water Resour. Manag.* **2007**, *21*, 1553–1566. [CrossRef]
32. Chae, S.T.; Chung, E.S.; Jiang, J. Robust Siting of Permeable Pavement in Highly Urbanized Watersheds Considering Climate Change Using a Combination of Fuzzy-TOPSIS and the VIKOR Method. *Water Resour. Manag.* **2022**, *36*, 951–969. [CrossRef]
33. Mateusz, P.; Danuta, M.; Małgorzata, L.; Mariusz, B.; Kesra, N. TOPSIS and VIKOR Methods in Study of Sustainable Development in the EU Countries. *Procedia Comput. Sci.* **2018**, *126*, 1683–1692. [CrossRef]
34. Sadeghi, M.; Razavi, S.H.; Saberi, N. Application of Grey TOPSIS in Preference Ordering of Action Plans in Balanced Scorecard and Strategy Map. *Informatica* **2013**, *24*, 619–635. [CrossRef]
35. Shekhovtsov, A.; Salabun, W. A Comparative Case Study of the VIKOR and TOPSIS Rankings Similarity. *Procedia Comput. Sci.* **2020**, *176*, 3730–3740. [CrossRef]
36. Her, Y.; Yoo, S.H.; Cho, J.; Hwang, S.; Jeong, J.; Seong, C. Uncertainty in Hydrological Analysis of Climate Change: Multi-Parameter vs. Multi-GCM Ensemble Predictions. *Sci. Rep.* **2019**, *9*, 4974. [CrossRef] [PubMed]
37. European Environment Agency. *Environmental Indicators: Typology and Overview*; EEA: Copenhagen, Denmark, 1999.
38. Rehman, J.; Sohaib, O.; Asif, M.; Pradhan, B. Applying Systems Thinking to Flood Disaster Management for a Sustainable Development. *Int. J. Disaster Risk Reduct.* **2019**, *36*, 101101. [CrossRef]
39. Malmir, M.; Javadi, S.; Moridi, A.; Neshat, A.; Razdar, B. A New Combined Framework for Sustainable Development Using the DPSIR Approach and Numerical Modeling. *Geosci. Front.* **2021**, *12*, 101169. [CrossRef]
40. Bruno, M.F.; Saponieri, A.; Molfetta, M.G.; Damiani, L. The DPSIR Approach for Coastal Risk Assessment under Climate Change at Regional Scale: The Case of Apulian Coast (Italy). *J. Mar. Sci. Eng.* **2020**, *8*, 531. [CrossRef]
41. Marler, R.T.; Arora, J.S. The Weighted Sum Method for Multi-Objective Optimization: New Insights. *Struct. Multidiscip. Optim.* **2010**, *41*, 853–862. [CrossRef]
42. Zadeh, L.A. Optimality and Non-Scalar-Valued Performance Criteria. *IEEE Trans. Autom. Control* **1963**, *8*, 59–60. [CrossRef]
43. Goicoechea, A.; Hansen, D.R.; Duckstein, L. *Multiobjective Analysis with Engineering and Business Applications*; Wiley: New York, NY, USA, 1982.
44. Opricovic, S. *Multicriteria Optimization of Civil Engineering Systems*; Faculty of Civil Engineering: Belgrade, Serbia, 1998.

45. Opricovic, S.; Tzeng, G.H. Compromise Solution by MCDM Methods: A Comparative Analysis of VIKOR and TOPSIS. *Eur. J. Oper. Res.* **2004**, *156*, 445–455. [CrossRef]
46. Chen, S.-J.; Hwang, C.-L. Fuzzy Multiple Attribution Decision Making Methods. In *Fuzzy Multiple Attribute Decision Making*; Springer: Berlin/Heidelberg, Germany, 1992.
47. Hwang, C.-L.; Yoon, K. *Multiple Attribute Decesion Making*; Springer: Berlin/Heidelberg, Germany; New York, NY, USA, 1981.
48. Shannon, C.E.; Weaver, W. *The Mathematical Theory of Communication*; University of Illinois Press: Urbanan, IL, USA, 1947.
49. Dalkey, N.; Helmer, O. An Experimental Application of the Delphi Method to the Use of Experts. *Manag. Sci.* **1963**, *9*, 458–467. [CrossRef]
50. Chen, C.-T. Extensions Ofthe TOPSIS for Group Decision-Making under Fuzzy Environment. *Fuzzy Sets Syst.* **2000**, *114*, 1–9. [CrossRef]
51. Deng, J.-L. Introduction to Grey System. *J. Grey Syst.* **1989**, *1*, 1–24.
52. Deng, J.-L. Control Problems of Grey Systems. *Syst. Control Lett.* **1982**, *1*, 288–294. [CrossRef]
53. Oztaysi, B. A Decision Model for Information Technology Selection Using AHP Integrated TOPSIS-Grey: The Case of Content Management Systems. *Knowl.-Based Syst.* **2014**, *70*, 44–54. [CrossRef]
54. Yip, S.; Ferro, C.A.T.; Stephenson, D.B.; Hawkins, E. A Simple, Coherent Framework for Partitioning Uncertainty in Climate Predictions. *J. Clim.* **2011**, *24*, 4634–4643. [CrossRef]
55. Morim, J.; Hemer, M.; Wang, X.L.; Cartwright, N.; Trenham, C.; Semedo, A.; Young, I.; Bricheno, L.; Camus, P.; Casas-Prat, M.; et al. Robustness and Uncertainties in Global Multivariate Wind-Wave Climate Projections. *Nat. Clim. Chang.* **2019**, *9*, 711–718. [CrossRef]