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Social vulnerability of rural households to flood hazards in western mountainous regions of Henan province, China

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Abstract. Evaluating social vulnerability is a crucial issue in risk and disaster management. In this study, a household social vulnerability index (HSVI) to flood hazards was developed and used to assess the social vulnerability of rural households in western mountainous regions of Henan province, China. Eight key indicators were identified using existing literature and discussions with experts from multiple disciplines and local farmers, and their weights were determined using principle component analysis (PCA) and an expert scoring method. The results showed that (1) the ratio of perennial work in other places, hazard-related training and illiteracy ratio (15+) were the most dominant factors of social vulnerability. (2) The numbers of high, moderate and low vulnerability households were 14, 64 and 16, respectively, which accounted for 14.9, 68.1 and 17.0 % of the total interviewed rural households, respectively. (3) The correlation coefficient between household social vulnerability scores and casualties in a storm flood in July 2010 was significant at 0.05 significance level ($r = 0.748$), which indicated that the selected indicators and their weights were valid. (4) Some mitigation strategies to reduce household social vulnerability to flood hazards were proposed, which included (1) improving the local residents' income and their disaster-related knowledge and evacuation skills, (2) developing emergency plans and carrying out emergency drills and training, (3) enhancing the accuracy of disaster monitoring and warning systems and (4) establishing a specific emergency management department and comprehensive rescue systems. These results can provide useful information for rural households and local governments to prepare, mitigate and respond to flood hazards, and the corresponding strategies can help local households to reduce their social vulnerability and improve their ability to resist flood hazard.

1 Introduction

Flood hazard risk has increased over the past several decades and will continue to increase in the future, and the casualties and economic losses caused by flood disasters are following a similar and increasing trend in the world (Terry and Lisa, 2014; Walter, 2004). A number of studies have indicated that regional flood disasters are caused by the interaction of flood hazards and the vulnerability of flood-hazard-prone areas (Zhang et al., 2010; Hsieh, 2014). It is more difficult to prevent a flood hazard from becoming a flood disaster than to reduce the vulnerability of flood-hazard-prone areas (Liu and Liang, 2014). In order to effectively reduce the adverse effects of a flood disaster, it is necessary to enhance the understanding of the social vulnerability of flood-hazard-prone areas (Cutter et al., 2003, 2013; Zhang and You, 2014). Since Cutter developed a social vulnerability index to measure the social vulnerability to environmental hazards (Cutter et al., 2003), there has been growing concern and interest in this area (Bjarnadottir et al., 2011; Noriega and Ludwig, 2012; Zebardast, 2013; Siagian et al., 2014; Garbutt et al., 2015). For example, Noriega and Ludwig (2012) assessed the social vulnerability to local earthquake risk in Los Angeles County, California, United States, and they found that "knowledge of the relationship between earthquake hazard and the demographic characteristics of people in the area at risk is essential to mitigate the local impact from earthquakes". Zebardast (2013) constructed a social vulnerability index for

earthquake hazards using a hybrid factor analysis and analytical network process model, and their case study showed that their method was a robust approach to construct a composite social vulnerability index. Using the social vulnerability index approach, Siagian et al. (2014) determined three main driving factors (socioeconomic status and infrastructure; gender, age and population growth; family structure) affecting social vulnerability to natural hazards in Indonesia. They also pointed out that the spatial distribution characteristics of social vulnerability to natural hazards could be easily identified when they were mapped using the ArcView geographical information system (GIS). Garbutt et al. (2015) presented an open source vulnerability index and mapped the social vulnerability to flood hazards in Norfolk, England. They found that flood affected areas were more likely to be composed of the elderly, sick and poor, and high vulnerability areas were found to be disproportionately impacted by flooding. All these studies provide a good understanding of social vulnerability to natural hazards. However, these studies focused on contributing to theoretical research or empirical study at national or regional scales (Garbutt et al., 2015; Zhou et al., 2014; Cutter and Finch, 2008; Cutter et al., 2013). Studies at the household level are very limited. Hence, studying and developing a household-level social vulnerability index for flood hazards is an important contribution to examine social vulnerability to natural hazards, because it can provide a new perspective from the individual house level in comparison to national or regional levels. Social vulnerability research at national or regional scales is macroscopical, where the results provide some macroscopical rather than specific and detailed information. For decision-making purposes, while studying at national or regional levels is useful for the government to make macrodecisions, it makes it difficult for the government or household to create operational coping strategies. For example, examining social vulnerability at household level provides details about why households' social vulnerability is at a high, low or moderate level. The households can then apply corresponding strategies to reduce their social vulnerability and improve their resilience to natural hazards accordingly. Meanwhile, the results can also be used by the government to be more specific in their decision-making. Rural areas are some of the most important flood-hazard-prone areas (Eakin and Bojorquez-Tapia, 2008; Ghimire et al., 2010), and more than 600 million people live in a rural area in China. Therefore, understanding social vulnerability at the rural household level is crucial for both rural households and local governments to prepare, mitigate and respond to natural hazards (Ghimire et al., 2010; Linnekamp et al., 2011).

The objectives of this paper were (1) to identify and prioritize key influencing factors of social vulnerability to flood hazards at household level, (2) to develop and use a household social vulnerability index to assess household social vulnerability to flood hazards in western mountainous regions of Henan province, China, and (3) to propose some targeted mitigation strategies to reduce household social vulnerability to flood hazards. The results could provide useful information for both rural households and local governments to prepare, mitigate and respond to flood disasters.

2 Household social vulnerability index (HSVI)

Several methods can be used to evaluate the social vulnerability to natural hazards, such as an assessment method based on historical disaster data and scenario-based, GIS-based and index-based assessment methods (Li et al., 2008). Each assessment method has its advantages and disadvantages. In the assessment method based on historical disaster data, the established disaster database is used to construct a certain index and assess the disaster risk. For example, the disaster risk index can be obtained based on the EM-DAT database, which can show the population loss risk in a catastrophe by using the ratio of the number of deaths and the number of people exposed to a disaster. The advantages of this method are convenient data, simple calculation and accurate results, and the disadvantage is that it is just suitable for the macroscopic spatial scale, such as the global or national scale, and it is difficult to be used on a small spatial scale, such as the community or household scale. The scenario-based method is mainly based on the construction of different disaster scenarios, and then with the help of some models and numerical simulation software, can show the disaster evolution process and the vulnerability of hazard-prone areas. The advantage of this method is that it can be more convenient to display the processes and results, and its disadvantage is that the calculation processes are complex and need computer programming and profound mathematical knowledge. The steps of using a GIS-based method are (1) obtaining the data, (2) putting the data into GIS software, (3) running the overlay and spatial analysis function of GIS software and (4) calculating and mapping the results. The advantage of this method is that the results can be showed clearly in the form of maps, and its disadvantage is that all the data must be spatial data or be able to be changed to spatial data. The index-based assessment method was used here mainly because (1) it can effectively reveal the spatial and temporal patterns, as well as the evolution of vulnerability to a natural hazard at different scales, and (2) the assessment results among different regions are comparable due to the use of the same assessment index system (Cutter et al., 2003; Garbutt et al., 2015). There are five steps for using the index-based method to assess household social vulnerability to flood hazards as follows.

1. Determination of assessment scales: first of all, it is necessary to determine the research scale because the index-based assessment method can be used at different scales with different indictors. In this study, the rural household level was chosen.

2. Selection of indictors: there are a number of factors affecting the social vulnerability of rural households to flood hazards. In order to make the selected factors as comprehensive as possible, two methods were used in this study. One method was to have discussions with experts from multiple disciplines and local farmers (Ghimire et al., 2010), and another was to obtain indicators from the existing literature (Cutter et al., 2003; Werg et al., 2013; Linnekamp et al., 2011).

3. Collection and processing of data: two methods, participatory rural appraisal (PRA) and household surveys, were used to gather the data. The PRA method was used to gather some supporting information (Chambers, 1994; Cornwall and Pratt, 2011), such as peoples' socioeconomic status and attitudes to flood hazards. A household survey (individual interviews) was used to collect the quantitative data of social vulnerability indicators (Ghimire et al., 2010).

When the data were gathered together, it was necessary to normalize them to establish a uniform dimension. Meanwhile, some indicators have favorable impacts, while some have unfavorable impacts on social vulnerability to flood hazards. In order to resolve these problems, extreme standardization was carried out.

Positive correlation indicators:

$$x_i' = (x_i - \min x_i) / (\max x_i - \min x_i). \tag{1}$$

Negative correlation indicators:

$$x_i' = (\max x_i - x_i) / (\max x_i - \min x_i), \tag{2}$$

where x_i and x_i' are the original and standard values of indicator i, respectively, and $\max x_i$ and $\min x_i$ are the greatest and smallest values of the selected indicators' values, respectively.

4. Determination of index weights: the principle component analysis (PCA) method and the expert scoring method were used to determine the weights of each indicator. After the weights were obtained from the PCA, 20 experts from different fields (geography, hydrology, sociology and risk management) were invited to evaluate and adjust the results in order to make the weights more suitable for the local situation. The principles, steps and advantages of using PCA to determine index weight are described in detail in Qu (2012). The procedures used in this study are shown in Appendix B.

5. Calculation of household social vulnerability: based on the standardized data and determined index weight, a household social vulnerability index (HSVI) was constructed and used to study household social vulnerability to flood hazards. The HSVI can be expressed by

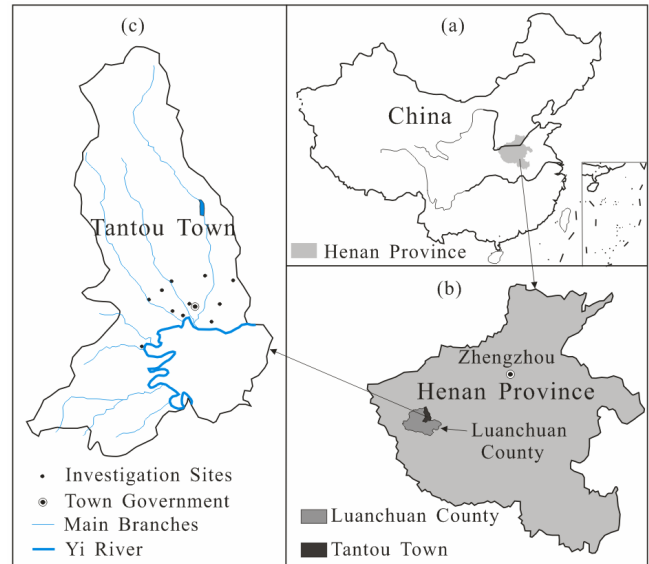$$\text{HSVI} = \sum_{i=1}^{n} x_i \times w_i, \tag{3}$$

Figure 1. Maps of study area. **(a)** Location of Henan province in China. **(b)** Location of the study area in Henan province. **(c)** Investigation sites and distribution of rivers in the study area.

where HSVI is the household social vulnerability index and x_i and w_i are the standardized data and the weight value of index i, respectively.

3 A case study

3.1 Study area

Eleven villages located in the western mountainous regions of Henan province (the center regions of China) were chosen as the study area (Fig. 1). The total area of the 11 villages is $88.2\,\text{km}^2$, most of which is hilly land. The area of arable land ($7.2\,\text{km}^2$) only accounts for 8.2 % of the total area. The income per capita is less than USD 250 per year, and the poverty rate is higher than that in China (Xi, 2012). The annual mean precipitation is about 750 mm, about 60 % of which occurs during the period of June to September. Rainstorms can easily result in a flood because of the steep and narrow riverbeds, poor flood discharge capacity and intense human activities (Shao et al., 2013).

These villages were chosen as the study area mainly because (1) the conditions of nature, society and economy are very similar to those of most other villages in the western mountainous regions of Henan province, and (2) it was easy to obtain sufficient and reliable data because these villages had undergone some severe flood disasters in recent years.

3.2 Selected indictors and weights

Based on the existing literature (Cutter et al., 2003; Werg et al., 2013; Linnekamp et al., 2011) and interactive discus-

sions with 30 local farmers and 20 experts from different study fields (geography, hydrology, sociology and risk management), and using the semi-structured interview method (Harrell and Bradley, 2009), eight indicators were identified to assess the social vulnerability at household level to flood hazards. The selected indicators and their weights, definitions, measurement methods and underlying assumptions are shown in Table 1. The weight of each indicator was determined using the PCA method (Qu, 2012) and the expert scoring method. Table 1 showed that the indicator with the biggest weight value (0.17) was the ratio of perennial work in other places, the indicator with the smallest weight value (0.09) was the dependency ratio and the weight values of other indicators ranged from 0.10 to 0.14.

3.3   Data collection

A door-to-door questionnaire investigation was carried out by the author's research team during the period of 10–15 April 2014. The requirement for participants was that they could answer a questionnaire and have been affected by a flood disaster. One hundred households were chosen according to the local officials' suggestions. The criteria to choose survey targets were that (1) the household had been affected by flood hazard, (2) the flood hazards had resulted in property damage or loss of life, (3) the family characteristics should be as different as possible and (4) the residents in the households were able to understand and answer a questionnaire clearly. All the 100 copies of the questionnaire were collected on the spot, and 6 copies were eliminated due to the inconsistent and incomplete answers. The standard data of the questionnaire are shown in Appendix A.

3.4   Household social vulnerability assessment

According to the factors shown in Table 1, the data collected from 94 households were firstly processed by using Eqs. (1) and (2). Secondly, the household social vulnerability (HSV) scores were calculated using Eq. (1). Lastly, the HSV scores were divided into three grades using the mean value (MV) and standard deviation (SD) of HSV scores. If the HSV score was greater than 1 SD from the MV [(HSV score) > (MV + 1 SD)], the household was in the high vulnerability category, if the HSV score was lower than 1 SD from the MV [(HSV score) < (MV − 1 SD)], the household was in the low vulnerability category and other HSV scores [(MV − 1 SD) ≤ (HSV score) ≤ (MV + 1 SD)] were in the moderate vulnerability category. In this study, the SD, MV, maximum and minimum of HSV scores were 0.11, 0.59, 0.21 and 0.87, respectively. Therefore, the ranges of low, moderate and high vulnerability category for a household were [0.21, 0.48], [0.48, 0.70], and (0.70, 0.87], respectively.

The results showed that (1) the numbers of high, moderate and low vulnerability households were 14, 64 and 16, respectively, which accounted for 14.9 %, 68.1 % and 17.0 %

of the total interviewed households, respectively. (2) Seen from the spatial distribution of household social vulnerability in the 11 villages (Fig. 2), there were three high vulnerable villages, Manying, Shimen and Zhaozhuang. (3) Table 2 reveals that compared with the low vulnerability households, the ratio of perennial work in other places, hazard-related training and illiteracy ratio (15+) had the greatest impacts on moderate and high vulnerable households, and the ratios of high and moderate vulnerability scores to low vulnerability scores were greater than 2.5 and 3.3, respectively. Access to hazard-related information and income per capita had the smallest impact, while the impacts of family size and vehicles per capita were moderate (Table 2). (4) The correlation coefficient of HSV scores and casualties was valid at 0.05 significance level ($r = 0.748$).

4   Discussion

4.1   Key problems in using index-based assessment method

The index-based assessment method is one of the most widely used assessment methods (Cutter et al., 2003; Garbutt et al., 2015; Cutter and Finch, 2008); however three problems, index system, index weight and index validity, should be considered before using this method. (1) There are a number of factors affecting the social vulnerability of households. On the one hand, it is difficult to describe the characteristics of social vulnerability if there were only few indicators, but on the other hand, if too many indicators were selected and used, there were also some problems, such as inaccessible data, complex calculation and poor operability (Cutter et al., 2003; Murphy and Scott, 2014). It is important that the selected indicators are in a manageable level, for which the PCA is a good method to use (Liu et al., 2013). For example, Cutter and Finch (2008) used the PCA method to reduce 42 social vulnerability variables to 11 independent indicators, and studied the temporal and spatial changes in social vulnerability to natural hazards using the indicators. In this paper, eight indicators were selected based on existing references and discussions with experts from multiple disciplines and local farmers (Table 1). Eight indicators should be a manageable level and they are easily quantified (Cutter and Finch, 2008). (2) Index weights are crucial to the accuracy of assessment results. The methods used to determine index weight can be divided into three categories. The first category includes subjective weighting methods, such as Delphi and experts grading method. The second category includes objective weighting methods, such as the entropy method and PCA. The third category includes integrated subjective and objective weighting methods, such as the analytic hierarchy process. Each of these methods has its advantages and disadvantages (Wang et al., 2012), and different index weights could affect the scores of assessment results. Therefore, how

Table 1. Selected indicators and their weights, definitions, measurement and underlying assumptions to social vulnerability (SV).

Indicator	Weight	Definition	Measurement	Assumptions
Family size	0.13	Total number of family members	Number of family members	The more the family members, the higher the SV because there are more people exposed to flood hazards in a big family.
Dependency ratio	0.09	Number of dependents (aged 0–18 and over the age of 65) compared to number of working-age people (aged 19–64)	(Number of dependents/number of people aged from 19 to 64) $\times 100\%$	The larger the ratio, the greater the burden on the average working-age people, and the higher the SV.
Illiteracy ratio (15+)	0.12	Rate of illiteracy (people are over the age of 15 and with inability to read and write) compared to family size	(Number of illiteracy/family size) $\times 100\%$	The higher the ratio, the lower the ability to access hazard-related information and resources, and the higher the SV.
The ratio of perennial work in other places	0.17	Number of people (who work in other places and cannot return home for a long time) compared to family size	Number of people who work in other place/family size	The more people work in other place, the higher dependents ratio, and the higher the SV.
Income per capita	0.14	The average income earned per person in a family	The total family income/family size	The higher the income per capita, the more the accumulation of wealth and the greater the ability to access hazard-related information and resources, and the lower the SV.
Access to hazard-related information	0.12	The ability to receive disaster risk information	Number of information-receiving tools, including telephone, cell phone, TV and Internet	The more information-receiving tools, the greater the ability to access risk information, and the lower the SV.
Vehicles per capita	0.10	Total number of vehicles in a family compared to family size	Number of vehicles/family size	The more vehicles per capita, the greater the ability to evacuate from a disaster, and the lower the SV.
Hazard-related training	0.14	Times hazard-related training has been taken part in in the last 5 years	No $= 0$; one time $= 0.5$; two or more times $= 1$	The knowledge, attitudes and response to disasters can be improved by attending training (listening to lectures and participating in emergency exercises). Therefore, the more times such training is attended, the lower the SV.

Note: the indicators of the ratio of perennial work in other places and access to hazard-related information came from experts and existing references (Cutter et al., 2003; Werg et al., 2013; Linnekamp et al., 2011).

to determine the reasonable index weights is an important problem to be solved in assessment research. (3) A comparison between the assessment results and a post-event situation is a feasible method to test the validity of selected indicators and their weights. In this study, we calculated the correlation coefficient between scores of household social vulnerability and the casualties of each household in a storm flood in July 2010. The results showed that the correlation coefficient was significant at 0.05 significance level ($r = 0.748$), which in-

dicated that the selected social vulnerability indicators and their weights were valid.

4.2 How to reduce social vulnerability

There has been much exciting research on how to reduce social vulnerability, but this has mainly focused on country, region and river basin scales. For example, based on the analysis of driving factors of social vulnerability to natural hazards in Indonesia, Siagian et al. thought that it was a good
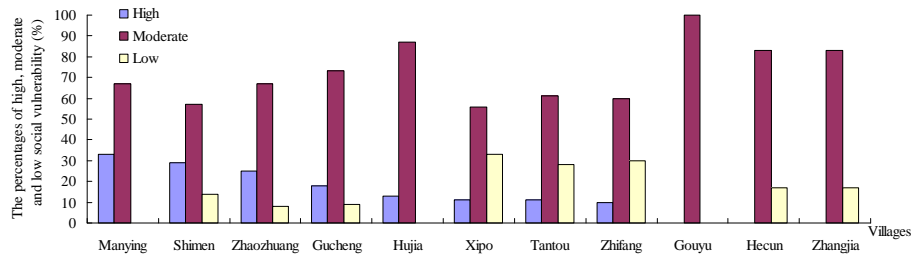
Figure 2. Spatial distribution of household social vulnerability (%).

Table 2. The mean scores of low, moderate and high vulnerable households for each index ($\times 100$).

Indicator	Low	Moderate	High	Ms / Ls	Hs / Ls
Ratio of perennial work in other places	2.03	7.19	11.4	3.54	5.62
Hazard-related training	2.19	6.45	9.5	2.95	4.34
Illiteracy ratio (15+)	2.00	5.14	6.66	2.58	3.34
Family size	6.26	8.31	11.03	1.33	1.76
Vehicles per capita	5.68	7.62	8.61	1.34	1.52
Dependency ratio	1.97	2.14	2.78	1.08	1.41
Access to hazard-related information	9.83	11.02	11.64	1.12	1.18
Income per capita	11.23	12.48	12.99	1.11	1.16

Note: Ms / Ls is the ratio of moderate vulnerability score to low vulnerability score;
Hs / Ls is the ratio of high vulnerability score to low vulnerability score.

way to reduce the social vulnerability by integrating social vulnerability maps in early warning systems (Siagian et al., 2014). Chen et al. (2013) put forward some suggestions to reduce social vulnerability in the Yangtze River Delta region, such as reducing the unequal distribution of social resources and improving the employment rate (Chen et al., 2013). The studies at household level were limited, especially regarding flood hazards (Chen et al., 2013; Siagian et al., 2014). In this study, the target strategies to reduce the household social vulnerability to flood disasters were discussed based on the assessment results (Table 2). At first, the ratio of perennial work in other places should be reduced as soon as possible, because it was the most dominant factor which resulted in high vulnerability. According to the investigation, in the 94 households, the number of people whose work in other places is perennial due to limited local job opportunities was 141, which accounted for 27.2 % of the total people (519), 52.4 % of the population aged between 18 and 64 and 82.5 % of the people aged between 18 and 49, respectively. In order to solve this problem, the reasons why the local residents preferred working in other places to staying at home need to be understood. The most important reason was that the high cost of farming and low price of agricultural products resulted in the low income of a family. Besides, the agricultural income in these regions is not guaranteed due to the variation of climate conditions. Another important reason was that there were few companies or factories to provide work opportunities for local residents. Therefore, the ratio of perennial work in other places should be reduced by estab-

lishing agricultural insurance and increasing work opportunities to guarantee the local residents' income. The disaster-related knowledge and evacuation skills of the local residents should then be enhanced through disaster-related training. Some unexpected observations were found during this survey. For example, 64.2 % of the people interviewed thought there were no occurrences of floods in this region, while there had been three occurrences of flood catastrophes in the past 50 years. Only 23.2 % of the people interviewed regularly received training pertaining to hazard or evacuation. As a result, a certain level of training about flood hazards should be held often in order to improve the hazard-related knowledge and evacuation skills of local residents. Finally, the literacy ratio should be improved. From the perspectives of communities or governments, the following measures could be effective to reduce the social vulnerability to flood disasters: (1) preparing flood hazards mitigation plans based on risk assessment results of flood hazards, (2) improving the accuracy of disaster monitoring and warning systems, (3) establishing specialized emergency management department and comprehensive rescue systems and (4) developing an emergency plan and carrying out emergency drills and training.

5   Conclusions

In order to understand the rural household social vulnerability to flood hazards, a household social vulnerability index was developed, and the household social vulnerability of the

selected 11 villages was assessed. Some mitigation strategies to reduce the household social vulnerability were proposed based on the assessment results. There are some interesting findings. (1) Eight key indicators, influencing social vulnerability to flood hazards at household level, were identified using existing literature and interactive discussions with experts and local farmers, and the weight of each indicator was determined using the PCA method and the expert scoring method. (2) The results showed that the numbers of high, moderate and low vulnerability households were 14, 64 and 16, respectively, which accounted for 14.9 %, 68.1 % and 17.0 % of the total evaluated households, respectively. The correlation coefficient of HSV scores and casualties was significant at 0.05 significance level ($r = 0.748$), which indicated that the selected social vulnerability indicators and their weights were valid. (3) The ratio of perennial work in other places, hazard-related training and illiteracy ratio (15+) were the most dominant factors which resulted in higher vulnerability. Access to hazard-related information and income per capita had the smallest impact on higher vulnerability, and the impacts of family size and vehicles per capita were moderate. (4) To reduce the household social vulnerability to flood hazards, reducing the ratio of perennial work in other places, and enhancing the hazard-related knowledge and evacuation skills were effective measures and must be carried out as soon as possible.

Appendix A

Table A1. The standard data and assessment results.

	FS	DR	IR	RPW	PCI	AHI	VPC	HRT	Scores	Ranks
1	1.00	0.25	0.42	1.00	0.97	1.00	1.00	1.00	0.87	high
2	1.00	0.25	0.42	1.00	1.00	1.00	1.00	0.50	0.80	high
3	0.57	1.00	1.00	0.63	0.91	0.96	0.53	0.50	0.76	high
4	1.00	0.25	0.42	0.79	0.97	1.00	0.87	0.50	0.75	high
5	0.86	0.19	0.72	0.68	0.91	0.99	1.00	0.50	0.75	high
6	0.43	0.25	0.83	0.79	0.80	0.94	0.67	1.00	0.74	high
7	0.86	0.33	0.23	0.46	0.95	0.99	1.00	1.00	0.74	high
8	0.86	0.33	0.48	0.68	0.95	0.99	1.00	0.50	0.74	high
9	0.86	0.33	0.23	0.46	0.95	0.99	0.86	1.00	0.73	high
10	0.86	0.19	0.72	0.68	0.88	0.91	0.86	0.50	0.72	high
11	0.86	0.19	0.72	0.68	0.91	0.91	0.81	0.50	0.72	high
12	0.86	0.19	0.72	0.68	0.91	0.91	0.81	0.50	0.72	high
13	0.86	0.33	0.23	0.46	0.91	0.99	0.81	1.00	0.71	high
14	1.00	0.25	0.63	0.40	0.97	1.00	0.83	0.50	0.70	high
15	0.57	0.17	0.67	0.32	0.85	0.96	1.00	1.00	0.70	moderate
16	0.43	0.25	0.83	0.79	0.93	0.94	0.67	0.50	0.69	moderate
17	0.71	0.25	0.55	0.52	0.93	0.98	1.00	0.50	0.69	moderate
18	0.71	0.25	0.55	0.52	0.93	0.98	1.00	0.50	0.69	moderate
19	0.71	0.25	0.55	0.52	0.93	0.98	1.00	0.50	0.69	moderate
20	1.00	0.25	0.42	1.00	0.90	0.94	0.75	0.00	0.69	moderate
21	0.86	0.19	0.72	0.68	0.88	0.91	0.53	0.50	0.69	moderate
22	0.71	0.25	0.55	0.52	0.89	0.89	0.45	1.00	0.69	moderate
23	0.43	0.25	0.83	0.79	0.87	0.94	0.67	0.50	0.68	moderate
24	0.71	0.50	0.28	0.27	0.89	0.98	0.78	1.00	0.68	moderate
25	0.71	0.25	0.55	0.52	0.98	0.98	0.78	0.50	0.67	moderate
26	0.57	0.17	0.67	0.32	0.85	0.96	0.73	1.00	0.67	moderate
27	0.71	0.25	0.55	0.52	0.93	0.98	0.78	0.50	0.67	moderate
28	0.86	0.19	0.72	0.68	0.95	0.99	0.81	0.00	0.66	moderate
29	0.71	0.25	0.55	0.52	0.89	0.98	0.78	0.50	0.66	moderate
30	0.71	0.25	0.55	0.52	0.98	0.98	0.61	0.50	0.66	moderate
31	0.71	0.25	0.55	0.52	0.93	0.89	0.78	0.50	0.65	moderate
32	0.71	0.25	0.55	0.52	0.89	0.89	0.78	0.50	0.65	moderate
33	0.71	0.25	0.55	0.52	0.89	0.98	0.67	0.50	0.65	moderate
34	0.71	0.25	0.55	0.27	0.93	0.98	1.00	0.50	0.64	moderate
35	0.71	0.25	0.55	0.52	0.89	0.98	0.61	0.50	0.64	moderate
36	0.71	0.25	0.55	0.52	0.89	0.80	0.78	0.50	0.64	moderate
37	0.57	0.17	0.67	0.32	0.91	0.96	1.00	0.50	0.64	moderate
38	0.86	0.33	0.23	0.46	0.95	0.99	0.67	0.50	0.64	moderate
39	0.71	0.25	0.55	0.27	0.89	0.98	0.78	0.50	0.62	moderate
40	0.57	0.17	0.67	0.32	0.91	0.96	0.80	0.50	0.62	moderate
41	0.71	0.50	0.28	0.27	0.89	0.98	0.83	0.50	0.61	moderate
42	0.71	0.25	0.55	0.27	0.89	0.89	0.83	0.50	0.61	moderate
43	0.71	0.25	0.55	0.27	0.89	0.89	0.83	0.50	0.61	moderate
44	0.57	0.17	0.67	0.32	0.91	0.96	0.73	0.50	0.61	moderate
45	0.57	0.17	0.67	0.32	0.85	0.96	0.80	0.50	0.61	moderate
46	0.71	0.25	0.55	0.27	0.89	0.89	0.78	0.50	0.61	moderate
47	0.57	0.17	0.67	0.32	0.91	0.86	0.80	0.50	0.60	moderate
48	0.43	0.25	0.83	0.79	0.80	0.94	0.67	0.00	0.60	moderate
49	0.57	0.17	0.33	0.32	0.96	0.96	1.00	0.50	0.60	moderate
50	0.43	0.25	0.42	0.40	0.87	0.94	1.00	0.50	0.60	moderate

Table A1. Continued.

51	0.71	0.25	0.55	0.27	0.89	0.98	0.61	0.50	0.60	moderate
52	0.71	0.50	0.28	0.27	0.89	0.89	0.78	0.50	0.60	moderate
53	0.57	0.17	0.00	0.32	0.91	0.86	0.80	1.00	0.59	moderate
54	0.57	0.17	0.67	0.32	0.85	0.86	0.73	0.50	0.59	moderate
55	0.86	0.33	0.23	0.46	0.95	0.99	0.86	0.00	0.59	moderate
56	0.86	0.33	0.23	0.46	0.91	0.84	0.38	0.50	0.58	moderate
57	0.57	0.17	0.33	0.63	0.85	0.86	0.53	0.50	0.58	moderate
58	0.71	0.50	0.28	0.27	0.89	0.89	0.61	0.50	0.58	moderate
59	0.43	0.25	0.83	0.79	0.87	0.80	0.41	0.00	0.57	moderate
60	0.57	0.17	0.33	0.32	0.85	0.96	0.80	0.50	0.57	moderate
61	0.57	0.17	0.33	0.32	0.85	0.96	0.80	0.50	0.57	moderate
63	0.43	0.25	0.00	0.79	0.87	0.80	0.67	0.50	0.57	moderate
64	0.86	0.33	0.23	0.46	0.91	0.91	0.67	0.00	0.55	moderate
65	0.57	0.17	0.00	0.32	0.91	0.86	1.00	0.50	0.54	moderate
66	0.43	0.25	0.42	0.40	0.80	0.80	0.67	0.50	0.54	moderate
67	0.71	0.25	0.55	0.27	0.93	0.89	0.78	0.00	0.54	moderate
68	0.57	0.17	0.00	0.32	0.80	0.96	1.00	0.50	0.54	moderate
69	0.57	0.17	0.00	0.32	0.96	0.96	0.73	0.50	0.54	moderate
70	0.57	0.17	0.00	0.32	0.85	0.96	0.80	0.50	0.53	moderate
71	0.57	0.17	0.67	0.32	0.85	0.86	0.73	0.00	0.52	moderate
72	0.57	0.17	0.33	0.63	0.85	0.75	0.73	0.00	0.52	moderate
73	0.57	0.17	0.00	0.32	0.91	0.86	0.73	0.50	0.52	moderate
74	0.57	0.17	0.00	0.32	0.85	0.86	0.73	0.50	0.51	moderate
75	0.57	0.17	0.33	0.00	0.91	0.86	0.73	0.50	0.50	moderate
76	0.57	0.17	0.00	0.00	0.91	0.96	1.00	0.50	0.50	moderate
77	0.43	0.25	0.00	0.40	0.80	0.80	0.67	0.50	0.49	moderate
78	0.57	0.17	0.00	0.32	0.85	0.86	0.53	0.50	0.49	moderate
79	0.57	0.17	0.33	0.32	0.85	0.86	0.80	0.00	0.49	moderate
80	0.57	0.17	0.33	0.32	0.85	0.86	0.73	0.00	0.48	low
81	0.57	0.17	0.33	0.63	0.85	0.75	0.33	0.00	0.48	low
82	0.57	0.17	0.00	0.32	0.80	0.75	0.60	0.50	0.48	low
83	0.43	0.25	0.00	0.00	0.80	0.94	1.00	0.50	0.47	low
84	0.57	0.17	0.33	0.32	0.85	0.75	0.73	0.00	0.47	low
85	0.57	0.37	0.67	0.00	0.85	0.86	0.53	0.00	0.46	low
86	0.43	0.25	0.00	0.00	0.80	0.94	0.67	0.50	0.44	low
87	0.43	0.25	0.00	0.00	0.80	0.94	0.67	0.50	0.44	low
88	0.57	0.17	0.33	0.00	0.85	0.96	0.73	0.00	0.44	low
89	0.57	0.37	0.67	0.00	0.80	0.75	0.33	0.00	0.42	low
90	0.57	0.17	0.00	0.32	0.85	0.86	0.53	0.00	0.42	low
91	0.43	0.25	0.00	0.00	0.80	0.80	0.41	0.50	0.40	low
92	0.43	0.25	0.00	0.00	0.80	0.67	0.75	0.00	0.35	low
93	0.43	0.25	0.00	0.00	0.80	0.80	0.41	0.00	0.33	low
94	0.43	0.25	0.00	0.00	0.80	0.94	0.17	0.00	0.32	low
95	0.14	0.00	0.00	0.00	0.53	0.53	0.50	0.00	0.21	low

Note: the abbreviations of the indicators are as follows: FS: family size, DR: dependency ratio, IR: illiteracy ratio (15+), RPW: ratio of perennial work in other places, PCI: income per capita, AHI: access to hazard-related information, VPC: vehicles per capita and HRT: hazard-related training.

Appendix B: Procedures and results using principle component analysis (PCA) to determine the weights of indicators

There are four steps to calculate the weights of indicators using PCA with the help of SPSS software.

The first step is using the KMO test (Kaiser–Meyer–Olkin). A KMO value higher than 0.5 demonstrates that the sampling data are suitable to perform PCA (Lolli and Di Girolamo, 2015). The KMO value, calculated for indicator variables in Appendix A: The standard data and assessment results is 0.757, which indicates that it is suitable to perform PCA.

The second step is to calculate initial eigenvalues and rotated eigenvalues of the PCA, including total initial eigenvalue, variance (%) and cumulative (%). The value of cumulative (%) should be equal or higher than 80 %, which demonstrates that the information of the extracted principle components could cover most of the information of the initial indictors. Table B1 shows the initial eigenvalues and rotated eigenvalues of the PCA performed on the indicator variables in Appendix A.

The third step is to calculate the values of the rotated component matrix (Table B2).

The fourth step is to calculate the weights of each indicator. The weight of the ith indicator (w_i) can be expressed by

$$w_i = \frac{\sum_{j=1}^{k} (\frac{a_{ij}}{\sqrt{\lambda_j}} \times v_j)}{\sum_{i=1}^{n} \left[\sum_{j=1}^{k} (\frac{a_{ij}}{\sqrt{\lambda_j}} \times v_j) \right]} i = 1, 2 \ldots 8, j = 1, 2, 3, 4, \quad \text{(B1)}$$

where a_{ij} is the value of the ith indicator at the jth rotated principle component and λ_j and v_j are the values of total initial eigenvalue and variance (%) at the jth rotated principle component, respectively.

The weights of all indicators can then be obtained using Eq. (B1) as follows: $w = [w_1, w_2, \ldots w_8] = [0.14, 0.12, 0.12, 0.12, 0.16, 0.16, 0.08, 0.11]$.

In order to make the results more suitable for the local situation, 20 experts from different fields (geography, hydrology, sociology and risk management) were invited to evaluate and adjust the weights. Finally, the weights listed in Table 1 were used in this paper.

Table B1. Initial eigenvalues and rotated eigenvalues of PCA performed on the indicator variables in Appendix A.

Component	Initial eigenvalues			Rotated eigenvalues		
	Total	Variance (%)	Cumulative (%)	Total	Variance (%)	Cumulative (%)
1	3.33	41.6	41.6	2.39	29.8	29.8
2	1.28	16.0	57.5	1.49	18.6	48.4
3	1.02	12.8	70.3	1.41	17.7	66.1
4	0.77	9.7	80.0	1.11	13.9	80.0
5	0.62	7.8	87.8			
6	0.42	5.3	93.1			
7	0.32	4.0	97.1			
8	0.23	2.9	100.0			

Table B2. Rotated component matrix.

	Component			
	1	2	3	4
FS	0.87	0.22	0.01	0.09
DR	0.17	0.05	0.08	0.93
IR	0.07	0.88	0.09	0.12
RPW	0.37	0.76	0.00	−0.07
PCI	0.86	0.22	0.18	0.11
AHI	0.65	0.15	0.51	0.13
VPC	0.52	−0.03	0.53	−0.42
HRT	0.09	0.06	0.91	0.09

Extraction method: principle component analysis.
Rotation method: varimax with Kaiser normalization.

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