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Spatial Distribution of Vulnerability to Extreme Flood: in provincial scale of China

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Abstract. Extreme flood (EF) disasters in China are characterized by large influence range, high frequency, strong burst and uneven distribution in time and space. Once the EF disaster occurs, it will pose a great threat to the people's life safety, economic, natural and social environment. Compared with the hazards and exposure factors of EF, the vulnerability of disaster regions shows great differences due to China's vastness and complex social and environmental background of disasters, which leads to less large-scale study at provincial-level on EF vulnerability. This study calculated the vulnerability to EF from the favorable and unfavorable factors of flood resistance of four aspects including life, economy, environment and society. The Cloud-improved Entropy Method is used to calculate the index weight, and the Fuzzy Variable Theory is used to calculate the comprehensive vulnerability grads. The vulnerability ranking of 31 provinces or regions in China was made according to the differences of population, social structure, economy and environment among these regions. Furthermore, synthesizing disaster science and geographic mapping, the spatial distribution map of vulnerability to EF in China was generated, which shows that vulnerability to EF in most regions of China is in "moderate" or "severe" grade. The spatial distribution of the EF risk vulnerability shows (1) a decreasing trend from the regions with high population density to regions with low population density, (2) a decreasing trend from economically developed regions to economically backward regions, (3) a decreasing trend from the eastern coastal regions to the central agricultural provinces and then to the southwest, northwest and northeast regions in China. The outcome of this study maybe one of the first efforts providing research database for vulnerability to EF in large scale of China, and it is useful for future regional research and risk management.

1 Introduction

In recent years, climate change has caused frequent extreme flood (EF) (Li, et al., 2021; Tebaldi, et al., 2006). EF caused by rainstorms, typhoons (hurricanes), flash flood and dam break flood have brought extremely severe challenges to mankind (Ge, et al., 2020, 2021). China is one of the countries most affected by EF (Ge, et al., 2017, 2020; Li, et al., 2019) From July 6 to 12, 2018, Sichuan Basin and some areas in Northwest China were hit by heavy rainfall, causing flood, debris flows, hail and other disasters. According to statistics, the disaster affected 6.113 million people, 25 casualties and missing, 12,000

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houses collapsed and 195,000 houses were damaged to varying degrees, 385,000 hectares of crops were affected, the direct economic loss was 33.42 billion yuan in 4 provinces of Chongqing, Sichuan, Shaanxi and Gansu (Ministry of Emergency Management of the People's Republic of China, 2018). On July 2019, due to days of heavy rainfall, catastrophic flood occurred in Pingxiang of Jiangxi, Leiyang of Hunan and other middle and lower reaches of the Yangtze River, resulting in 10.319 million people affected, 37 casualties, 3 people were missing, 21,000 houses collapsed, 171 thousand hectares of cultivated land failed to harvest, and a direct economic loss of 32.43 billion yuan (Ministry of Emergency Management of the People's Republic of China, 2019). From July 17 to 23, 2021, Henan Province was hit by a torrential rain rarely seen in history and a serious flood disaster occurred. The disaster affected 14.786 million people in 150 counties (cities and districts) of Henan Province, 398 people died and were missing due to the disaster, and the direct economic loss was 120.06 billion yuan. (Ministry of Emergency Management of the People's Republic of China, 2020). It can be seen that EF has caused non negligible losses to downstream life, economy and environment.

Disaster vulnerability is the loss faced by human society because of disasters bearing capacity of human and society under various pressures and negative influences. It is not only the loss of individual, but also the loss of the whole society. Disaster vulnerability involves people's life safety, health, living conditions, social wealth, production capacity, social order, social recovery ability and so on. People gradually realize that it is more important to improve the adaptability of disaster-bearing bodies than to change the disaster-causing factors in order to reduce vulnerability. Ziegler et al. (2016) investigated the life loss vulnerability of deadly flash flood and debris flows in Ladakh (India), researched the impact of the disaster governance strategies on the reduction vulnerability in Ladakh. Ge et al. (2021) researched the risk of life-loss in the case of dam breach with the interval analysis, considering the uncertainty and the mechanism of the vulnerability influencing index. Lee et al. (2021) assessed the vulnerability of the Bangladesh region to flood on socioeconomic, health and coping capacity vulnerability and composite social-health vulnerability. Moreira et al. (2021) highlight global trends and future research directions by providing an updated description of the flood vulnerability indices. Ritter et al. (2020) carried out the real time assessment of flash flood by using a regional high resolution method. It is pointed that the whole region should be considered in the study of flood disasters. Adikari et al. (2010) researched the vulnerability of regions in Asia to flood and their impacts, and put forward that global changes, internal migration patterns, development practices and political instability factors have an impact on vulnerability of EF. Zhang et al. (2019) studied the impact of flood in Anhui province of China in 2016. The flood risk agencies are advised to develop programs to prevent and control flood risk especially in regions close to dams and among high vulnerability areas. Duo et al. (2020) developed a hazards model to evaluate the coastal flood's impact. The process was taken into account the uncertainty of the vulnerability and indicated the damage showing great spatial difference. Taylor et al. (2011) studied the threat of large-scale flood to environments, and pointed out that the risk are greatly affected by the group vulnerability in the region. The above shows that the research on vulnerability has attracted extensive attention, and the research on regional vulnerability has gradually become a hot spot.

Many scholars have done a lot of research on the affecting factors and assessment of regional vulnerability. Yu et al. (2020) assessed the social vulnerability of Shenzhen, China, to storm surges. Zeng et al. (2012) used the method based on remote

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sensing to establish a model of social vulnerability for county-scale regions. He put forward a new concept defined as "population density based on land use", with other two indicators: age structure and distance to hospital. Min Kim et al. (2021) assessed the risk of flood and flashing flood based on three dimensions: exposure, sensitivity, and adaptive capacity. Li et al. (2018) and Li et al. (2020) studied the factors affecting the downstream environment and the vulnerability of life loss and analyzed the weight distribution of influencing factors, providing a technical basis for future research. Li et al. (2021) suggested that the land use types are impact by the EF and show great geomorphic variation. Tanner and Arvai (2018) focused on large-scale regions events that affect tens of thousands of people, and revealed that judgments about vulnerability—as a function of how people perceive physical distance—do differs according to one's evacuation experience. Chang and Chen (2016) studied spatial heterogeneity of local flood vulnerability indicators and pointed out that regions show great differences in the face of disasters. Muller (2013) comprised the interpretation of very high-resolution satellite data, the analysis of GIS, and census data as well as house-hold surveys and expert interviews, to researched flood vulnerability map at the scale of the administrative unit of a building block. Seo et al. (2020) monitored and assessed the ecological risk and its spatial distribution of the Yellow and Bohai seas. Chen et al. (2021) analysis flood risk and resulting loss in southern China by utilizing a method combing entropy weight and TOPSIS, and he assess southern China from both temporal and spatial perspectives. Taylor et al. (2013) studied the exposure risks in flood via GIS method and estimated the spatial flood vulnerability across the London. Liu et al. (2016) developed a household social vulnerability index (HSVI) for flood disasters and used it to assess the social vulnerability of rural households in mountainous areas in western Henan Province, China. You and Zhang (2015) assessed the flood vulnerability of the Huaihe River Basin in China based on the catastrophe evaluation method.

The above researches shows that there are great differences in vulnerability between different regions. Therefore, for China, due to the great differences in geographical location, economy, environment and society among provinces, it is necessary to conduct provincial scale analysis. However, most of the current researches are aimed at a specific region (such as a community, a city or a watershed, etc.), and only consider the impact caused by environmental differences. There is still a lack of vulnerability analysis on China's provincial scale and considering the impact of social factors. Given the aforementioned problems, a systematic evaluation method of the vulnerability at provincial level in China is explored in this study. The objective of this study is as follow: (1) In addition to environmental factors, social factors are also considered. Construct a more comprehensive in-dex system in terms of favorable and unfavorable effects to resistance EF；(2) Variable Fuzzy set model is constructed to assess the grade of EF vulnerability of 31 provinces or regions in China by processing the statistical data within these provinces and regions；(3) The calculation results will be analyzed to explore the spatial distribution of EF vulnerability of scale in provinces of China; (4) It will provides important decision-making basis for flood control, disaster reduction, disaster relief and disaster reduction, and provides reference for similar research in the future.

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2 Materials and Methods

2.1 Evaluation Method

Based on the fuzzy uncertainty of the risk indicator of EF vulnerability, this study puts forward the Variable Fuzzy Set theory and Cloud-improved Entropy weighting method (Li et al., 2018, 2019). The solidification of membership degree in traditional fuzzy mathematics theory is corrected by using dynamic membership function (Li et al., 2018, 2019; Ge et al., 2020). In this manuscript, we make full use of the expectation of cloud model and cloud entropy parameters, learn from the processing method of entropy weight method for index differences, take into account the subjectivity and objectivity of weight, and scientifically reflect the importance of risk factors (Li et al., 2018, 2019; Ge et al., 2020). The evaluating process of vulnerability to EF are shown in Figure1.

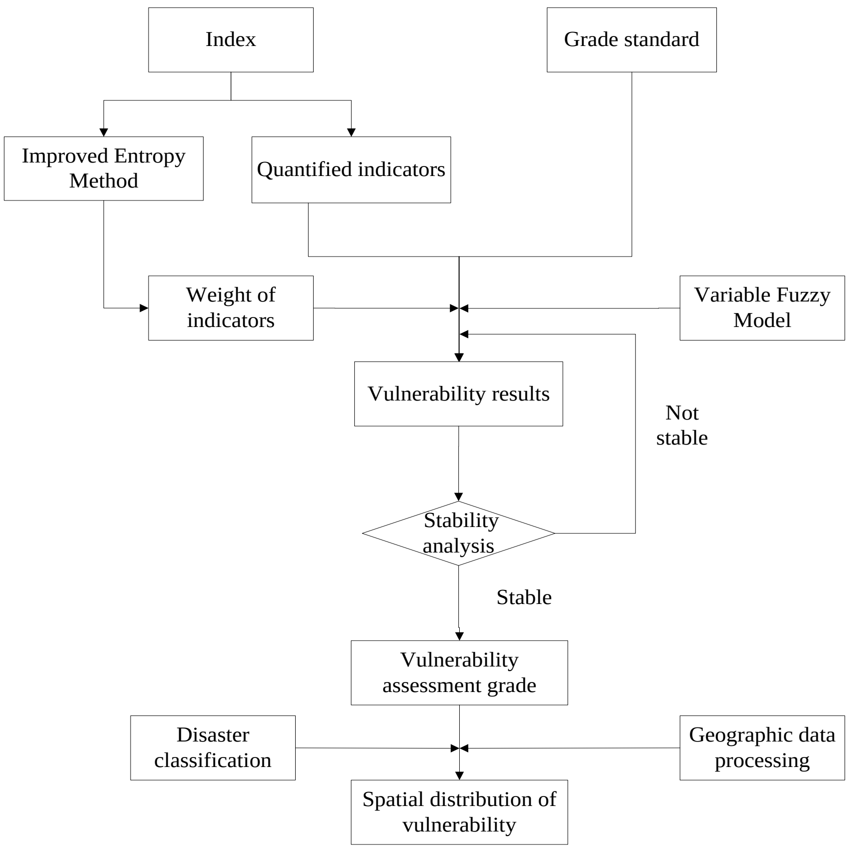

Figure 1 Spatial distribution calculation process of vulnerability facing EF

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2.1.1 Index System

This study combined with the theory and the achievement of the research on natural disaster vulnerability (Guo et al., 2013), general vulnerability index (PVI) (Cardona et al., 2011) and social vulnerability assessment index (Cutters, 1996), to establish the index system of vulnerability facing EF and divided them into three layers: target layer, system layer and index layer.

The target layer is the vulnerability to EF disaster. The system layer is based on the concept and connotation of EF disaster vulnerability, which is embodied in the environment, economy, life and society as the key factors affecting the vulnerability of the disaster bearing body. The index layer reflects the relationship structure of the system behavior and represented by a certain comprehensive index. It can be further divided into two categories: favorable and unfavorable of flood resistance (Gruijters and Fleuren, 2017). Favorable index describes the resilience of the disaster affected body and its ability to recover after the disaster, including population at risk (R_p), per capital GDP (G_p), water environment (W_E) and soil environment (S_E), while unfavorable ones describe the sensitivity of the disaster affected body including self-rescue ability (S_A), transport network density (T_D), provincial importance (P_I) and social disaster tolerance index (S_I). To sum up, the index system of the vulnerability to EF disasters is shown in Table 1.

Table 1 Index system of vulnerability factors of EF

Target layer	System layer	Index layer
Index of vulnerability factors of EF disaster	Life-loss vulnerability	Risk population (R_p)
		Self-rescue ability (S_A)[1]
	Economic vulnerability	Per capital GDP (G_p)
		Transport network density (T_D)
	Environmental vulnerability	Water environment (W_E)
		Soil environment (S_E)

2.1.2 Calculating Model

(1) Construction of the Matrix of the evaluation value and standard value of index

If there are n sample sets of provinces or regions to be evaluated, as $\{X_1, X_2, \cdots; X_n\}$, each sample has m index eigenvalues, then the matrix of the sample eigenvalue to be evaluated can be expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} = \left(x_{ij} \right) \tag{1}$$

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(2) Determination of matrix of the standard interval of indicators

If the evaluation interval of the indicators of the samples to be evaluated is divided by c levels, the matrix of the standard interval of evaluation indicators is:

$$Y=\begin{bmatrix} [a_{11},b_{11}] & [a_{12},b_{12}] & \cdots & [a_{1c},b_{1c}] \\ [a_{21},b_{21}] & [a_{22},b_{22}] & \cdots & [a_{1c},b_{1c}] \\ \vdots & \vdots & \ddots & \vdots \\ [a_{31},b_{31}] & [a_{32},b_{32}] & \cdots & [a_{1c},b_{1c}] \end{bmatrix}=\left([a_{ih},b_{ih}]\right) \tag{2}$$

Where $[a_{ih}, b_{ih}]$ is the standard interval of indicators i of level h, and a_{ih}, b_{ih} are the upper and lower limits of the interval.

(3) Determination of the matrix of standard interval point value

M_{ih} is the point value when Index i (i = 1, 2, $\cdots$m) in the standard interval $[a_{ih}, b_{ih}]$ has a relative membership degree of 1 to the level h. M_{ih} can be determined based on the physical meaning and the actual situation, for level 1 $M_{i1}=a_{i1}$, for level r $M_{ir}=a_{i1r}$, for intermediate level l, when r is odd, M_{il} = $(a_{i1}+b_{il})$ /2. The general model of point value M_{ih} satisfying the above conditions is:

$$M_{ih}=\frac{r-h}{r-1}\times a_{ih}+\frac{h-1}{r-1}\times b_{ih} \tag{3}$$

Where for h = 1, $M_{i1}=a_{i1}$; for h = c, M_{ic} = a_{ic}, for $h=l=\frac{c+1}{2}, M_{il}=\frac{a_{ij}+b_{il}}{2}$. By formula (3), matrix $M=(M_{ih})$ can be obtained from the matrix Y.

(4) Determination of relative membership degree of the indicator x_{ij} to each level

If the evaluation indicator x_{ij} of the sample u_j falls into $[M_{ih}, M_{i(h+1)}]$, the interval between the adjacent two levels of the matrix M, level h and level (h +1), then the relative membership degree of Index i to level h can be calculated by the following formula:

$$\begin{cases} \mu_{ih}(u_j)=0.5\left(1+\dfrac{b_{ih}-x_{ij}}{b_{ih}-M_{ih}}\right), x_{ij}\in[M_{ih},b_{ih}] \\ \mu_{ih}(u_j)=0.5\left(1-\dfrac{b_{ih}-x_{ij}}{b_{ih}-M_{i(h+1)}}\right), x_{ij}\in[b_{ih},M_{i(h+1)}] \\ \mu_{ih}(u_j)=1,\quad x_{ij}\in M_{ih} \end{cases} \tag{4}$$

According to physical concept, when Index i is less than level h and greater than level (h+1), its relative membership should be equal to 0, that is:

$$\mu_{i(<h)}(u_j)=0,\mu_{i(>(h+1))}(u_j)=0 \tag{5}$$

When x_{ij} falls outside the range of M_{i1} and M_{ic}, according to physical concept:

$$\mu_{i1}(u_j)=\mu_{i2}(u_j)=1 \tag{6}$$

(5) Determination of the Comprehensive Membership Degree of the Index

The comprehensive membership vectors are normalized, and the risk grade eigenvalues of the evaluation samples are calculated by the level eigenvalue formula:

$$H = \sum_{h=1}^{c} v_h' \cdot h \tag{7}$$

Where v_h' is the normalized relative membership degree; H is the level eigenvalue of the evaluation sample.

2.2 Data source

In order to conduct vulnerability analysis more accurately, the data includes mainly official government yearbooks, reports and online official database. R_P, S_A, G_P and T_D are calculated according to the statistics of the yearbook data (Sheng and Ye, 2014); The W_E and S_E are based on the basic data and government gazette of the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (Resource and Environment Science and Data Center); P_I and S_I are based on the analysis of previous research results (Bankoff, 2007; Zhang, 2008). Evaluation indexes are constructed in the same type of data source for the consistency of data caliber.

2.2.1 Index value basis and its standard

(1) Risk population (R_P)

In general, a disaster's impact on a region has a significant correlation with its population density. The safety of people in a region is one of the most fundamental indicators of a vulnerability. It is indicated through the large-scale population density of the provinces or the regions, which can reflect the risk of the downstream population more reasonably. From a spatial perspective. The eastern half of China has a much higher population density and that of the lands of the west and the northwest. The proportion of permanent residents in the eastern, western, central and northeastern regions is 37.98%, 27.04%, 26.76% and 8.22%, respectively. The total population of such provinces as Guangdong, Shandong, Henan Sichuan and Jiangsu is large. The population density is relatively large in the eastern coastal regions such as North China, the Yangtze River Delta, and the Pearl River Delta, as well as along the Sichuan Basin and the Longhai railway (Census Office of the State Council, 2012; Ministry of Civil Affairs of the People's Republic of China, 2010). The R_P is calculated according to the following formula:

$$R_P = P / A \tag{8}$$

Where: R_P denotes the risk population; P denotes the regional population; A denotes the regional area.

(2) Self-rescue ability (S_A)

The young and middle-aged populations are physically stronger, so they tend to have the ability to rescue themselves and others when disasters occur. Therefore, they are regarded as the main social force for resuming production and life after a disaster. According to the China and international labor force classification standards (Samuel and Mirjam, 2018; Blien and

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Hirschenauer, 2018; Du et al., 2019; National Bureau of Statistics of the People's Republic of China, 2010), the 15 to 64 year-old is considered as the labor force. The S_A is calculated according to the following formula:

$$S_A = 1 - (N_{14} + N_{65}) / N \tag{9}$$

Where: S_A denotes the proportion of self-help population; N_{14} denotes the number of people under 14 years old; N_{65} denotes the number of people over 65 years old; N denotes the total region population.

(3) Per capital GDP (G_P)

Regional and urban-rural disparities are the important factors leading to regional disparities in disaster prevention in China. In terms of economic development, the eastern regions are the most developed, the central regions the second, and the western regions are the least developed. The economic development gap among these three regions is obvious. From the perspective of losses caused by disasters, the more intensive social and economic activities of an area, the more its social assets exposed to disasters due to the concentration of social wealth. Once damaged by disasters, the area will suffer greater economic losses (National Bureau of Statistics of the People's Republic of China, 2010). This study divides China's per capital GDP according to the adjustment of the World Bank's classification of “high, middle and low-income” economies in 2013, with the statistics and ranking of China's per capital GDP in 2013. G_P is calculated according to the following formula:

$$G_P = G_T / N \tag{10}$$

Where: G_p denotes the per capital GDP, G_T denotes the total GDP of the region, N denotes the total population.

(4) Transport network density (T_D)

Convenient transportation leads to the efficient materials rescue, medical rescue and fire rescue. In terms of the distribution of natural environment, land resources and traffic in China, regions in southwestern and western China often lie near the rivers in a striplike shape, accompanied by mountains. This type of terrain condition is greatly unfavorable for the relief and recovery work after the EF disasters. T_D is calculated according to the following formula:

$$T_D = L_T / A \tag{11}$$

Where: T_D denotes the traffic density, L_T denotes the regional total highway length, A denotes the measure of regional area.

(5) Water environment (W_E)

Water environment refers to that the pollutants around the downstream river, pesticide residues in farmland, domestic garbage of downstream residents, industrial waste and construction waste of downstream cities and towns flow into the downstream water body due to flood discharge, impact and entrainment, resulting in significant changes in water quality in the river. The decline of water quality will affect the survival and reproduction of aquatic animals and plants, the drinking water safety of residents, and the production of industry and agriculture. In 2013, the Ministry of Water Resources evaluated the water quality of 208,000 km of rivers in China. Based on the basic geographic data of the Resource and Environment Science Data Center of the Chinese Academy of Sciences and the survey of 208,000 km of rivers in China in the Water Resources Bulletin of 2013, the water quality of the southwest and northwest rivers is excellent, the water quality of the

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Pearl and southeast rivers is good, the water quality of the Yangtze and Songhua rivers is medium, the water quality of the Yellow, Liaohe, Huaihe river is poor, and Haihe rivers is worst. The spatial distribution data of nine catchments is shown in Fig. 2.

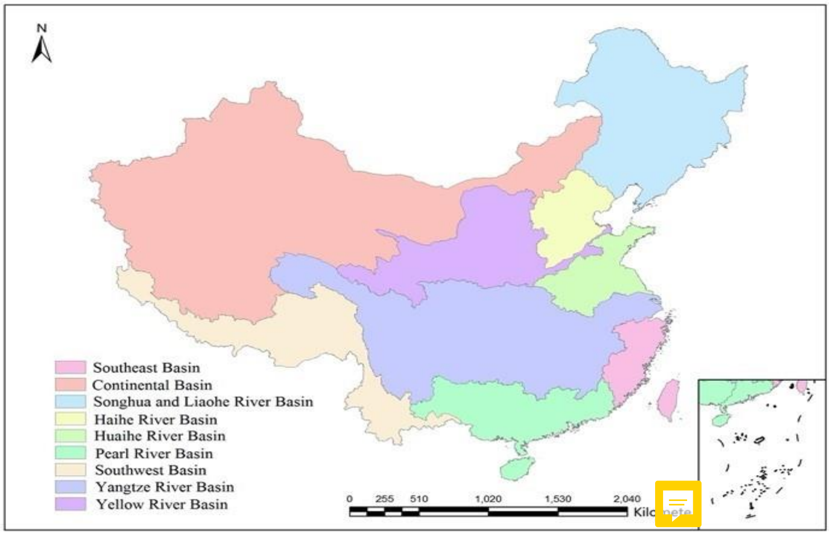

Figure 2 Spatial distribution data of nine catchments in China

(6) Soil environment (S_E)

Soil environment refers to the change of soil quality under the comprehensive influence of soil ecological indicators, organic matter content and damage degree of pollution sources in the downstream area caused by flood. This change is mostly reflected in malignant changes, which leads to the decline of soil quality grade, thus affecting the growth of plants and trees, the decline of crop yield and quality, and even the toxic substances contained in the polluted soil are enriched in the fruits, and people and livestock are poisoned after eating. Considering the vastness of China, it is impossible to get accurate soil environmental quality reports for each province or city. So the division is based on the vulnerability of land types according to the basic geographic data of the Resource and Environment Science Data Center of the Chinese Academy of Sciences. According to their sensitivity to EF, settlements and wetlands are the most vulnerable one to EF, desert ecosystems are the least vulnerable one to EF, and the vulnerability of farmland, grassland and forest ecosystems to EF is medium. The spatial distribution of ecological environment in China is shown in Figure. 3.

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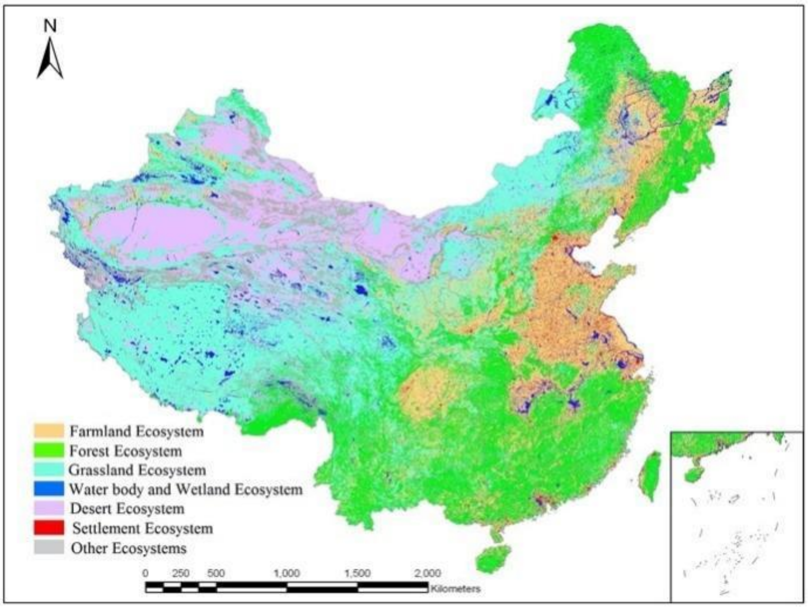

Figure 3 Spatial distribution data of terrestrial ecosystem types in China in 2010

(7) Provincial importance (P_I)

According to the administrative level of provinces and cities, this study takes the economy, politics, ethnic minority groups distribution, railway, agricultural output value as the relevant factors. Some provinces have a greater influence on national railways and agriculture, such as Henan and Hubei, and some provinces and cities, such as Beijing and Shanghai, enjoy higher administrative levels and political importance, while they are more vulnerable to EF.

(8) Social disaster tolerance index (S_I)

Because of the great differences in disaster relief funds, disaster awareness and reconstruction ability between the developed regions and the underdeveloped ones, the influence on the society vulnerability of disaster varies. According to the previous research results focusing on the impact of the social impact of disaster (Zhang, 2008; Ge et al., 2020), the social disaster tolerance index reflects the disaster resistance, disaster relief and recovery ability of provinces and cities. The disaster bearing capacity of the regions can be reflected more accurately and objectively by analyzing them from multiple dimensions.

2.2.2 Rating Standard

This manuscript classify the degree of flood risk vulnerability and divides the vulnerability interval into five grades: slight vulnerability, low vulnerability, moderate vulnerability, high vulnerability and very high vulnerability. Based on the Graham method and previous research results (Scheuer et al., 2011), as well as the analysis of existing factors above, the criteria of influencing factors of vulnerability facing EF are shown in Table 2.

Table 2 Criteria for determining the influencing factors of flood risk vulnerability

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System layer	Index layer	Level 1	Level 2	Level 3	Level 4	Level 5
		Slight	**Low**	**Moderate**	**High**	**Very high**
Life-loss vulnerability	R_P(people/km^2)	Below 250	250-500	500-750	750-1000	Above 1000
	S_A (%)	Above 78.88	75.07-78.88	71.26-75.07	67.45-71.26	Below 67.45
Economic vulnerability	G_P (¥)	Below 39000	39001-52000	52001-65000	65001-78000	Above 78000
	T_D (km/km^2)	Above 1.4	1.1-1.4	0.7-1.1	0.4-0.7	Below 0.4
Environmental vulnerability	W_E	[0-0.2]	(0.2-0.4]	(0.4-0.6]	(0.6-0.8]	(0.8-1]
	S_E	[0-0.2]	(0.2-0.4]	(0.4-0.6]	(0.6-0.8]	(0.8-1]
Social vulnerability	P_I	[0-0.2]	(0.2-0.4]	(0.4-0.6]	(0.6-0.8]	(0.8-1]
	S_I	Above 3.04	2.81-3.04	2.58-2.81	2.35-2.58	Below 2.35

(1) Quantitative value of indicators

According to the data base and value basis mentioned in the preceding section, the survey data and data are sorted out, and the values of 31 provinces and cities (Hong Kong, Macao, and Taiwan's data are not included) in China are obtained as shown in Table 3.

Table 3. Vulnerability influencing factor of 31 regional value

Province/city region	R_P (people/km^2)	S_A (%)	G_P (¥)	T_D (km/km^2)	W_E	S_E	S_I	P_I
Beijing	1195.09	82.7	94238	1.26	0.19	0.81	3.05	0.99
Tianjin	1100.16	81.68	101689	1.22	0.12	0.79	2.76	0.78
Hebei	487.1	75.02	38835	0.97	0.08	0.85	2.49	0.38
Shanxi	259.57	75.34	34901	0.86	0.26	0.58	2.2	0.24
Inner Mongolia	63.73	79	68277	1.12	0.81	0.41	2.97	0.33
Liaoning	313.99	78.05	61745	0.67	0.38	0.81	2.82	0.46
Jilin	168.8	79.04	47198	0.53	0.35	0.61	3.29	0.39
Heilongjiang	92.52	79.72	38602	0.25	0.29	0.41	3.1	0.34
Shanghai	3630.49	81.25	90749	2.49	0.56	0.78	3.13	0.99
Jiangsu	832.28	75.72	74699	1.47	0.32	0.82	2.78	0.79
Zhejiang	599.76	76.74	68593	1.13	0.52	0.41	2.85	0.81
Anhui	528.32	73.09	31795	1.18	0.49	0.83	2.45	0.24
Fujian	582.26	75.82	58057	0.87	0.78	0.38	3.03	0.58
Jiangxi	327.42	71.2	31836	0.95	0.51	0.46	2.68	0.32
Shandong	616.65	74.65	56463	1.46	0.31	0.85	2.7	0.62
Henan	654.3	71.31	34187	1.53	0.3	0.91	2.66	0.57

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Hubei	387.79	76.53	42686	1.11	0.48	0.67	2.68	0.43
Hunan	341	72.51	36906	0.96	0.51	0.48	2.62	0.52
Guangdong	1118.67	74.44	58678	1.11	0.7	0.42	2.97	0.9
Guangxi	256.99	69.2	30709	0.45	0.77	0.46	2.79	0.11
Hainan	486.6	74.95	35491	0.69	0.79	0.39	2.56	0.06
Chongqing	551.17	63.64	42977	1.52	0.55	0.61	2.45	0.79
Sichuan	374.46	71.59	32516	0.98	0.54	0.61	2.69	0.58
Guizhou	232.58	66.5	22980	0.87	0.57	0.51	2.12	0.13
Yunnan	118.55	72.14	25158	0.54	0.9	0.48	2.12	0.08
Tibet	16.83	63.91	26071	0.06	0.99	0.61	2.65	0.52
Shaanxi	265.08	76.48	42752	0.85	0.31	0.52	2.22	0.48
Gansu	119.04	73.83	24442	0.42	0.87	0.31	2.3	0.05
Qinghai	53.55	75.49	36657	0.28	0.85	0.39	2.13	0.17
Ningxia	112.49	71.71	40174	0.39	0.85	0.42	2.86	0.06
Xinjiang	36.03	71.13	38114	0.12	0.96	0.15	2.65	0.74

3 Results

3.1 Weight determination

In view of the problems of strong subjectivity of expert scoring, difficult index comparison and too average weight distribution in the traditional method of determining weight when there are many indicators, the entropy weight method is improved by using the cloud model, and the cloud entropy is fully considered when applying SCM (Statistical Cloud Model) to convert the subjective opinions of experts, so as to obtain more scientific and accurate weight calculation results (Li et al., 2018, 2019; Ge et al., 2020). According to the expert's scoring results, the corresponding influencing factor indicators are extracted, and the weight of the indicators is calculated by using the Cloud-improved Entropy weight method (Li et al., 2018, 2019; Ge et al., 2020).

Suppose there are n indicators (column vectors) and m experts (row vectors). Each indicator computes the expectation and variance according to the cloud model. The statistical equation for calculating the jth indicator is as follows.

$$Ex_j = \overline{x_j} = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \quad (i=1,..,m;\ j=1,\dots,n) \tag{12}$$

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$$En_j = \sqrt{\frac{\pi}{2}}\frac{1}{m}\sum_{i=1}^{m}\left|x_{ij} - Ex_j\right| \quad (i=1,..,m;\ j=1,\dots,n) \tag{13}$$

$$He_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(x_{ij} - Ex_j\right)^2 - En_j^{\,2}} \quad (i=1,..,m;\ j=1,\dots,n) \tag{14}$$

$$\omega_j = \begin{cases} \dfrac{Ex_j}{ln\left(1+En_j\right)+1}\cdot\dfrac{1}{\sum_{j=1}^{n}\dfrac{Exj}{ln\left(1+En_j\right)+1}} & (En_j \neq 0) \\ \dfrac{Ex_j}{\sum_{j=1}^{n}Ex_j} & (En_j = 0) \end{cases} \tag{15}$$

Where: E_x is expectation, E_N is entropy, H_E is hyper-entropy, ω_j is weight. If the En_j is not equal to 0, the equation of the weight is revised and the cloud entropy is involved in the calculation. The larger the cloud entropy, the more divergence of opinions the expert has on the index, so the weight of the index should be reduced. The smaller the entropy is, the smaller the expert's disagreement on the indicator, so the weight of the indicator should be increased. When the minimum entropy En_j is equal to 0, indicating that the indicators of the experts have the same score, then the weight of the equation remains unchanged. According to the above equations, the weight calculation results are shown in Table 4.

Table 4 Weights distribution of vulnerability influencing factor

Index	R_P	S_A	G_P	T_D	W_E	S_E	S_I	P_I
Weight	0.211	0.135	0.108	0.106	0.109	0.109	0.114	0.108

3.2 Results of vulnerability level

When the index of 31 provinces and municipalities substituted into the corresponding scope of matrix, applied with the Variable Fuzzy comprehensive evaluation model form formula (1) to (4), the corresponding subjection matrix of each level could be calculated. With different variable parameter combination, after the stability and rationality of different eigenvalue scopes are analyzed, the level eigenvalues could be calculated by formula (6) and (7). The result is demonstrated in Table 5.

Table 5 Weights distribution of vulnerability influencing factor

Province/City	***a*=1，*p*=1**	***a*=2，*p*=1**	***a*=1，*p*=2**	***a*=2，*p*=2**	***mean value of H***
Beijing	3.423	3.963	3.319	3.760	3.616
Tianjin	3.454	3.922	3.300	3.689	3.591
Hebei	2.684	2.560	2.786	2.611	2.660

Shanxi	2.447	2.144	2.609	2.260	2.365
Inner Mongolia	2.460	2.120	2.514	2.007	2.275
Liaoning	2.636	2.261	2.834	2.364	2.524
Jilin	1.998	1.846	2.073	1.759	1.919
Heilongjiang	1.673	1.556	1.701	1.491	1.605
Shanghai	3.804	4.686	3.481	4.224	4.049
Jiangsu	3.533	3.688	3.503	3.585	3.577
Zhejiang	3.062	2.948	3.169	2.971	3.038
Anhui	2.966	2.981	2.970	2.956	2.968
Fujian	2.829	2.865	2.862	2.852	2.852
Jiangxi	2.614	2.690	2.513	2.498	2.579
Shandong	3.234	3.046	3.308	3.115	3.176
Henan	3.244	3.182	3.135	3.154	3.179
Hubei	2.718	2.564	2.763	2.548	2.648
Hunan	2.721	2.871	2.520	2.590	2.675
Guangdong	3.461	3.398	3.535	3.571	3.491
Guangxi	2.388	2.137	2.526	2.321	2.343
Hainan	2.559	2.430	2.656	2.462	2.527
Chongqing	3.552	3.609	3.457	3.405	3.506
Sichuan	2.854	2.967	2.632	2.693	2.786
Guizhou	2.735	2.441	2.782	2.496	2.613
Yunnan	2.561	2.011	2.660	2.204	2.359
Tibet	2.720	2.072	2.810	2.315	2.479
Shaanxi	2.582	2.371	2.668	2.401	2.506
Gansu	2.341	1.662	2.560	1.988	2.138
Qinghai	2.317	1.653	2.518	1.882	2.092
Ningxia	2.234	1.714	2.472	1.892	2.078
Xinjiang	2.461	1.725	2.701	2.152	2.260

4 Discussion

According to the calculation results of table 5, it is sorted in Figure. 4.

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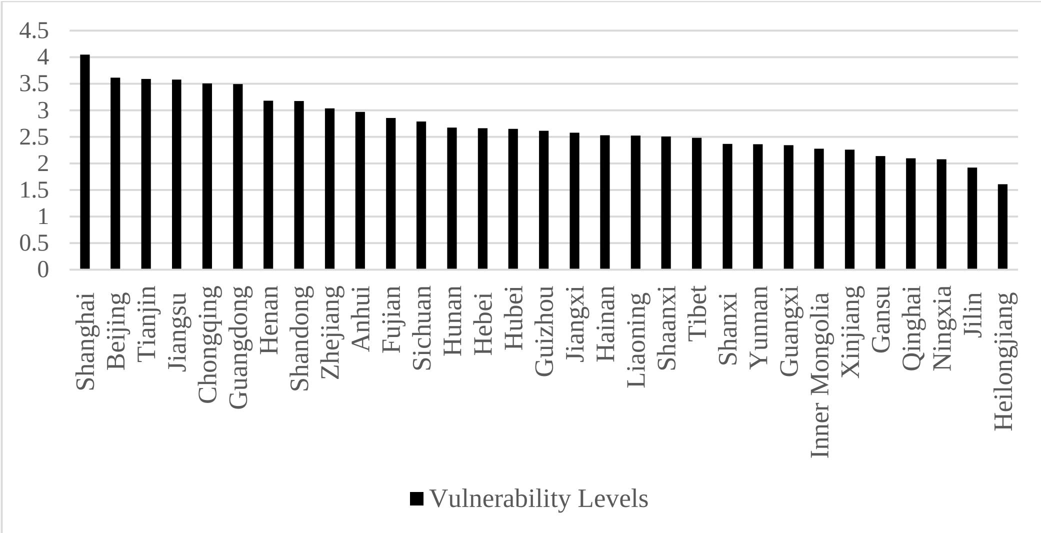

Figure 4 Ranking of vulnerability levels in each province/region

4.1 Vulnerability spatial distribution results

According to the guidelines of the Natural Disaster Risk Classification Method (Zhang and Li, 2014) and grading methods of natural disaster risk issued by the Ministry of Civil Affairs of the People's Republic of China (2012), in this manuscript, an average and second average analysis are performed on the level feature value data of the vulnerability. The grade data is divided into four levels: “slight”, “moderate”, “severe” and “extremely serious”. ArcGIS9 software is used to convert the original geographic map into a shape format, and the coordinate map is converted into a Gauss Kruger projection map. The spatial distribution of vulnerability facing EF in China is shown in Figure 5.

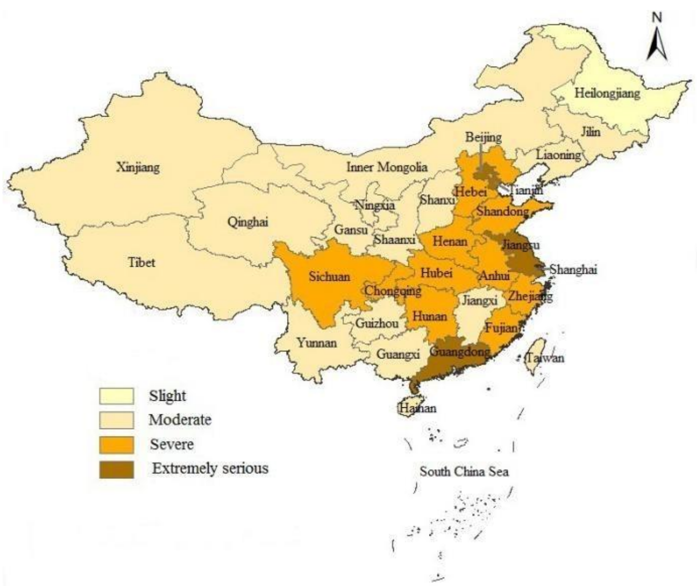

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Figure 5 Spatial distribution of vulnerability to EF in China

It can be seen from the Fig. 5：

(1) The "extremely serious" grades of vulnerability to EF are in Beijing, Shanghai, Tianjin, Guangdong and Jiangsu, which are mostly developed municipalities or provinces with large populations.

(2) Hebei, Henan, Shandong, Sichuan, Chongqing, Hunan, Hubei, Anhui, Zhejiang and Fujian are the provinces or cities with the "severe" level of vulnerability to EF. Most of the provinces are in the Yangtze River, Yellow River and Huaihe River basins with large populations and relatively developed economies.

(3) The provinces with "moderate" level of vulnerability are Jilin, Liaoning, Inner Mongolia, Shanxi, Shanxi, Ningxia, Qinghai, Gansu, Xinjiang, Tibet, Yunnan, Guizhou, Jiangxi and Guangxi, which are mainly in the west and northwest of China. Most of them have relatively low population density and are less developed in Northeast China.

(4) Heilongjiang province is only one with "slight" vulnerability to EF.

4.2 The spatial distribution law of the vulnerability to EF in China

(1) From the perspective of population density, the distribution of vulnerability facing EF in China shows a decreasing trend from a region with a high population density to one with a low population density.

(2) From the perspective of economic development, the distribution of vulnerability to EF in China shows a decreasing trend from developed regions to backward ones.

(3) From the perspective of geographical space, the distribution of vulnerability facing EF in China shows a decreasing trend from the eastern coastal regions to the central agriculturally developed provinces, and then to the southwest, northwest and northeast regions.

In general, the vulnerability to EF in most regions of China is in "moderate" or "severe" grade. Developed province-level municipalities and the provinces with a large population are in extremely serious grade, even though they are strong in disaster prevention and control capabilities. The regions in the Yangtze River, the Yellow River and the Huaihe river basin have a large population, and most of them are major grain-producers and economically developed provinces in China. When EF disaster happens the loss will be very serious. So more attention should be paid to these regions. With the exception of Heilongjiang, most of the provinces or regions, such as those in the northwest, southwest and northeast China, are ethnic minority regions and economically underdeveloped regions. Though the vulnerability in these regions is lower, but they have a low traffic road network density, resulting in weak disaster-carrying capability and the disaster reduction capability. Once serious EF disasters occur, they will bring great difficulty to the transfer of affected people and property, and are likely to cause indirect losses triggered by poor disaster relief and slow recovery, greatly threatening the downstream society. Heilongjiang province has become the only one whose vulnerability facing EF disasters is slight. The reasons include its low population density and high proportion of labor force, and its high disaster prevention and relief capability.

5 Conclusions

The spatial distribution of vulnerability to EF in China varys, and the distribution of disaster-bearing bodies such as population, economy and natural environment also varies greatly with the regions. In this study, the spatial distribution of vulnerability to EF in China is analyzed based on the disaster system theory. 31 provinces or regions in China are taken as research units. The favorable and unfavorable aspects of flood resistance of vulnerability of life, economy, environment and society are taken as evaluation indexes, which were processed by the Cloud-improved Entropy Weight calculation model and the Variable Fuzzy Set model to obtain the vulnerability level. Finally, the spatial distribution pattern and distribution law of vulnerability to EF disaster in China are studied via statistical yearbooks, bulletins and geographic information data. The results show that the vulnerability to EF disaster in China is mainly in the moderate or serious level. The distribution of vulnerability to EF shows a decreasing trend from regions with a high population density to one with a low population density, from economically developed regions to economically backward ones, and from the eastern coastal regions to the central agriculturally developed provinces and then to the southwest, northwest and northeast regions. This manuscript studies the vulnerability at provincial scale in China, plays a guiding role in improving the disaster resistance ability of local governments, and puts forward feasible research ideas for the follow-up vulnerability research.

Data availability

All data, models, and code generated or used during the study appear in the manuscript.

Author contributions

Conceptualization, W.L. and J.Y.; methodology, J.L. and W.G.; validation W.L. and H. Z.; formal analysis, W.L. and W.G.; investigation, W. L. and J.Y.; writing—original draft preparation, W.L.; writing—review and editing, W.L. and W.G.; supervision, Y.T.; funding acquisition, W.L.

Competing interests

The contact author has declared that neither they nor their co-authors have any competing interests.

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References

Adikari, Y.; Osti, R.; Noro, T. Flood-related disaster vulnerability: an impending crisis of megacities in Asia. J. Flood Risk Manag. 2010, 3(3), 185-191. https://doi.org/10.1111/j.1753-318X.2010.01068.x

Bankoff, G. Comparing vulnerabilities: Toward charting an historical trajectory of disasters. Hist. Social Res. 2007, 32(3 (121)), 103-114.

Blien, U.; Hirschenauer, F. A new classification of regional labour markets in Germany. Letters Spat. Resour. Sci. 2018, 11(1), 17-26. https://doi.org/10.1007/s12076-017-0194-x

Chang, H.; Chen, T. Spatial heterogeneity of local flood vulnerability indicators within flood-prone areas in Taiwan. Environ. Earth Sci. 2016, 75(23), 14-84. https://doi.org/10.1007/s12665-016-6294-x

Chen, Y.; Li, J.; Chen, A. Does high risk mean high loss: Evidence from flood disaster in southern China. Sci. Total Environ. 2021, 785, 147127. https://doi.org/10.1016/J.SCITOTENV.2021.147127

Cardona, O.; Carreño, M. Updating the Indicators of Disaster Risk and Risk Management for the Americas. J. Integr. Disaster Risk Manag. 2011, 1(1). https://doi.org/10.5595/idrim.2011.0014

Cutter, S. Vulnerability to environmental hazards. Progress in Human Geography, 1996, 20(4), 529-539.

Census Office of the State Council. Tabulation on the 2010 population census of the People's Republic of China. China Statistics Press, Beijing. 2012.

Duo, E.; Fernandez-Montblanc, T.; Armaroli, C. Semi-probabilistic coastal flood impact analysis: from deterministic hazards to multi-damage model impacts. Environ. Int. 2020, 143, 105-884. https://doi.org/10.1016/j.envint.2020.105884

Du, P.; Xu, S.; Wu, M. Rural Migrant Workers' Welfare and Labor Protection in China under the Labor Contract Law. China Econ. 2019, 14(02), 83-96. https://doi.org/10.19602/j.chinaeconomist.2019.3.07

Ge, W.; Sun, H.; Zhang, H.; Li, Z.; Gelder, P. Economic risk criteria for dams considering the relative level of economy and industrial economic contribution. Sci. Total Environ. 2020, 725, 138-139. https://doi.org/10.1016/j.scitotenv.2020.138-139

Ge, W.; Wang, X.; Li, Z.; Zhang, H.; Guo, X.; Wang, T.; Gao, W.; Lin, C.; Gelder, P. Interval analysis of loss of life caused by dam failure. J. Water Res. Plan. Man. 2021, 147(1), 0402-0098. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001311

https://doi.org/10.5194/nhess-2022-136
Preprint. Discussion started: 7 June 2022

Ge, W.; Li, Z.; Liang, R.; Li, W.; Cai, Y. Methodology for Establishing Risk Criteria for Dams in Developing Countries, Case Study of China. Water Resour. Manag. 2017, 31, 4063–4074. https://doi.org/10.1007/s11269-017-1728-0

Ge, W.; Sun, H.; Zhang, H.; Li, Z.; Gelder, P. Economic risk criteria for dams considering the relative level of economy and industrial economic contribution. Sci. Total Environ. 2020, 725, 138-139. https://doi.org/10.1016/j.scitotenv.2020.138-139

Ge, W.; Li, Z.; Li, W.; Wu, M.; Li, J.; Pan, Y. Risk evaluation of dam-break environmental impacts based on the set pair analysis and cloud model. Nat. Hazards. 2020, 104, 1641-1653. https://doi.org/10.1007/s11069-020-04237-9

Guo, Y. Natural disasters and social vulnerability. China social sciences press, Beijing. 2013.

Gruijters, S.; Fleuren, B. Measuring the unmeasurable. Human Nat. 2017, 29(1), 33-44. https://doi.org/10.1007/s12110-017-9307-x

Li, Z.; Zhang, Y.; Wang, J.; Ge, W.; Li, W.; Song, H.; Guo, X.; Wang, T.; Jiao, Y. Impact evaluation of geomorphic changes caused by extreme floods on inundation area considering geomorphic variations and land use types. Sci. Total Environ. 2021, 754, 142-424. https://doi.org/10.1016/j.scitotenv.2020.142424

Tebaldi, C.; Hayhoe, K.; Arblaster, J.; Meehl, G. Going to the extremes. Clim. Change. 2006, 79, 185-211. https://doi.org/10.1007/s10584-006-9051-4

Li, W.; Li, Z.; Ge, W.; Wu, S. Risk Evaluation Model of Life Loss Caused by Dam-Break Flood and Its Application. Water. 2019, 11(7), 1359. https://doi.org/10.5194/nhess-9-1881-2009

Li, Z.; Li, W.; Ge, W. Weight analysis of influencing factors of dam break risk consequences. Nat. Hazards Earth Syst. Sci. 2018, 18(12), 3355-3362. https://doi.org/10.5194/nhess-18-3355-2018

Li, W.; Li, Z.; Ge, W.; Zhang, H. Environmental impact evaluation model of dam breach-considering the uncertainty feature of environment. Desalin. Water Treat. 2020, 183, 131-138. https://doi.org/10.5004/dwt.2020.25205

Lee, D.; Ahmadul, H.; Patz. J.; Block, P. Predicting social and health vulnerability to floods in Bangladesh. Nat. Hazards Earth Syst. Sci. 2021, 21(6), 1807–1823. https://doi.org/10.5194/nhess-21-1807-2021

Liu, D. and Li, Y. Social vulnerability of rural households to flood hazards in western mountainous regions of Henan province, China, Nat. Hazards Earth Syst. Sci. 2016, 16(5), 1123–1134. https://doi.org/10.5194/nhess-16-1123-2016.

https://doi.org/10.5194/nhess-2022-136
Preprint. Discussion started: 7 June 2022

Li, Z., Li, W., Ge, W., Xu, H, Dam breach environmental impact evaluation based on set pair analysis-variable fuzzy set coupling model. Journal of tianjin university (science and technology). 2019, 52(03), 49-56

Moreira, L.; de Brito, M.; Kobiyama, M. Review article: A systematic review and future prospects of flood vulnerability indices, Nat. Hazards Earth Syst. Sci. 2021, 21(5), 1513–1530. https://doi.org/10.5194/nhess-21-1513-2021, 2021.

Min, K.; Song, K.; Chon. J. Key coastal landscape patterns for reducing flood vulnerability. Sci. Total Environ. 2021, 759, 143454. https://doi.org/10.1016/j.scitotenv.2020.143454

Muller, A. Flood risks in a dynamic urban agglomeration: a conceptual and methodological assessment framework. Nat. Hazards. 2013, 65(3), 1931-1950. https://doi.org/10.1007/s11069-012-0453-5

Ministry of Civil Affairs of the People's Republic of China. China civil affairs statistical yearbook2010, China Statistics Press, Beijing. 2010.

Ministry of Civil Affairs of the People's Republic of China. Grading methods of natural disaster risk, 2012. MZT031-2012. Standards Press of China, Beijing. 2012.

National Bureau of Statistics of the People's Republic of China. China statistical yearbook 2010, China Statistics Press, Beijing. 2010.

National Bureau of Statistics of the People's Republic of China. China regional economic statistics yearbook 2010. China Statistics Press, Beijing. 2010.

Ritter, J.; Berenguer, M.; Corral, C.; Park, S.; Sempere-Torres, D. Reaffirm: real-time assessment of flash flood impacts - a regional high-resolution method. Environ. Int. 2020, 136, 105-375. https://doi.org/10.1016/j.envint.2019.105375

Resource and Environment Science and Data Center. https://www.resdc.cn/.

The national disaster reduction Commission and the emergency management department have sent a working group to the disaster area to launch the national level IV disaster relief emergency response in Sichuan and Gansu provinces. Ministry of Emergency Management of the People’s Republic of China. 2018. http://www.mem.gov.cn/xw/zhsgxx/201807/t20180712_242461.shtml

Seo, J.; Seongjin, H.; Seonju, K.; Jongmin, L.; Taewoo, K.; Beomgi, k.; Bong-Oh, K.; Zhou, Y.; Shi, B.; Liu, P.; Hu, W.; Huang, B.; Wang, T.; Jong, S. Large-scale monitoring and ecological risk assessment of persistent toxic substances in riverine, estuarine, and coastal sediments of the yellow and bohai seas. Environ. Int. 2020, 137, 105-517. https://doi.org/10.1016/j.envint.2020.105517

Sheng, L.; Ye, Z. China Statistical Yearbook for Regional Economy. China Statistics Press, Beijing. 2014.

Samuel, M.; Mirjam, S. Hiring costs and labor market tightness. Labour Econ. 2018, 52, 122-131. https://doi.org/10.1016/j.labeco.2018.04.010

Scheuer, S.; Haase, D.; Meyer, V. Exploring multicriteria flood vulnerability by integrating economic, social and ecological dimensions of flood risk and coping capacity: from a starting point view towards an end point view of vulnerability. Nat. Hazards. 2011, 58(2), 731-751. https://doi.org/10.1007/s11069-010-9666-7

The national disaster reduction Commission and the emergency management department urgently launched the national level IV disaster relief emergency response for the rainstorm and flood disaster in Jiangxi. Ministry of Emergency Management of the People's Republic of China. 2019. http://www.mem.gov.cn/xw/bndt/201906/t20190609_298949.shtml

The national headquarters of flood control has launched level III emergency response for flood control and disaster relief in Henan Province, and has sent a working group to the site to assist in flood fighting and rescue. Ministry of Emergency Management of the People's Republic of China. 2021. http://www.mem.gov.cn/xw/bndt/202107/t20210720_392440.shtml

Taylor, J.; Lai, K.; Davies, M.; Clifton, D.; Ridley, I.; Biddulph, P.; Flood management: prediction of microbial contamination in large-scale floods in urban environments. Environ. Int. 2011, 37(5), 1019-1029. https://doi.org/10.1016/j.envint.2011.03.015

Tanner, A.; Arvai, J.; Perceptions of Risk and Vulnerability Following Exposure to a Major Natural Disaster. The Calgary Flood of 2013. Risk Anal. 2018, 38(3), 548-561. https://doi.org/10.1111/risa.12851

Taylor, J.; Biddulph, P.; Davies, M.; Lai, K. Predicting the microbial exposure risks in urban floods using gis, building simulation, and microbial models. Environ. Int. 51(JAN.), 2013, 182-195. https://doi.org/10.1016/j.envint.2012.10.006

Yu, H., Shen, Y., Kelly, R. M., et al. Trends in social vulnerability to storm surges in Shenzhen, China, Nat. Hazards Earth Syst. Sci. 2020, 20(9), 2447–2462. https://doi.org/10.5194/nhess-20-2447-2020.

You, W. and Zhang, Y. Evaluation of social vulnerability to floods in Huaihe River basin: a methodology based on catastrophe theory, Nat. Hazards Earth Syst. Sci. Discuss. 2015, 3(8), 4937–4965. https://doi.org/10.5194/nhessd-3-4937-2015.

https://doi.org/10.5194/nhess-2022-136
Preprint. Discussion started: 7 June 2022

Natural Hazards and Earth System Sciences Discussions

Ziegler, A.; Cantarero, S.; Wasson, R.; Srivastava, P.; Spalzin, S.; Chow, W.; Gillen, J. A clear and present danger: Ladakh's increasing vulnerability to flash floods and debris flows. Hydrol. Processes. 2016, 30(22), 4214-4223. https://doi.org/10.1002/hyp.10919

Zhang, N.; Song, D.; Zhang, J.; Liao, W.; Huang, C. The impact of the 2016 flood event in anhui province, china on infectious diarrhea disease: an interrupted time-series study. Environ. Int. 2019, 127. https://doi.org/10.1016/j.envint.2019.03.063

Zeng, J.; Zhu, Z.; Zhang, J.; Ouyang, T.; Qiu, S.; Zou, T.; Zeng, T. Social vulnerability assessment of natural hazards on county-scale using high spatial resolution satellite imagery: a case study in the Luogang district of Guangzhou, South China. Environ. Earth. Sci. 2012, 65(1), 173-182. https://doi.org/10.1007/s12665-011-1079-8

Zhang, M. Research on the Assessment of Disaster-carrying Capability and Disaster Comprehensive Risk in Urban Place. Dalian University of Technology. 2008.

Zhang, P.; Li, N. The Standardization of Natural Disasters Risk Grading Methods in China. J. Catastrophol. 2014, 29(2), 60-64.