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Research article

Spatial and temporal changes of social vulnerability of cities to natural hazards in Zhejiang province, China

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ABSTRACT

Understanding how social dynamics interact with natural hazards is one of the main challenges at global and local scales in the world for studying social vulnerability to natural hazards. In this study, we explore the spatial and temporal changes of social vulnerability of cities in Zhejiang province to natural hazards in China for the last decade. Based on the Zhejiang province's census data and the demographics and socioeconomic data during the period from 2009 to 2018, we have characterized social vulnerability through the Social Vulnerability Index (SoVI) for 11 cities throughout the province during 2009–2018 and examined spatial changes in social vulnerability using equal interval method. The results indicated that although the comprehensive vulnerability of Zhejiang province shows a declining trend at a county level, the social vulnerability of different city at the provincial level has obvious differences.

1. Introduction

How to deal with natural hazards and reduce its negative impact on human society has become a core issue in the world [1–3]. With the in-depth research on the prevention and reduction of disasters, a series of study on vulnerability, which was first proposed by Timmerman (1981) [4] and defined as the susceptibility of a system to be impacted by a disaster, has increased in recent 20 years [5–8], although its definition changes according to the discipline [9,10]. Because vulnerability is the result among the social, cultural, and political processes, so it tends to change over time and space [11]. Furthermore, vulnerability can be mainly divided into natural vulnerability and social vulnerability [12–14]. The latter mainly studies an inherent property of a system arising from its internal characteristics [15] and the adaptability and resilience of human society in the face of natural hazards [16]. In recent years, a considerable body studies have applied the social vulnerability index (SoVI) to quantify and visualize the spatial distribution of vulnerability using the census data, environmental indicators, or economic development indicators [12], which has emerged at local, regional to national scales in the world [16–24].

With the development of the urbanization and economy, China has been frequently damaged by kinds of natural hazards with significant casualties and economic losses, such as flood hazards and forest fire hazard [25–28], especially in its cities [27]. Cities can easily be at risk of disasters owing to the dense population and high concentration of social wealth. Therefore, there have been limited attempts to study social vulnerability among cities in China for developing better disaster risk reduction planning and practice. Although the vulnerability of cities to environmental hazards has been studied in America [29], the developed country is not entirely

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applicable to the China's situation, despite providing some useful references. Moreover, few studies on the social vulnerability to natural hazards in China only occurred in a city [30,31]. Thus, it is highly required to fill the gap by revealing the spatial and temporal changes of social vulnerability of cities to natural hazards in China at the provincial level. Zhejiang province is used as a case study owing to its significant disaster risk [28,32,33] and heterogeneous social environments of cities, which has great significance for improving the disaster resistance capacity and management level of the whole province in future decades. The framework of SoVI [12] is used to analyze social vulnerability at the city level. The spatial-temporal changes in SoVI from 2009 to 2018 at the city level are quantified using the software platform of ArcGIS 10.2 (spatial statistic tools).

2. Materials and methods

2.1. Study area

Zhejiang province is a region heavily populated, most developed province and located in the Yangtze River Delta of Southeast China (Fig. 1). It covers a total area of 101,800 km^2. Administratively, Zhejiang province includes 11 cities, namely, Hangzhou city, Ningbo city, Wenzhou city, Jiaxing city, Huzhou city, Shaoxing city, Jinhua city, Quzhou city, Zhoushan city, Taizhou city, and Lishui city. The total population of Zhejiang province was 57.37 million in 2018.

On the other hand, Zhejiang province is also highly exposed to the occurrence of multiple natural hazards. According to the classification standards of natural hazards in China [34], the natural hazards in Zhejiang province mainly include 4 types from 2009 to 2018, namely meteorological and hydrological hazards (drought, flood, typhoon, lightning, low temperature, as well as snow and ice), geological hazards (landslide, collapse, debris flow, and ground collapse), marine hazards (storm surge, wave, and red tide), and biological hazards (plant diseases and pests, forest fire), all of which have caused many casualties and direct economic losses in recent years. For example, during 2000–2016, the occurrences of forest fire hazard were 6,848 times in Zhejiang province causing economic losses over RMB 0.233 billion yuan [28,32], which belongs to biological hazards and are the most recurrent natural hazards in recent decades. Moreover, forest fire hazards occurred most frequently in Wenzhou city and Lishui city, but least in Jiaxing city [28]. On the other hand, a total of 1,099 marine hazards occurred in Zhejiang province from 2000 to 2016 and caused about 275 deaths or missing direct economic losses RMB 18.544 billion yuan [33]. Moreover, marine hazards occurred most frequently in Wenzhou city, Taizhou city, Ningbo city, and Zhoushan city [33]. Over the past 50 years, Zhejiang province has occurred more than 26 droughts, 18 floods, 39 typhoons causing direct economic losses over RMB 88 billion yuan and affecting more than 10,000 people [35]. Additionally, geological hazards are the second recurrent natural hazards in Zhejiang province from 2000 to 2018, occurring 5,491 times and causing economic losses over RMB 0.878 billion yuan [36]. All the natural hazards in Zhejiang province are caused by both natural factors (climatic factor, topographic factor, and hydrologic factor) and social factors including the engineering activity, anthropogenic factor, and resource extraction.

2.2. Data sources

Because the social vulnerability of natural hazards changes with the development of society and economy, to assessed and quantify

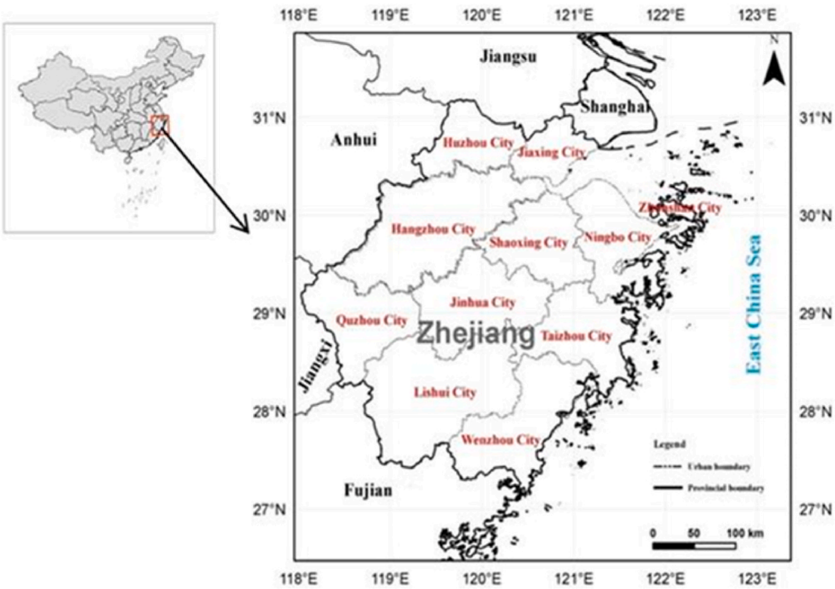

Fig. 1. Location and administrative divisions of Zhejiang province.

the temporal–spatial changes of social vulnerability of cities in Zhejiang province, the annual socioeconomic and demographic data during the period of 2009–2018 were used. These data were obtained from the Zhejiang Statistical Yearbook (2010–2019), the Statistical Yearbook of each city in Zhejiang province (2010–2019), and the Zhejiang's Natural Resources and Environment Statistical Yearbook (2010–2019). These statistical data not only include variables representing the socioeconomic characteristics (e.g. GDP, percentage of the tertiary industry, and Per capita total expenditure), but also include the variables, such as green coverage of built-up area and density of domestic highway, which represent sociocultural characteristics.

2.3. Selection of variables for SoVI analysis

2.3.1. Construction of evaluation index system

According to the previous SoVI studies [12], especially of city level assessments in China [19,30,31,37], the present situation of natural geography, social economy and natural hazards in Zhejiang province, and the variables used for appraising paradigmatic neighborhoods of disaster governance in China [38]. Moreover, we had to select these variables accessible at a city level. On the other hand, many indicators permit to quantify the complexity connected with social vulnerability. Previous studies recognize the demographic variables, economic variables, and so on, as the significant factors affecting vulnerability [31,39,40]. Based on the above mentioned, 28 evaluation indexes were selected preliminarily from four aspects of social population, social economy, social structure and social culture. Then the social vulnerability assessment system of Zhejiang province based on natural hazards was established (Table 1).

2.3.2. Selection of variables

Based on the social and economic statistics data for each city of Zhejiang province in 2018, the evaluation indexes of social vulnerability based on natural hazards were screened. First, the 28 evaluation indicators (Table 1) were standardized; second, the indicators were screened by Pearson correlation analysis, and the indicators with repeated information were eliminated; then, the evaluation indicators were analyzed by principal component analysis (PCA); Finally, the final evaluation index of social vulnerability in Zhejiang province was obtained by deleting the evaluation index with smaller factor load.

2.3.2.1. Standardization of indicators

$$\text{Positive indicator}: Z_{ij} = \frac{X_{ij} - X_{j\,\min}}{X_{j\,\max} - X_{j\,\min}};\ \text{Negative indicator}: Z_{ij} = \frac{X_{j\,\max} - X_{ij}}{X_{j\,\max} - X_{j\,\min}} \tag{1}$$

Table 1
Evaluation system of social vulnerability to natural hazards in Zhejiang province.

Field	Factor	Evaluation index	Positioning with respect to vulnerability
Social population	Population pressure	Z_1: Natural population growth rate (‰)	Positive
		Z_2: Population density (person/km^2)	Positive
	Disadvantaged group	Z_3: Proportion of female population (%)	Positive
		Z_4: Proportion of the population under the age of 18 (%)	Positive
		Z_5: Proportion of population over 60 years old (%)	Positive
		Z_6: Number of primary school students (10,000)	Positive
		Z_7: Unemployed population (10,000)	Positive
		Z_8: Employees of primary industry (10,000)	Positive
Social economy	Economic development	Z_9: Per capita gross regional product (RMB 10,000 yuan)	Negative
		Z_{10}: Economic density (RMB 10^8 yuan/km^2)	Negative
		Z_{11}: Proportion of built-up area (%)	Negative
		Z_{12}: Percentage of the tertiary industry (%)	Negative
	Revenue and expenditure	Z_{13}: Total revenue (RMB 10,000 yuan)	Negative
		Z_{14}: Per capita total revenue (RMB 10,000 yuan)	Negative
		Z_{15}: Total expenditure (RMB 10,000 yuan)	Negative
		Z_{16}: Per capita total expenditure (RMB 10,000 yuan)	Negative
Social structure	Social security	Z_{17}: Number of health technician per 10,000 persons	Negative
		Z_{18}: Number of medical beds per 10,000 persons	Negative
		Z_{19}: Number of medical and health institutions	Negative
		Z_{20}: Proportion of urban and rural residents participating in basic endowment insurance (%)	Negative
		Z_{21}: Number of urban minimum living allowance residents	Negative
		Z_{22}: Per capita expenditure on social security and employment (RMB 10,000 yuan)	Negative
	Social capital	Z_{23}: Average annual wage of on-the-job workers (RMB 10,000 yuan)	Negative
Social culture	Social civilization	Z_{24}: Proportion of students in school (%)	Negative
		Z_{25}: Number of teachers per 10,000 persons	Negative
	Culture of disaster resistance	Z_{26}: Green coverage of built-up area (%)	Negative
		Z_{27}: Per capita area of green space (m^2)	Negative
		Z_{28}: Density of domestic highway (km/10,000 persons)	Negative

In the evaluation system, because the dimension of each evaluation index is different, it will affect the evaluation results when the level of difference between the indicators is large. In order to ensure the accuracy of the evaluation results, the range standardization method is used in this study to process the original data.

where Z_{ij}、X_{ij}、$X_{j\ \min}$、$X_{j\ \max}$ respectively are the normalized value, original value, minimum value and maximum value of the ith city in the jth indicator, thereby obtaining the normalized numerical matrix Z:

$$Z = \begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{1n} \\ Z_{21} & Z_{22} & \cdots & Z_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ Z_{m1} & Z_{m2} & \cdots & Z_{mn} \end{bmatrix} \tag{2}$$

where m is the number of cities, and n is the number of indicator.

2.3.2.2. Pearson correlation analysis. In this study, we use the software for SPSS 20.0 to perform the first index screening. Firstly, according to the test results, the 28 indexes are all normal distribution data, so we can do Pearson correlation analysis to test the correlation between indexes. Then we deal with the standardized index data by the method of Pearson correlation analysis, thereby obtaining the Pearson correlation coefficient matrix (Table A, Supplementary information). It is generally considered that the greater the absolute value of correlation coefficient is, the stronger the correlation between indicators is. When the correlation coefficient is between 0.8 and 1.0, it is generally considered to be very strong correlation, indicating that the correlation between indicators is very strong, there is duplication of response information, and some indicators need to be eliminated so as to make the indicator system concise and clear. The following requirements should be paid attention to when screening indicators: (1) the correlation coefficient between the excluded indicators and other indicators is greater than 0.8; (2) the P value between the excluded indicators and other indicators is less than 0.05; (3) compared with the other indexes in the same layer, the eliminated indexes have less influence on the criterion layer.

According to the above mentioned and the Pearson correlation coefficient matrix (Table A, Supplementary information), the index Z_4 has strong correlation with the Z_1, Z_3, Z_5, Z_8 and Z_{24}, respectively, so the Z_4 is excluded from the evaluation system (Table 1). Similarly, the index Z_{24} has strong correlation with the Z_8 and Z_{25}, respectively, so the Z_{24} is excluded; the index Z_{22} has strong correlation with the Z_{16} and Z_{23}, respectively, so the Z_{22} is excluded; the index Z_5 has strong correlation with the Z_3 and Z_8, respectively, so the Z_5 is excluded; the index Z_{10} has strong correlation with the Z_2, Z_9 and Z_{11}, respectively, so the Z_{10} is excluded; the index Z_{20} has strong correlation with the Z_{17}, Z_{18} and Z_{25}, respectively, so the Z_{20} is excluded; the index Z_{13} has strong correlation with the Z_7, Z_{14} and Z_{15}, respectively, so the Z_{13} is excluded. On the other hand, compared with the index Z_{14}, the Z_9 can better reflect a region's economic power, so the Z_{14} is excluded. Because just enough health technicians are needed to treat the affected population in the process of disaster relief, therefore, the Z_{18} (Number of medical beds per 10,000 persons) is excluded from the evaluation system compared with the index Z_{17} (Number of health technician per 10,000 persons).

Moreover, because there are already the Z_{17} and the Z_{18} as well as Z_{19} at the social level may cause the information to overlap, the Z_{19} (Number of medical and health institutions) is excluded from the evaluation system compared with the index Z_6 (Number of primary school students). On the other hand, compared with the index Z_2 (Population density), the Z_{11} (Proportion of built-up area) is a better index for evaluating a region's economic development level, so the Z_2 is excluded from the evaluation system; but compared with the index Z_3 (Proportion of female population), the effect of Z_{11} on target layer is more obvious than that of Z_3, so the Z_3 is excluded from the evaluation system. In addition, from the point of view of the Z_7 (Unemployed population) versus Z_{15} (Total expenditure), because the Z_{16} (Per capita total expenditure) and Z_{15} have similarities, there may be duplication of information, so the Z_{15} is excluded from the evaluation system (Table A, Supplementary information).

Table 2
Original evaluation indexes of social vulnerability in Zhejiang province.

Field	Factor	Evaluation indicator	Positioning with respect to vulnerability
Social population	Population pressure	Z_1: Natural population growth rate (‰)	Positive
	Disadvantaged group	Z_6: Number of primary school students (10,000)	Positive
		Z_7: Unemployed population (10,000)	Positive
		Z_8: Employees of primary industry (10,000)	Positive
Social economy	Economic development	Z_9: Per capita gross regional product (RMB 10,000 yuan)	Negative
		Z_{11}: Proportion of built-up area (%)	Negative
		Z_{12}: Percentage of the tertiary industry (%)	Negative
	Revenue and expenditure	Z_{16}: Per capita total expenditure (RMB 10,000 yuan)	Negative
Social structure	Social security	Z_{17}: Number of health technician per 10,000 persons	Negative
		Z_{21}: Number of urban minimum living allowance residents	Negative
	Social capital	Z_{23}: Average annual wage of on-the-job workers (RMB 10,000 yuan)	Negative
Social culture	Social civilization	Z_{25}: Number of teachers per 10,000 persons	Negative
	Culture of disaster resistance	Z_{26}: Green coverage of built-up area (%)	Negative
		Z_{27}: Per capita area of green space (m^2)	Negative
		Z_{28}: Density of domestic highway (km/10,000 persons)	Negative

Based on the above mentioned, the 13 indicators should be eliminated and 15 indexes should be retained through Pearson correlation analysis, thereby getting the original evaluation indexes of social vulnerability in Zhejiang province (Table 2).

2.3.2.3. Principal component analysis (PCA). Based on the Pearson correlation analysis, we use the software for SPSS 20.0 to perform second index screening and to analyze the selected 15 indexes using the Principal component analysis (PCA). The general principle of extracting the number of principal components is to select the eigenvalue >1 as well as the cumulative variance contribution rate >85%. As shown in Table 3, we can obtain the first 5 principal components representing 89.90% of all indexes. Further, we analyze the first 5 principal components and obtain the load matrix of each principal component (Table 4).

Because the load value of the index is an important criterion to measure the influence of the evaluation index on the evaluation result, it is generally believed that the greater the absolute value of the index load, the clearer the interpretation of the principal component, and the more the index should be retained. As shown in Tables 4 and in the first principal component, the indexes with larger absolute value of load are Z_8, Z_1 and Z_{25}, respectively. Similarly, in the second principal component, the indexes with larger absolute value of load are Z_{17}, Z_{23}, Z_{16} and Z_{12}, respectively; in the third principal component, the indexes with larger absolute value of load are Z_{28}, Z_7, Z_6 and Z_9, respectively; in the fourth and fifth principal components, the indexes with larger absolute value of load are Z_{21} and Z_{26}, respectively. Finally, the 13 indexes are selected as the final evaluation variables for the assessment of social vulnerability in Zhejiang province from annual statistical data set with the consideration of real situations of Zhejiang province (Table 5). These raw variables were selected from the perspectives of social population, socioeconomic status, social structure, and sociocultural status, which included the following 8 major factors, namely population pressure, disadvantaged group, economic development, revenue and expenditure, social security, social capital, social civilization, and culture of disaster resistance (Table 5).

(1) **Social population.** Social population includes both population pressure and disadvantaged group factors. In this field, the selected variables include age and gender which reflect the unique needs of some groups to cope with a disaster [40,41], unemployed population and the number of students which would translate into greater social vulnerability to hazards [11,12] (Table 2).
(2) **Socioeconomic status.** Socioeconomic status indicates the capacities to cope with and recover from losses caused by natural hazards, which includes both economic development and revenue and expenditure factors. Therefore, a low socioeconomic level intimates greater difficulties in handling a disaster and accordingly higher levels of vulnerability [42,43]. In this field, the variables such as per capita gross regional product, economic density, and per capita total revenue were included (Table 2).
(3) **Social structure.** Social structure is another field related to vulnerability. It is typically associated with the social security and social capital. The former both enhances abilities to resist disaster and increases **capacities** of resilience [12]. This field was represented by such number of health technician per 10,000 persons, number of medical and health institutions, and average annual wage of on-the-job workers as variables in this study.
(4) **Sociocultural status.** Sociocultural **status** represents the knowledge or awareness of population to natural hazards and emergency capability. Higher educational levels indicate a greater capacity to understand information and therefore associated with a lower level of vulnerability [44,45]. To characterize sociocultural status, the variables measuring the number of people in the population with higher educational levels were used.

All 13 variables were normalized by using correlation coefficient method and the weight of evaluation indicators was calculated by the variation coefficient method [46–48] to calculate the SoVI. These variables were mainly obtained from the 2010–2019 census data at the city level of Zhejiang province [36,49], which include both variables indicating socioeconomic status (e.g. GDP, population and employment) and variables representing sociocultural status (e.g. green space and coverage).

2.4. Weight calculation of variables for SoVI analysis

This study used entropy method [50] to calculate the weights of variables. First, we eliminate the differences both positive and negative indicators by dimensionless data processing.

$$\text{Positive indicator}: Z_{ij} = \frac{X_{ij}}{X_{j\max}} \quad \text{Negative indicator}: Z_{ij} = \frac{X_{j\min}}{X_{ij}} \quad (\mathrm{i}=1,2,\ldots,\mathrm{m};\ \mathrm{j}=1,2,\ldots,\mathrm{n}) \tag{3}$$

where Z_{ij}, X_{ij}, $X_{j\max}$ and $X_{j\min}$ respectively are the normalized value, original value, maximum value and minimum value of the *i*th city in the *j*th variable.

Table 3
Eigenvalue and variance contribution rate.

Principal component	Eigenvalue	Variance contribution rate (%)	Cumulative variance contribution rate (%)
1	4.368	29.123	29.123
2	3.300	22.002	51.125
3	3.138	20.921	72.045
4	1.527	10.183	82.228
5	1.151	7.673	89.901

Table 4
Load matrix of each principal component.

Principal component Index	1	2	3	4	5
Z_1	0.831	-.086	0.152	0.092	0.406
Z_6	0.593	-.020	0.764	0.037	-.108
Z_7	0.036	-.078	0.824	0.440	-.245
Z_8	0.904	0.128	0.058	-.280	-.088
Z_9	0.477	0.492	-.628	-.185	0.230
Z_{11}	0.622	-.157	-.605	-.017	-.290
Z_{12}	-.363	0.624	-.161	0.581	0.099
Z_{16}	0.489	0.762	0.265	-.186	-.143
Z_{17}	-.171	0.887	-.086	0.109	0.234
Z_{21}	0.362	-.076	-.091	0.788	-.091
Z_{23}	-.026	0.837	0.166	-.216	-.283
Z_{25}	-.827	0.490	0.045	.009	0.125
Z_{26}	0.286	-.071	0.500	-.012	0.750
Z_{27}	0.709	0.517	-.003	.264	-.110
Z_{28}	-.305	0.171	0.836	-.299	-.084

Table 5
Fields, factors and final variables for the assessment of social vulnerability.

Field	Factor	Variable	Index number	Positioning with respect to vulnerability
Social population (4)	Population pressure	V_1: Natural population growth rate (‰)	Z_1	Positive
	Disadvantaged group	V_2: Number of primary school students (10,000)	Z_6	Positive
		V_3: Unemployed population (10,000)	Z_7	Positive
		V_4: Employees of primary industry (10,000)	Z_8	Positive
Socioeconomic status (3)	Economic development	V_5: Per capita gross regional product (RMB 10,000 yuan)	Z_9	Negative
		V_6: Percentage of the tertiary industry (%)	Z_{12}	Negative
	Revenue and expenditure	V_7: Per capita total expenditure (RMB 10,000 yuan)	Z_{16}	Negative
Social structure (3)	Social security	V_8: Number of health technician per 10,000 persons	Z_{17}	Negative
		V_9: Number of urban minimum living allowance residents	Z_{21}	Positive
	Social capital	V_{10}: Average annual wage of on-the-job workers (RMB 10,000 yuan)	Z_{23}	Negative
Sociocultural status (3)	Social civilization	V_{11}: Number of teachers per 10,000 persons	Z_{25}	Negative
	Culture of disaster resistance	V_{12}: Green coverage of built-up area (%)	Z_{26}	Negative
		V_{13}: Density of domestic highway (km/10,000 persons)	Z_{28}	Negative

Next, the weight (Y) of index value of the jth variable in the ith city can be calculated as follows:

$$Y_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{m} Z_{ij}} \ (\mathrm{i}=1,2,\ldots,\mathrm{m};\ \mathrm{j}=1,2,\ldots,\mathrm{n}) \tag{4}$$

Then, the equation to calculate the entropy value (E) of the jth variable is listed as follows:

$$E_j = -K\sum_{i=1}^{m} Y_{ij} \ln Y_{ij}\ K = \frac{1}{\ln m}, E_j \geq 0 \ (\mathrm{i}=1,2,\ldots,\mathrm{m};\ \mathrm{j}=1,2,\ldots,\mathrm{n}) \tag{5}$$

Further, the difference coefficient (d) of the jth variable is calculated by the following equation:

$$d_j = 1 - E_j \ (\mathrm{j}=1,2,\ldots,\mathrm{n}) \tag{6}$$

Last, the equation to calculate the weight (W) of the jth variable is listed as follows:

$$W_{\mathrm{j}} = \frac{d_j}{\sum_{j=1}^{n} d_j} \ (\mathrm{j}=1,2,\ldots,\mathrm{n}) \tag{7}$$

The index weight of social vulnerability assessment in Zhejiang province from 2009 to 2018 was obtained by using the method of entropy value calculated by Excel (Table 6).

3. Results and discussion

Based on the above equations (3)–(7) (i = 1, 2, …, 11; j = 1, 2, …, 13), the SoVI of all 11 cities as well as the whole Zhejiang province from 2009 to 2018 in social population (Table B1, Supplementary information), socioeconomic status (Table B2, Supplementary information), social structure (Table B3, Supplementary information), sociocultural status (Table B4, Supplementary information) and comprehensive SoVI (Table B5, Supplementary information) were obtained. Further, social vulnerability to natural hazards in Zhejiang province from 2009 to 2018 was classified into 5 grades using equidistant grading (Table B6, Supplementary information).

3.1. Temporal–spatial distribution of social vulnerability in social population from 2009 to 2018

As shown in Figs. 2a and 3, from 2009 to 2018, Hangzhou city, Ningbo city, Wenzhou city, Jinhua city and Taizhou city have higher levels of vulnerability in social population, but Huzhou city and Zhoushan city have lower levels of vulnerability. The reason is in close relation to both the natural population growth rate and amount of disadvantaged group. In the studied period, the natural population growth rate in Hangzhou city, Ningbo city, Wenzhou city, Jinhua city and Taizhou city is higher in the whole Zhejiang province, respectively. Moreover, the number of primary school students, unemployed population and employees of primary industry among these cities are at the forefront of the whole Zhejiang province. Additionally, Ningbo city is the highest in the unemployed population from 2009 to 2018 and Wenzhou city is the highest in both the natural population growth and number of primary school students from 2009 to 2018. These cause higher levels of vulnerability in social population among Hangzhou city, Ningbo city, Wenzhou city, Jinhua city and Taizhou city.

On the other hand, as shown in Fig. 2f, the overall vulnerability index of social population of Zhejiang province shows a downward trend, among which 2009–2016 shows a state of volatility, and 2016–2018 shows a downward trend of volatility. In 2009, the largest number of primary industry employees in the province was 6.427 million, making them more vulnerable to natural hazards and resulting in the highest social population vulnerability index of Zhejiang province. Moreover, the natural population growth rate in 2017 was 6.36 per thousand, up from 5.70 per thousand in 2016, however, the number of primary school students, the number of unemployed population and the number of employees of primary industry fell from 3.55 million, 299,300 and 4,920,300 in 2016 to 3.54 million, 298,600 and 4,862,800 in 2017, respectively. Therefore, the social population vulnerability index has declined greatly, causing the lowest social population vulnerability index of Zhejiang province in 2017.

Moreover, the natural population growth in Huzhou city and Zhoushan city is lower; the number of primary school students, unemployed population and employees of primary industry in these two cities are lower in the whole province (e.g. the number of primary school students and employees of primary industry in Zhoushan city is the lowest from 2009 to 2018). These are beneficial to the stability of society, thereby lowering the level of vulnerability in social population in both Huzhou city and Zhoushan city.

Additionally, the SoVI of social population from 2009 to 2018 shows a decreasing trend from the provincial level (Fig. 2f). Because the number of primary industry employees who are more vulnerable to natural hazards in 2009 was the largest in the study period, exceeding 642.7×10^4 persons, the SoVI of social population was the highest in this year. But the SoVI of social population was the lowest in 2017 owing to the decreasing of the numbers in primary school students, unemployed population, and employees of primary industry (Fig. 2f).

3.2. Temporal–spatial distribution of social vulnerability in socioeconomic status from 2009 to 2018

During the period of 2009–2018, Wenzhou city, Jinhua city and Taizhou city have higher levels of vulnerability in socioeconomic status, but Hangzhou city, Ningbo city and Zhoushan city have lower levels of vulnerability (Figs. 2b and 4). The reason is that Wenzhou city, Jinhua city and Taizhou city have lower levels in per capita both GDP and expenditure, but Hangzhou city, Ningbo city and Zhoushan city have higher levels in per capita both GDP and expenditure and percentage of the tertiary industry. For example, the per capita GDP and percentage of the tertiary industry in Hangzhou city from 2009 to 2018 are the highest in the whole Zhejiang

Table 6
Weight of the variables for social vulnerability assessment in Zhejiang province from 2009 to 2018.

Variable	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
V_1	0.170	0.184	0.191	0.123	0.120	0.094	0.104	0.071	0.035	0.034
V_2	0.151	0.159	0.142	0.170	0.175	0.177	0.189	0.186	0.123	0.130
V_3	0.212	0.180	0.191	0.240	0.219	0.194	0.199	0.187	0.110	0.104
V_4	0.088	0.095	0.097	0.105	0.107	0.124	0.132	0.130	0.089	0.093
V_5	0.045	0.037	0.035	0.037	0.036	0.037	0.040	0.039	0.027	0.026
V_6	0.004	0.004	0.004	0.003	0.004	0.004	0.004	0.004	0.004	0.004
V_7	0.044	0.046	0.054	0.053	0.055	0.049	0.056	0.051	0.031	0.033
V_8	0.013	0.009	0.010	0.009	0.009	0.010	0.009	0.009	0.006	0.006
V_9	0.156	0.144	0.135	0.135	0.151	0.189	0.140	0.197	0.493	0.490
V_{10}	0.005	0.006	0.006	0.004	0.004	0.005	0.007	0.008	0.006	0.006
V_{11}	0.005	0.006	0.005	0.006	0.007	0.006	0.006	0.006	0.004	0.004
V_{12}	0.025	0.027	0.024	0.003	0.003	0.003	0.003	0.003	0.001	0.001
V_{13}	0.083	0.105	0.108	0.111	0.111	0.107	0.111	0.108	0.071	0.071

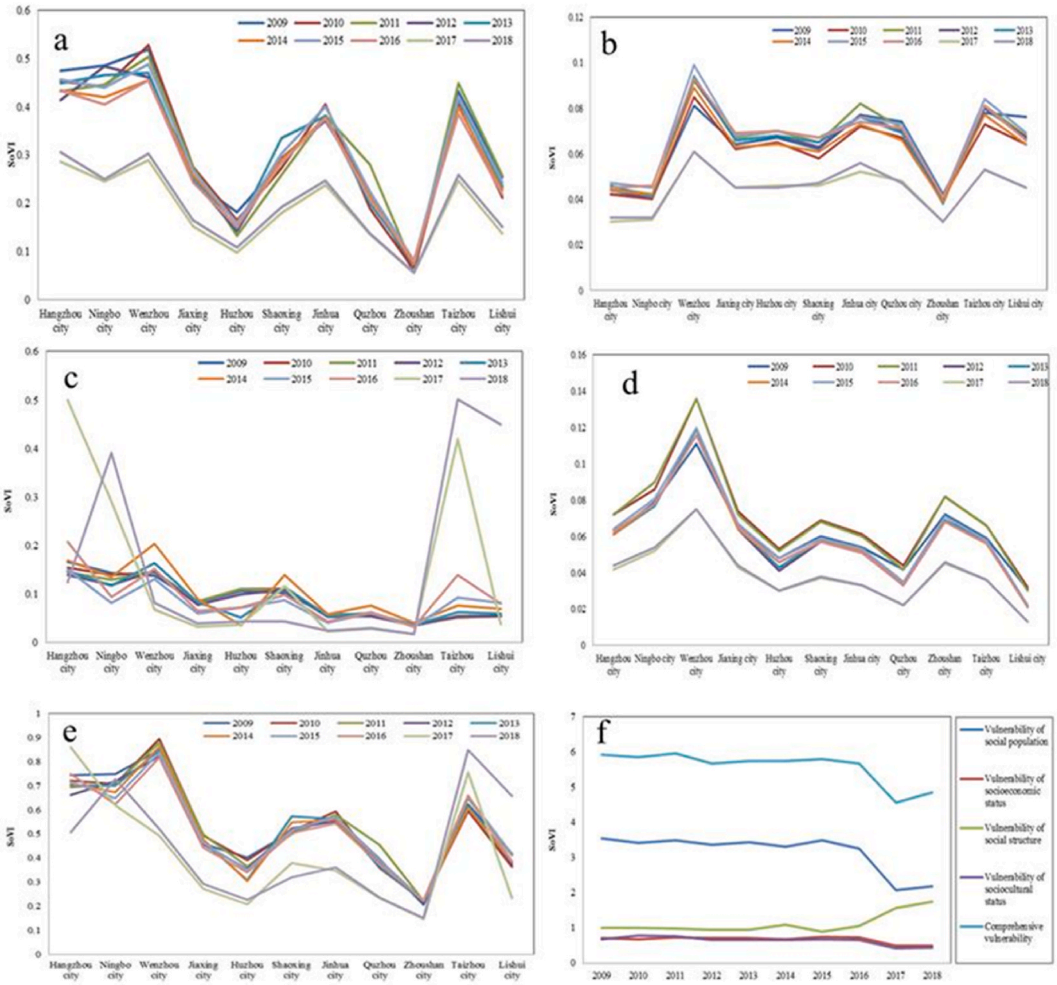

Fig. 2. Temporal distribution of SoVI for cities and Zhejiang province: a) Social population; b) Socioeconomic status; c) Social structure; d) Sociocultural status; e) Comprehensive SoVI; f) Zhejiang province.

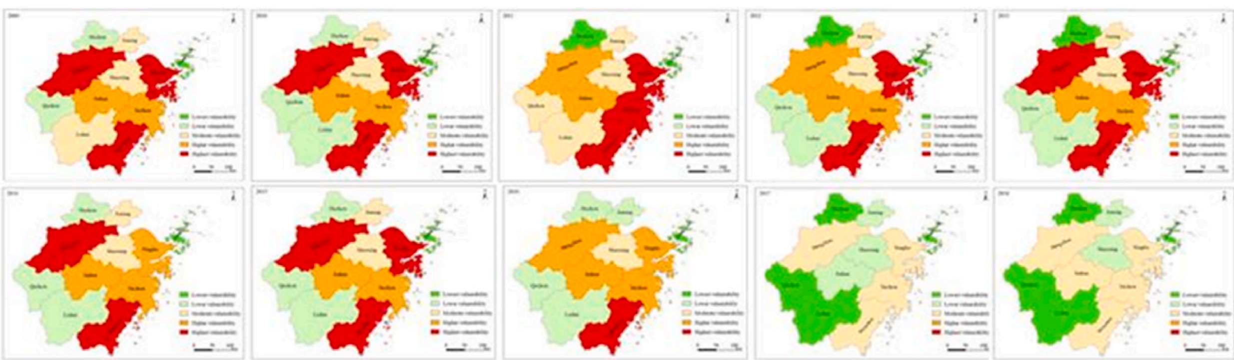

Fig. 3. Spatial distribution of vulnerability in social population from 2009 to 2018.

province, and the per capita total expenditure in Zhoushan city is the highest in the whole Zhejiang province during 2009–2018. These indicate that the rapid economic development and reasonable industrial structure in Hangzhou city and Zhoushan city have caused lower level of vulnerability in socioeconomic status.

On the other hand, from the provincial level, the SoVI of socioeconomic status from 2009 to 2018 also indicates a decreasing trend (Fig. 2f). With the economic development level of Zhejiang province, its economic strength in dealing with natural hazards was

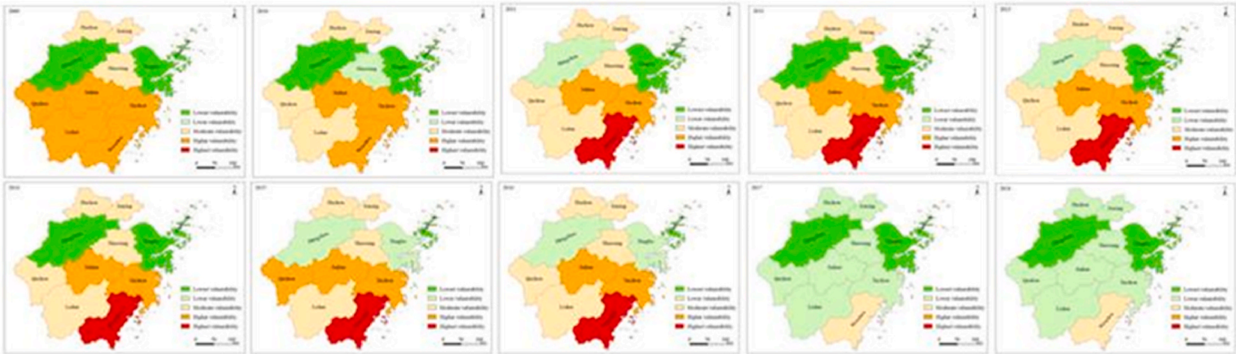

Fig. 4. Spatial distribution of vulnerability in socioeconomic status from 2009 to 2018.

enhanced and its abilities between disaster-resistance and disaster-recovery were strengthened, thereby resulting in decreasing trend of SoVI in socioeconomic status. For example, the per capita GDP of Zhejiang province keeps growing during 2009–2018, reaching 9.86×10^4 RMB yuan in 2018, 2.25 times more than in 2009. This increased economic resilience to natural hazards for the whole province.

3.3. Temporal–spatial distribution of social vulnerability in social structure from 2009 to 2018

As shown in Figs. 2c and 5, Hangzhou city, Ningbo city, Taizhou city and Lishui city have higher levels of vulnerability in social structure during the studied period. The reason is in close relation to the number of health technician per 10,000 persons, number of urban minimum living allowance residents and average annual wage of on-the-job workers. For example, in 2017, the number of health technician per 10,000 persons of Hangzhou city is the highest in the whole province but its number of urban minimum living allowance residents is the highest, which are more vulnerable to natural hazards, thereby resulting in higher level of vulnerability. At same year, the number of urban minimum living allowance residents of Taizhou city is second only to Hangzhou city, thereby causing its vulnerability in social structure.

On the other hand, in 2018, the number of urban minimum living allowance residents of Ningbo city, Taizhou city and Lishui city is higher level in Zhejiang province, respectively which is not conducive to the stable development of society, thus resulting in higher levels of social structural vulnerability in Hangzhou city, Ningbo city, Taizhou city and Lishui city.

Additionally, the SoVI of social structure from 2009 to 2018 shows an increasing trend from the provincial level (Fig. 2f). The SoVI fluctuated from 2009 to 2015 but showed a fast rising trend from 2015 to 2018. Because the number of urban minimum living allowance residents in 2015 was the least, the SoVI of social structure was the lowest in this year. But the SoVI of social structure was the highest in 2018 owing to the most urban minimum living allowance residents (Fig. 2f).

Moreover, the number of urban minimum living allowance residents (V_9) played a leading role in the vulnerability index of social structure, and its proportion was on the rise as a whole, and had the largest proportion in 2017 (93.13%) and 2018 (93.92%), respectively (Table 7). Because this variable (V_9) was a positive indicator (Table 5), so the higher the value of this variable (V_9), the higher the vulnerability level of social structure. According to the Zhejiang Statistical Yearbook (2010–2019), the number of urban minimum living allowance residents showed an overall growth trend during the period of 2009–2018, reaching 219,800 by 2018, more than double the number in 2009, and this indicated that some residents who are more vulnerable to natural hazards could still only maintain basic living, thereby resulting in the higher levels of vulnerability to social structures.

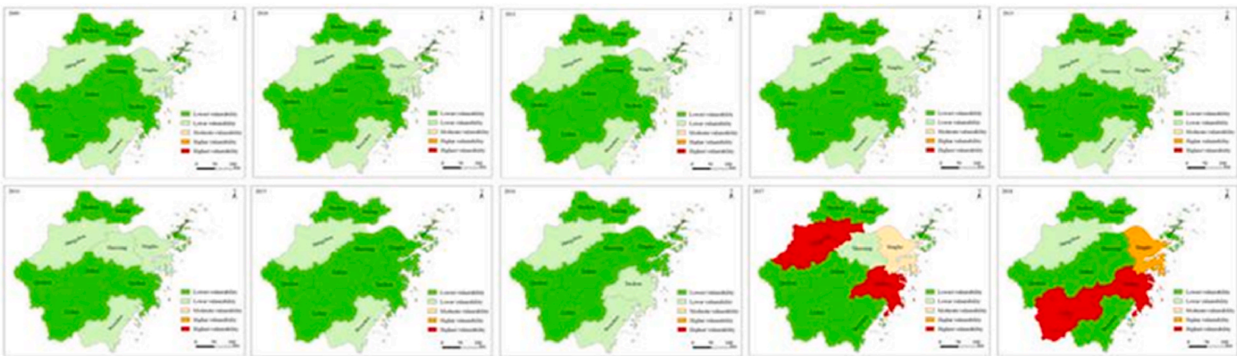

Fig. 5. Spatial distribution of vulnerability in social structure from 2009 to 2018.

Table 7
Proportion of variables for social structure vulnerability from 2009 to 2018 (%).

Variable	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
V_8	11.14	8.46	9.44	9.31	9.28	8.40	10.20	8.43	3.56	3.15
V_9	83.71	86.01	85.14	86.27	86.40	87.00	82.88	84.69	93.13	93.92
V_{10}	5.15	5.53	5.42	4.42	4.32	4.60	6.91	6.88	3.31	2.93

3.4. Temporal–spatial distribution of social vulnerability in sociocultural status from 2009 to 2018

During the period of 2009–2018, Wenzhou city has higher level of vulnerability in sociocultural status, but Quzhou city and Lishui city have lower levels of vulnerability (Figs. 2d and 6), which is in close relation to the number of teachers per 10,000 persons, green coverage of built-up area and density of domestic highway. On the one hand, the green coverage of built-up area and density of domestic highway of Wenzhou city are lower levels, among which the density of domestic highway is the lowest in the whole province from 2009 to 2018 that is not conducive to the smooth development of post-disaster relief, and the green coverage of built-up area is the lowest in the whole province within 7 years that is not good for the Wenzhou city against natural hazards.

On the other hand, the number of teachers per 10,000 persons, green coverage of built-up area and density of domestic highway of both Quzhou city and Lishui city are higher levels in the whole province, among which the density of domestic highway of Lishui city is the highest during 2009–2018 that is beneficial to improve the ability of post-disaster rescue, and the number of teachers per 10,000 persons is the highest in the whole province within 3 years that is beneficial for people to know more about natural hazards and be ready for disaster prevention.

Additionally, from 2009 to 2018, the SoVI of sociocultural status shows a decreasing trend from the provincial level (Fig. 2f). The reason is that the cultural education and disaster culture have been paid more attention and the disaster-prevention and disaster-relief ability of the region has been improved in Zhejiang province during 2009–2018. For example, the number of teachers keeps growing during 2009–2018, reaching 109.67×10^4 persons in 2018, one times more than in 2009, enhancing the disaster prevention capacity of Zhejiang province. Meanwhile, the green coverage rate of built-up areas increased from 39.42% in 2009 to 41.45% in 2018, improving the city's ability to withstand disasters. Additionally, the density of domestic highway also shows an increasing trend in the study period, which increased from 21.76 km per 10,000 persons in 2009 to 24.89 km per 10,000 persons in 2018, improving the post-disaster rescue capacity of whole province.

3.5. Temporal–spatial distribution of comprehensive vulnerability of Zhejiang province from 2009 to 2018

As shown in Figs. 2e and 7, the comprehensive social vulnerability level of cities in Zhejiang province has been changing constantly from 2009 to 2018, showing a descending state. In 2009, the cities with highest level of vulnerability are Ningbo city and Wenzhou city, but Zhoushan city is the lowest level of vulnerability (Fig. 6). During 2010–2015, Wenzhou city is the highest level of vulnerability and Zhoushan city is the lowest level of vulnerability every year. In 2016, the comprehensive SoVI of Zhejiang province is a slight drop. The number of city with highest level, higher level and moderate level of vulnerability is 2, only Zhoushan city with lowest level of vulnerability in this year. However, in 2017, the comprehensive SoVI of Zhejiang province is a rapid decline. The number of city with highest level of vulnerability is still 2, but the number of city with lowest level of vulnerability increases to 5 in this year. On the contrary, the comprehensive SoVI of Zhejiang province in 2018 is on the rise. The number of city with higher and moderate levels of vulnerability increases to 2, but the number of city with lowest level of vulnerability decreases to 4 in this year.

On the other hand, Hangzhou city, Ningbo city, Wenzhou city and Taizhou city are higher or highest level of vulnerability, but Zhoushan city lowest level of vulnerability during 2009–2016. In 2017, Hangzhou city, Ningbo city and Taizhou city are higher or highest level of vulnerability. In 2018, Ningbo city, Taizhou city and Lishui city are higher or highest level of vulnerability.

Additionally, as shown in Fig. 2f, the comprehensive SoVI from 2009 to 2018 shows a decreasing trend from the provincial level. The SoVI fluctuated during 2009–2016 but showed a decreasing trend from 2016 to 2018. The comprehensive SoVI declines from 5.930 in 2009 to 4.857 in 2018, but was the lowest in 2017 in the study period, with 4.560.

As shown in Table 8, social vulnerability in social population accounts for the largest share of the comprehensive SoVI, ranging from 44.89% to 60.23%, but the SoVI of social population from 2009 to 2018 shows a decreasing trend, showing an important influence on the trend of the comprehensive SoVI. Moreover, social vulnerability in both socioeconomic status and social structure also shows a decreasing trend, showing smaller influence on the comprehensive SoVI. However, the proportion of social vulnerability in social structure is second only to that of social population in the comprehensive SoVI, ranging from 15.36% to 35.98%, but the SoVI of social structure from 2009 to 2018 shows a increasing trend and achieves the largest share in 2018, showing an important influence on the trend of the comprehensive SoVI.

4. Conclusions

In the present study, the spatial and temporal changes of social vulnerability of cities to natural hazards have been explored in Zhejiang province through socioeconomic and demographic data from 2009 to 2018. Our results reveal that (1) in temporal scale, vulnerability of 11 cities in social population, socioeconomic status, and sociocultural status and comprehensive vulnerability of Zhejiang province show a declining trend, but the vulnerability of social structure shows an increasing trend during 2009–2018. (2) in

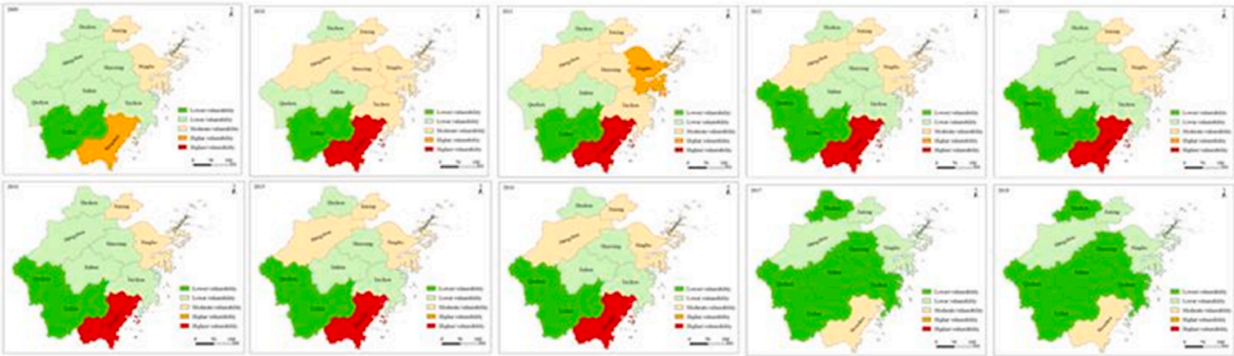

Fig. 6. Spatial distribution of vulnerability in sociocultural status from 2009 to 2018.

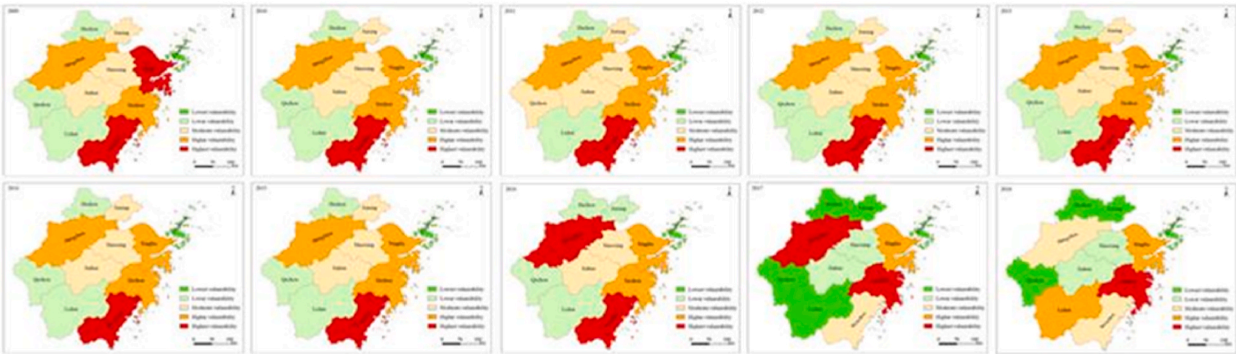

Fig. 7. Spatial distribution of comprehensive vulnerability in Zhejiang province from 2009 to 2018.

Table 8
Proportion of indicators of comprehensive social vulnerability (%).

Indicator	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Vulnerability of social population	59.74	58.29	58.48	59.36	59.70	57.73	60.23	57.24	45.47	44.89
Vulnerability of socioeconomic status	11.87	11.40	12.11	12.49	12.34	11.86	12.74	12.76	10.69	10.15
Vulnerability of social structure	16.88	17.07	16.50	16.66	16.53	19.04	15.36	18.46	34.46	35.98
Vulnerability of sociocultural status	11.50	13.23	12.90	11.49	11.42	11.37	11.67	11.54	9.38	8.98

spatial scale, from 2009 to 2018, Hangzhou city, Ningbo city, Wenzhou city, Jinhua city and Taizhou city have higher levels of vulnerability in social population but Huzhou city and Zhoushan city have lower levels of vulnerability; Wenzhou city, Jinhua city and Taizhou city have higher levels of vulnerability in socioeconomic status, but Hangzhou city, Ningbo city and Zhoushan city have lower levels of vulnerability; Hangzhou city, Ningbo city, Taizhou city and Lishui city have higher levels of vulnerability in social structure; Wenzhou city has higher level of vulnerability in sociocultural status, but Quzhou city and Lishui city have lower levels of vulnerability; and Hangzhou city, Ningbo city, Wenzhou city, and Taizhou city have higher levels of comprehensive vulnerability, but Huzhou city, Quzhou city and Zhoushan city have lower levels of comprehensive vulnerability.

Our study also indicates that different city need for different disaster risk reduction strategies and plans at the provincial level although the regional comprehensive vulnerability shows a declining trend at a county level.

Data availability statement

The datasets used in this study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Shanzhong Qi: Writing – review & editing. **Shunli Hu:** Data curation. **Shufen Cao:** Data curation.

Declaration of competing interest

We have no conflicts of interest to disclose. All the authors approve the contents and the submission of this manuscript to this journal.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e27120.

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