Flood risk assessment in Ya’an, Sichuan, China based on the emergy theory

Xiaolong Shua,b, Yufeng Rena,c, Zhe Duanb, Xing Liub,*, Xiaojun Huaa,c and Huike Leib

a Hubei Key Laboratory for Smart Yangtze River and Hydroelectric Sciences, Yichang, Hubei 443133, China
b College of Water Conservancy and Hydropower Engineering, Sichuan Agricultural University, Ya’an, Sichuan 477200, China
c China Yangtze Power Co., Ltd, Yichang, Hubei 443133, China
*Corresponding author. E-mail: xingliud178@tom.com

ABSTRACT

The emergy theory provides a new approach for flood risk assessment from an ecological perspective. By employing the emergy method, we used five indicators (rainfall runoff, medical workers and students per 10,000 people, social fixed assets investment, unit land GDP, and land-use types) from three dimensions (natural environment, population, and social economy) and the GIS technique to assess the potential impact and risk of a flood disaster on different regions in Ya’an City. Our findings revealed regional differences in the distribution of flood risks in Ya’an City: Lushan County and Yucheng District face the highest risks, followed by Tianquan County and Mingshan District, and Shimian County has the lowest risk. The index method was employed to analyze the regional differences. By training a back-propagation neural network with data of flood disasters in the study area, we produced a flood risk distribution map. We found that Mingshan District, Lushan County and Yucheng District have higher risks than other regions. The results largely agree with what we obtained using the emergy method. Our study shows that flood risk assessment based on the emergy theory can provide a scientific basis for flood control and disaster relief initiatives.

Key words: assessment indicators, BP neural network, emergy theory, flood risk assessment

HIGHLIGHTS

• Emergy theory generates a new approach for flood risk assessment.
• Research findings were verified by the reality of the study area, ensuring the validity.
• Analysis for BP neural network training was conducted in the area experiencing a flood.
• The flood risks in the study area assessed by using the emergy theory are in agreement with the reality.

1. INTRODUCTION

Floods are one of the most common hazards worldwide, which have a wide-ranging impact and present a serious threat to socio-economic development and people’s lives and properties (Foudi Osés-Eraso & Tamayo 2015). In July 2020, most parts of Sichuan, Chongqing, Hubei, Anhui and Zhejiang around China experienced multiple rounds of heavy rainfall, resulting in severe flood disasters around many regions, leading to some major losses to the sustainable development of our national economy, jeopardizing the security of people’s lives and properties, and affecting social stability. Recently, flood risk assessment has been a heated topic in hydrology and catastropheology. Analysis of the flood hazard is key to disaster risk assessment and control and provides a timely solution to early warning, flood control, and disaster relief.

Currently, most efforts for flood risk assessment in China and abroad have been made with historical flood data, hydrological and hydrodynamic models, and index methods (Tanoue et al. 2016; Abdulrazzak et al. 2019; Yongzhi et al. 2021). Bhuiyan & Baky (2014) employed ArcGIS to map the flood hazard distribution around the low-lying areas of Bangladesh, and used digital elevation model (DEM) data to extract index factors, to work out the flood risk analysis diagram for different scales of floods. Kazakis et al. (2015) employed the analytic hierarchy process to determine the weight of total flow, altitude, land-use type and other attributes, and superposed different parameter information following their weighted values, and completed flood risk assessment. Lai et al. (2015) have selected 10 assessment indexes based on disaster-inducing factors, hazard-inducing environment, and hazard-affected bodies, built up a random woodland intelligence algorithm-based flood risk assessment model, and then used the GIS technology to assess the flood risks in the Dongjiang

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (http://creativecommons.org/licenses/by/4.0/).
River Basin. Sun et al. (2017) used the GIS software to summarize the flood risk analysis mode from the three aspects of historical data, system indexes, and remote sensing data, commented on the features and the shortcomings of some common models, and proposed that extended flood risk analysis models and enhanced application of the 3S technology to flood risk analysis would be the direction for us to enhance and extend flood risk analysis in the future. Hanif et al. (2020) has investigated the impact of short-term and long-term climate changes on the hydrological regime and flood risks, generated a flood map to identify the vulnerability, and formulated some flood adaptive strategies for 43 regions around the globe.

The indexes in these afore-mentioned research works usually are not inter-related, and for these works have determined the weights by analyzing the importance of the factors to work out the risk assessment indexes ultimately. They have ignored the potential relation between different indexes and would not help to assess the flood risks accurately. The energy analysis approach, created by American ecologist H. T. Odum, refers to a kind of energy accounting of the ecological–economic system to assess the status and function of different types of energy in the system, so it is a quantitative research method to assess flood risks (Huang & Odum 1991). This approach converts different types of incomparable energy into the same standard energy for comparison to quantitatively analyze the natural system and the human socio-economic system, the real value of resources and the environment, and their interrelationship (Luo et al. 2019, Wu et al. 2018), based on the emergy theory, calculated the rainstorm intensity, susceptibility, and adaptive capacity to assess the vulnerability of each district of Zhengzhou in Henan province to flood disasters, and the results showed that different districts have different demand for rainfall flood control, and the districts of higher vulnerability demand higher. Chang & Huang (2015) pointed out that the energy approach works to highlight the exposure, susceptibility, and adaptive capacity, and spatialized calculation of the energy indexes can help assess the risk of floods. Thereinto, the infrastructure management and regional planning are critical factors to flood risks. Based on the energy theory, this paper assesses the flood risks in Ya’an and is expected to provide a new research direction for flood risk assessment in the future.

This paper is organized as follows: First, the introduction introduces some approaches to flood risk assessment in China and abroad and the status quo of research on application of the energy theory to risk assessment. The Research Methods section elaborates on the principles of the emergy-based risk assessment model, an overview of the survey region, and data sources and processing. The Results and Discussion section uses the emergy method and the BP neural network-based index method to assess the risk of floods and analyze the results. The last section concludes the paper and points out some prospects for future efforts.

2. METHODS

2.1. The basis for application of emergy theory to flood risk assessment modeling

The emergy theory and method proposed by American ecologist H. T. Odum work to convert different types of incomparable energy into standardized comparable values based on the emergy conversion rate. This approach measures the emergy of different types of energies in the ecological system that consists of the human social system and the natural ecological system on the benchmark of solar energy. Based on solar energy, the energy in the ecosystem can be converted into the solar energy of a unified standard through the emergy conversion rate equation (Zhao 2013):

\[ E = \tau \times B \]  (1)

where \( E \) stands for emergy (seJ), \( \tau \) is the emergy conversion rate (seJ/J or seJ/g), and \( B \) is the volume of energy or substance (J/g).

The flood disaster risk energy system is established based on the causal relationship between the systems comprised of the city system and the nature-agriculture system to demonstrate the different energy and material flow between the ecosystem and the economic system (Wangyang et al. 2019). When rainfall takes place, the rainwater-stored energy (N1) may endanger the rainfall area. After deducting buildings’ and vegetation’s reainment, evapotranspiration and infiltration losses, rainfall is then converted into an overland runoff, and the energy stored in the total overland runoff accumulation represents the exposure in this region (N2). The exposure intensity (N3) is the ratio of the energy stored in the volume of runoff to the energy stored in the rainfall. When extreme weather takes place, the sum of the energy loss of the city
system (N4) and the energy loss of the nature-agriculture system (N5) is called susceptibility (N6). The possibility of flood disaster in the system has positive correlation with the energy it stores. Thanks to extreme weather, the environment also changes accordingly, and the disaster-stricken region is also affected; this impact is denoted by the potential impact index (N7). The potential impact index is related to the exposure and susceptibility and the product of susceptibility and exposure intensity. In addition to the natural environment, the factors affecting a region's disaster risk include the demographic factor (N8) and the socio-economic factor (N9). They together demonstrate the adaptive capacity of a system (N10) and the coping capacity of this region to any natural hazard. Finally, we use the potential impact and adaptive capacity to assess flood disaster risk in the survey region (N11). Table 1 lists the definitions of different energy flows. For the working principles, see 'Risk assessment modeling'.

2.2. Risk assessment modeling

A risk refers to how a system is adversely affected, which can be indicated by exposure, susceptibility, adaptive capacity, and potential impact indexes. By analyzing these constituent factors of risks, and exploring their interrelations, we can put forward some emergy indicators to represent the risk of floods and thus accurately assess the risk of floods in a region.

(1) Exposure $L$

Exposure refers to the extent to which a region is involved in a natural disaster; for instance, in a flood, a more susceptible region to a flood has higher exposure ($Wanzhi et al. 2019$). When a flood takes place, the exposure of a region to the flood can be represented by the total emergy of the accumulative runoff in this region, i.e., the product of the accumulative runoff and its corresponding energy conversion rate.

$$L = r \times \tau$$

where $L$ refers to exposure (seJ); $r$ is the runoff depth (mm); $\tau$ is the energy conversion rate (seJ/J or seJ/g).

(2) Susceptibility $M$

Susceptibility refers to the extent to which the system in a region is affected by extreme weather ($Chang & Huang 2015$). As a response of a system to extreme weather, susceptibility is not just decided by the scale of a hazard like a flood, but also dependent on relevant features of the disaster-stricken region. Different land-use types stock different energies, so when a flood disaster occurs, the impact on different regions of different land-use types also differs. Thus, we can analyze the susceptibility based on the emergy power intensity of

| Energy flow (seJ) | Description | Definition |
|------------------|-------------|------------|
| N1               | Potential exposure $I$ | Rainfall |
| N2               | Exposure $L$ | Total volume of runoff |
| N3               | Exposure intensity | $N2/N1$ |
| N4               | Natural-agricultural system susceptibility | Property losses in the natural-agricultural system caused by extreme weather |
| N5               | City system susceptibility | Property losses in the city system caused by extreme weather |
| N6               | Susceptibility $M$ | $N4 + N5$ |
| N7               | Potential impact index | $N6 \times N3$ |
| N8               | Population indicator | Demographic factor in the survey region |
| N9               | Social and economic indicator | Social and economic factors in the survey region |
| N10              | Adaptive ability $N$ | $N8 + N9$ |
| N11              | Risk | $N7/N10$ |
different land types (Jun et al. 2015). Therefore, the susceptibility of a region is denoted by the total energy stored by different land types.

\[
M = \rho \times A
\]  

(3) Adaptive capacity \(N\)

In addition to exposure, the risk of a system is also decided by its adaptive capacity. Adaptive capacity refers to the capacity of a system to make continuous progress and adjustments to adapt itself to the environment when any natural disaster is triggered off by extreme weather (Wahab & Ludin 2018). The adaptive capacity of a system constantly changes along with the changing environment, and different regions and groups have different adaptive capacity to the environment. For instance, an underdeveloped rural village has a lower adaptive capacity than a developed region of complete infrastructure, and adults have a much stronger adaptive capacity to the environment than children and the aged. Therefore, the adaptive capacity of a region should be assessed from the three aspects of society, economy, and demographics.

(4) Potential impact index \(I\)

When extreme weather occurs, the impact on the system can be denoted by the potential impact index (Yangfan 2018). The risk of a flood disaster is in positive correlation to the potential impact. The product of exposure and susceptibility denotes the potential impact index.

\[
I = i \times M
\]  

\[
i = \frac{L}{q}
\]  

where \(I\) refers to potential impact index (seJ), \(i\) is exposure intensity, \(M\) is the susceptibility of the region (seJ), \(L\) is exposure (seJ), and \(q\) is potential exposure (seJ).

(5) Risk index \(V\)

Risk index refers to the ratio of the potential impact to the adaptive capacity, indicating the damage of the disaster to a system in case of extreme weather (Chao et al. 2020). The risk is positively correlated to the system’s potential impact index, but in negative correlation to the adaptive capacity.

\[
V = \frac{I}{N}
\]

where \(V\) refers to the index of vulnerability, \(I\) is the potential impact index (seJ), and \(N\) is the adaptive capacity.

| Table 2 | Factors affecting adaptive capacity |
|---|---|
| **Contributing factors** | **Classification** | **Definition** |
| Society | Medical workers per 10,000 people | Medical workers/(total population of a region/10,000), indicating local medical capacity |
| | Enrolled students per 10,000 people | Students enrollment/(total population of a region/10,000), indicating overall education |
| Economy | Unit land GDP | Region GDP/region area, indicating local economic effectiveness, which has positive correlation to the adaptive capacity |
| | Total social fixed assets | In positive correlation to the adaptive capacity |
| Demography | Population density | Year-end resident population/region area, the region of higher-density population distribution seeing lower adaptive capacity |
| | Proportion of people below 14 and above 65 years old | Number of this group/resident population, this group being highly susceptible, and less adaptive to a natural disaster |
2.3. Overview of the study area

Ya’an (101°56’–103°23’E, 28°51’–30°56’N), located on the western margin of the Sichuan Basin, is in the transition zone from the Basin to the Qinggai-Tibet Plateau. It is a long stripe stretching about 220 km long from north to south and spreads about 70 km wide from east to west. Ya’an City has jurisdiction over six counties and two districts (Figure 1), covering a total area of 15,046 km². The city boasts quite diversified topographic features. Mountains cover the largest area within its borders, with higher terrain in its south, west, and north, and low-lying land in its center and east. Thanks to its unique ‘windward slope’ and ‘horn mouth’ terrains to lift up water vapor in a cyclic process for coagulation to form precipitation, the city has 218 annual mean rainfall days and is called the ‘Rainy City’. In all four seasons in a year it rains, so all districts and counties in Ya’an make a potentially high-risk region. Statistics showed that during the flood season in 2018, Ya’an experienced 18 regional rainstorms, 465,100 people in 157 townships (towns and sub-districts) in 8 counties (districts) of the city were affected, with a total economic loss up to 2.01 billion yuan. These figures indicate that the rainstorm and flood disasters exert a quite strong impact on the economic development of Ya’an, as is one important factor that hinders the economic development of Ya’an City.

2.4. Data sources

The data sources for this study and their specifications are shown in Table 3.

2.5. Data processing

The rainfall runoff data for this study were obtained from Ya’an Municipal Communiqué on Water Resources 2018. The number of medical workers, enrolled students, people below 14 and above 65 years old, social fixed assets investment, and GDP were obtained from Ya’an Statistics Yearbook and Sichuan Statistics Yearbook. The main land-use data of Ya’an were obtained from Natural Resources and Planning Bureau of Ya’an City, Ya’an Statistics Yearbook, and Resource and Environment Science and Data Center, China Academy of Sciences (Figure 2) in combination with the Geographic Information System (GIS). The data for the BP neural network were normalized to remove the dimension before the network training. Specifically, the data were normalized by Matlab to obtain the weights of various indexes and conduct overlay analysis in the GIS.

Figure 1 | Elevation map of Ya’an.
3. RESULTS AND DISCUSSION

3.1. Calculated results

Based on the above data, we calculated the exposure, susceptibility, and adaptive capacity of Ya’an City with the method mentioned in the section of Methods.

3.2. Exposure

Exposure is the product of accumulative runoff and its corresponding emergy conversion rate (Jun et al. 2015), which can be calculated via Equation (2). The results are shown in Table 5.

3.3. Susceptibility

A region’s susceptibility to disaster can be denoted by the total energy stored by different land-use types (Chang & Huang 2015). In this study, the susceptibility for different land-use types can be calculated with Equation (3). The results are shown in Table 6.
**Figure 2 |** Types of land use in Ya’an City.

**Table 4 |** Data of Ya’an City by type

| Region                          | Shimian | Hanyuan | Baoxing | Lushan | Tianquan | Xingyang | Yucheng | Mingshan |
|--------------------------------|---------|---------|---------|--------|----------|----------|---------|----------|
| Accumulative runoff (100 million m$^3$) | 49.29   | 27.30   | 42.33   | 22.59  | 60.27    | 44.98    | 23.57   | 9.85     |
| Medical workers (10,000 people)        | 111.00  | 65.00   | 73.00   | 67.00  | 102.00   | 78.00    | 171.00  | 56.00    |
| Enrolled students (10,000 people)       | 1,769.00| 1,298.00| 1,033.00| 1,197.00| 1,373.00 | 1,355.00 | 1,559.00| 1,224.00 |
| Social fixed assets investment (100 million RMB Yuan) | 51.04   | 45.54   | 25.96   | 28.59  | 48.24    | 47.30    | 106.49  | 62.83    |
| Unit land GDP on average (10,000 RMB/km$^2$) | 306.91  | 373.68  | 107.86  | 362.72 | 268.62   | 417.05   | 1,672.62| 1,314.24 |
| Farmland (km$^2$)                      | 87.00   | 295.00  | 42.00   | 84.00  | 123.00   | 94.00    | 192.00  | 166.00   |
| Woodland (km$^2$)                      | 798.00  | 501.00  | 818.00  | 256.00 | 1,971.00 | 416.00   | 475.00  | 147.00   |
| Area of land for mining and industry (km$^2$) | 3.00    | 3.00    | 1.00    | 1.00   | 2.00     | 1.00     | 3.00    | 8.00     |
| Area of land for residence (km$^2$)     | 153.00  | 17.00   | 212.00  | 43.00  | 50.00    | 20.00    | 193.00  | 43.00    |
| Area of land for transportation purpose (km$^2$) | 0.56    | 0.61    | 0.17    | 0.48   | 8.08     | 0.99     | 3.75    | 0.55     |
| Water bodies (km$^2$)                   | 36.00   | 74.00   | 4.00    | 4.00   | 3.00     | 3.00     | 10.00   | 4.00     |

**Table 5 |** Results of exposure calculation

| Indicators                      | Shimian | Hanyuan | Baoxing | Lushan | Tianquan | Xingyang | Yucheng | Mingshan |
|--------------------------------|---------|---------|---------|--------|----------|----------|---------|----------|
| Accumulative runoff (100 million m$^3$) | 49.29   | 27.30   | 42.33   | 22.59  | 60.27    | 44.98    | 23.57   | 9.85     |
| Exposure (10$^{20}$ seJ)         | 27.99   | 15.51   | 24.05   | 12.84  | 34.24    | 25.55    | 13.39   | 5.60     |
3.4. Adaptive capacity

When a natural disaster occurs due to extreme weather, the system, to alleviate the resulted losses, can constantly make progress and adjustment to adapt to the changing environment (Wanzhi et al. 2019). Moreover, the results of the adaptive capacity calculation are shown in Table 7.

The above calculated results reveal the following findings:

(1) Table 5 shows that the bigger the accumulation runoff in the system, the more energy it will store, and the higher the exposure will be. Tianquan County has the highest annual precipitation, and generates the largest accumulative runoff, resulting in high emergy storage, so Tianquan County is a region of the highest exposure. Mingshan District sees relatively low annual precipitation, so its accumulative runoff is relatively small, leading to relatively low emergy storage, so the exposure is also relatively low.

(2) Based on the emergy power density of different land-use types, we calculate the emergy of different land-use types for all districts and counties of Ya’an City. It can be seen from the results that areas with high energy values, such as residential areas, industrial and mining areas, and transportation, are highly sensitive, so floods are at greater risk. The areas with a low energy value, such as water and cultivated land, are less sensitive and less risky. Table 6 shows that compared with other districts and counties, Yucheng District has a relatively high proportion of land for residence, mining, and industrial purposes, the sensitivity is high, so it is

### Table 6 | Sensitivity calculation results

| Region                             | Shimian | Hanyuan | Baoxing | Lushan | Tianquan | Xingyang | Yucheng | Mingshan |
|------------------------------------|---------|---------|---------|--------|----------|----------|---------|----------|
| Farmland (km²)                     | 87.00   | 295.00  | 42.00   | 84.00  | 123.00   | 94.00    | 192.00  | 166.00   |
| Emergy (10^5 seJ)                  | 1.07    | 3.63    | 0.52    | 1.03   | 1.51     | 1.16     | 2.36    | 2.04     |
| Woodland (km²)                     | 798.00  | 501.00  | 818.00  | 256.00 | 1,971.00 | 416.00   | 475.00  | 147.00   |
| Emergy (10^6 seJ)                  | 4.82    | 3.03    | 4.94    | 1.55   | 11.91    | 2.51     | 2.87    | 0.89     |
| Area of land for residence (km²)   | 3.00    | 5.00    | 2.00    | 12.00  | 5.00     | 5.00     | 21.00   | 6.00     |
| Emergy (10^5 seJ)                  | 3.38    | 5.64    | 2.25    | 13.53  | 5.64     | 5.64     | 25.68   | 6.76     |
| Area of land for mining and industry (km²) | 3.00 | 3.00 | 1.00 | 1.00 | 2.00 | 1.00 | 3.00 | 8.00 |
| Emergy (10^5 seJ)                  | 5.44    | 5.44    | 1.81    | 1.81   | 3.63     | 1.81     | 5.44    | 14.52    |
| Area of land for transportation purpose (km²) | 0.56 | 0.61 | 0.17 | 0.48 | 8.08 | 0.99 | 3.75 | 0.55 |
| Emergy (10^5 seJ)                  | 1.59    | 1.73    | 0.48    | 1.36   | 22.90    | 2.81     | 10.63   | 1.56     |
| Water bodies (km²)                 | 36.00   | 74.00   | 4.00    | 4.00   | 3.00     | 3.00     | 10.00   | 4.00     |
| Emergy (10^6 seJ)                  | 9.74    | 20.02   | 1.08    | 1.08   | 0.81     | 0.81     | 2.71    | 1.08     |
| Susceptibility (10^24 seJ)         | 4.15    | 6.43    | 2.54    | 13.90  | 8.44     | 6.15     | 25.39   | 8.42     |

### Table 7 | Results of adaptive capacity calculation

| Region                              | Shimian | Hanyuan | Baoxing | Lushan | Tianquan | Xingyang | Yucheng | Mingshan |
|-------------------------------------|---------|---------|---------|--------|----------|----------|---------|----------|
| Medical workers (10,000 people)     | 111.00  | 65.00   | 73.00   | 67.00  | 102.00   | 78.00    | 171.00  | 56.00    |
| Emergy (10^22 seJ)                  | 1.49    | 0.87    | 0.98    | 0.90   | 1.37     | 1.04     | 2.29    | 0.75     |
| Enrolled students (10,000 people)   | 1,769.00| 1,298.00| 1,033.00| 1,197.00| 1,373.00 | 1,355.00 | 1,559.00| 1,224.00 |
| Emergy (10^22 seJ)                  | 4.14    | 3.04    | 2.42    | 2.80   | 3.21     | 3.17     | 3.65    | 2.87     |
| Social fixed assets investment (100 million RMB Yuan) | 51.04 | 45.54 | 25.96 | 28.59 | 48.24 | 47.30 | 106.49 | 62.83 |
| Emergy (10^24 seJ)                  | 5.27    | 2.92    | 1.67    | 1.83   | 3.09     | 3.03     | 6.83    | 4.03     |
| Unit land GDP on average (10,000 RMB Yuan/km²) | 506.91 | 373.68 | 107.86 | 362.72 | 268.62  | 417.05   | 1,672.62| 1,314.24 |
| Emergy (10^20 seJ)                  | 1.97    | 2.40    | 0.69    | 2.33   | 1.73     | 2.68     | 10.75   | 8.45     |
| Adaptive capacity (10^22 seJ)       | 5.98    | 5.34    | 3.04    | 3.35   | 5.65     | 5.54     | 12.48   | 7.36     |
vulnerable to flood threats. However, Hanyuan County and other areas with the large area of cultivated land and woodland are less sensitive. Therefore, these areas are less threatened by flood disasters, thus featuring relatively low susceptibility.

(3) The stronger the system’s adaptive capacity is, the stronger capacity it has against a flood disaster. Table 7 shows that different districts and counties in Ya’an City have different adaptive capacity. Yucheng and Mingshan districts boast better economic strength, medical and healthcare conditions, and popular education to see a stronger adaptive capacity. Hanyuan and Tianquan counties see favorable economic growth, but relatively low popular education, so they have a relatively poor adaptive capacity. Baoxing County, which is economically underdeveloped and has poorer medical services and a lower level of popular education, presents the poorest adaptive capacity among districts and counties in Ya’an.

3.5. Risk assessment
Based on the calculated results of exposure, susceptibility, and adaptive capacity, we use the calculation method mentioned in the Methods section to calculate the potential impact index and risk of a flood disaster to various districts and counties of Ya’an City. The calculated results are shown in Table 8.

With the calculated results in Table 8, the GIS software was used to obtain the potential impact indexes and a risk distribution map for various districts and counties of Ya’an City (Figure 3).

The potential impact index is related to the exposure and susceptibility of a region, which indicates the possible losses of a system in case of extreme weather (Yangfan 2018). Figure 3(a) presents the potential impact of a flood disaster on different districts and counties in Ya’an City. Yucheng District, thanks to a high population density, social fixed assets investment, and economic development, boasts a high level of accumulative social assets, so it will see the highest potential impact in case of a flood disaster. Baoxing and Shimian Counties, with a low population density and slow economic growth, see lower potential indices than other regions.

The risk of a system means that in the same case of a flood disaster, the higher risk emergy it has, the higher risk the system will see, and the more serious the impact will be. Figure 3(b) shows that Lushan County sees the highest risk index, followed by Yucheng District, and Shimian County witnesses the lowest risk index. Shimian County sees the lowest risk, for this county has more medical workers per 10,000 people than others, and high social fixed assets investment, so effective control measures can be taken in case of a flood disaster.

3.6. Model effect analysis
We built a BP neural network-based flood risk assessment model to have a comprehensive assessment of the emergy theory’s performance in flood disaster risk assessment. The artificial neural network uses a lot of simple processing units (neurons) to form a nonlinear dynamic system, which has learning, memorization, calculation, identification, predication, and many intelligent processing functions. It is different from the so-called electronic brain—electronic computer and the AI system deduced based on symbol, but an AI system that imitates our human brain neural system on another different level and to a different extent (Kuang 2017).

BP neural network is an error back-propagation learning algorithm, and its working principle is to convert an input vector into an output vector via the hidden layer and to map from the input space onto the output space. Its weight works to realize forward mapping using the network input of the current weight and the expected output to meet the mapping requirements for contrastive learning (Jing et al. 2020). The BP neural network does not only have an input layer node and an output layer node, but also have one or more hidden layer nodes. After signal input, we first should propagate it forward to the hidden layer nodes; under the activation function, the output signal from the hidden node is propagated to the output node, to ultimately output the results. Its main operation procedures are to: (1) provide the neural network with training examples, i.e., learning samples, including input and expected output, (2) determine the permissible error of the network between the actual output and

| Region         | Shimian | Hanyuan | Baoxing | Lushan | Tianquan | Xingyang | Yucheng | Mingshan |
|----------------|---------|---------|---------|--------|----------|----------|---------|----------|
| Potential impact index (10² seJ) | 3.32    | 5.14    | 2.03    | 11.12  | 6.75     | 4.92     | 20.31   | 6.74     |
| Vulnerability (10²) | 0.56    | 0.96    | 0.67    | 3.32   | 1.19     | 0.89     | 1.63    | 0.92     |
the expected input, and (3) change all connection weight values in the network, to make the generated output closer to the expected output, until it meets the demand for the determined permissible error.

To assess the flood disaster risk in Ya’an City, we first should consider the local natural and geographic environment and the socio-economic conditions to choose the assessment indicator factors from hydro-meteorology and topography geology and society. We select precipitation, runoff depth, drainage basin water storage, slope, elevation, population density, and GDP factors in this paper as assessment indicators to form the assessment indicator system, standardize the data, reduce its dimensions, and divide each indicator into five grades through the natural-break point method (Table 9). After standardization, we use the BP neural network, in combination with the actual flooding position, and conduct learning training to obtain the weights of all assessment indicators (Table 10). Then we use the raster calculator on the GIS platform to overlay all indicator factors according to their respective weights to obtain the hazard distribution map of Ya’an City (Figure 4). The training accuracy based on BP neural network is 0.768.

Figure 3 | Potential impact indices and risk profiles.

Table 9 | Range of indicators

| Risk ranking                  | Very low | Low     | Medium  | High     | Very high |
|-------------------------------|----------|---------|---------|----------|-----------|
| Precipitation                 | 0-0.176  | 0.176-0.282 | 0.282-0.478 | 0.478-0.639 | 0.639-1   |
| Runoff                        | 0-0.231  | 0.231-0.412 | 0.412-0.592 | 0.592-0.792 | 0.792-1   |
| Drainage basin water storage  | 0-0.369  | 0.369-0.522 | 0.522-0.643 | 0.643-0.749 | 0.749-1   |
| Slope                         | 0-0.478  | 0.478-0.604 | 0.604-0.718 | 0.718-0.843 | 0.843-1   |
| Elevation                     | 0-0.420  | 0.420-0.576 | 0.576-0.714 | 0.714-0.847 | 0.847-1   |
| Population density            | 0-0.141  | 0.141-0.471 | 0.471-0.510 | 0.510-0.945 | 0.945-1   |
| GDP                           | 0-0.146  | 0.146-0.379 | 0.379-0.641 | 0.641-0.829 | 0.829-1   |
The risk distribution map shows that most regions of relatively high flood hazard risk are in the east part of Ya’an City: Lushan County, Yucheng District, and Mingshan District face the highest risks. Yucheng and Mingshan districts boast relatively high-density population distribution and are more likely to be affected by a flood disaster’s damage, so corresponding disaster control and relief efforts should be made. Other districts and counties in Ya’an do not feature high risk, but their vegetation should also be protected, to prevent any flood disaster, and provide bases for local governments to carry out flood control and disaster relief. Comparing with some previous research efforts, we have found both indicate that a region, more developed in the economy with more accumulative assets, sees higher potential impact and boasts higher adaptive capacity (Wu et al. 2018).

In order to verify the objectivity of the research results, we compared the historical flood event in Ya’an City. On 22 August 2019, 47 towns and villages in seven counties (districts) of the city were affected, with 96,000 affected people and 22,500 emergency relocations, resulting in a direct economic loss of 3.078 billion yuan. The areas with the largest losses are Lushan and Yucheng, and the disasters are mainly concentrated in Lushan County. The actual loss is consistent with the experimental results. Overall, the prediction matches the actual flood disaster situation, which represents the actual situation of the region.
4. CONCLUSIONS

Using emergy analysis, we constructed a flood risk assessment indicator system of Ya’an City that involved susceptibility and adaptive capacity of the hazard-affected region. In combination with the BP neural network, we have made a risk assessment and contrastive analysis of the study area. The results go as follows:

(1) Two methods have been applied to various districts and counties of Ya’an City. The results show that more developed regions like Yucheng and Mingshan districts have the highest potential impact index but lower risk than other regions. This is because these two economically developed districts, well-equipped with medical facilities, have a high adaptive capacity and thus can effectively address various emergencies in case of a flood disaster. Lushan County is just the opposite. This study reveals that a system with a strong adaptive capacity can effectively lower its risk of a flood disaster.

(2) This study assesses the flood risks of various districts and counties of Ya’an City. In actual practice, the emergy theory has often been used to investigate the sustainable development capacity of an ecological-economic system. However, studies on its application to flood disaster risk assessment are rare, most of which stay in the stage of theoretical or methodological analysis and show defects in real-world application. This paper selects Ya’an area as the research area, and applies emergy theory to the risk analysis of Ya’an City, making the analysis results more objective. Moreover, it is also of great research value to explore whether the emergy theory could be applied to other fields.

ACKNOWLEDGEMENT

This study is funded by the Yangtze River Collaborative Fund for Hydro-sciences, Natural National Science Foundation of China (SFC; U2040210).

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES

Abdulrazzak, M., Elfeki, A., Kamis, A., Kassab, M., Alamri, N., Chaabani, A. & Noor, K. 2019 Flash flood risk assessment in urban arid environment: case study of Taibah and Islamic universities’ campuses, Medina, Kingdom of Saudi Arabia. Geomatics, Natural Hazards and Risk 10, 780–796.

Bhuiyan, S. R. & Baky, A. A. 2014 Digital elevation based flood hazard and vulnerability study at various return periods in Sirajganj Sadar Upazila, Bangladesh. International Journal of Disaster Risk Reduction 10, 48–58.

Chang, L. & Huang, S. 2015 Assessing urban flooding vulnerability with an Emergy approach. Landscape and Urban Planning 143, 11–24.

Chao, X., Nan, M., Fei, L., Xiaoming, L. & Zhiyun, O. 2020 Research on Urban Green Infrastructure Management in Macao from the Perspective of Ecosystem Service Demand. Classical Chinese Garden.

Chengguang, L., Chen, X., Shiwei, Z., Wang, Z. & Xushu, W. 2015 Flood risk assessment model based on random forest and its application. Shiuli Xuebao 46, 58–66.

Foudi, S., Osés-Eraso, N. & Tamayo, I. 2015 Integrated spatial flood risk assessment: the case of Zaragoza. Land Use Policy 42, 278–292.

Hanif, A., Dhanasekar, A., Keene, A., Li, H. & Carlson, K. 2020 Flood risk assessment methodology for planning under climate change scenarios and the corresponding change in land cover. Journal of Water and Climate Change 11 (4), 1370–1382.

Huang, S. & Odum, H. T. 1991 Ecology and economy: emergy synthesis and public policy in Taiwan. 32.

Jing, K., Xiaoxi, M., Haifian, W., Lu, W., Kai, S. & Altoa, T. 2020 Research progress of artificial neural networks in material science. Materials Reports 34 (21), 21172–21179.

Jun, X., Wei, S., Xinpeng, L., Si, H., Like, N. & Gippel, C. J. 2015 Revisions on water resources vulnerability and adaption measures under climate change. Advances in Water Science 26 (02), 279–286.

Kazakis, N., Kougias, I. & Patsialis, T. 2015 Assessment of flood hazard areas at a regional scale using an index-based approach and analytical hierarchy process: application in Rhodope–Evros region, Greece. Science of the Total Environment 538, 555–563.

Kuang, W. 2017 Overview of the development of artificial neural networks. Frontiers of Science and Technology 165–167.

Luo, P., Xiaorong, H., Xiaoyue, W. & Lang, Z. 2019 Research on the sustainability of water eco-economic system in Chengdu based on emergy analysis. Water Power 45 (09), 12–16.

Sun, Z., Zhu, X. & Pan, Y. 2017 Flood risk analysis: progress, challenges and prospect. Journal of Catastrophology 32, 125–130.

Tanoue, M., Hiranayashi, Y. & Ikeuchi, H. 2016 Global-scale river flood vulnerability in the last 50 years. Scientific Reports 6, 36021.
Wahab, A. M. & Muhamad Ludin, A. N. 2018 Flood vulnerability assessment using artificial neural networks in Muar Region, Johor Malaysia. *IOP Conference Series, Earth and Environmental Science* **169**, 12056.

Wangyang, Y., Chunbo, J., Jian, L. & Qi, Z. 2019 Hydrologic-hydrodynamic model and its application in flood risk analysis. *Journal of Hydroelectric Engineering* **38** (08), 87–97.

Wanzhi, L., Di, Y., Xiaoli, F. & Tiaofeng, Z. 2019 Risk assessment of rainstorm and flood disasters based on the hazard grades/indices in Qinghai Province. *Journal of Glaciology and Geocryology* **41** (3), 680–688.

Wu, Z., Shen, Y. & Wang, H. 2018 Assessment of vulnerability to flood disasters based on Emergy theory. *South-North Water Diversion and Water Resources Science and Technology* **16**, 9–14.

Yangfan, X. 2018 Flood Hazard Assessment Based on Spatial Multi-Criteria Decision Making and Heterogeneous Spatial Data Integration. Huazhong University of Science & Technology.

Yongzhi, L., Wenwen, T., Wenting, Z., Xingnan, Z. & Shuai, N. 2021 Review of flood disaster risk analysis based on disaster chain. *Water Resources Protection* **37** (1), 20–27.

Zhao, L. 2013 *Ecological Economics*. China Economic Publishing House, Beijing.

First received 1 April 2021; accepted in revised form 10 June 2021. Available online 22 June 2021.