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Research article

Flood Risk Assessment Based on the Information Diffusion Method and Artificial Neural Network

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Abstract

This paper presents a composite method for flood disaster risk assessment using a BP artificial neural network and information diffusion technique. Due to the fact that the traditional mathematical statistical model can hardly analyze flood risk issues when the sample size is small, information diffusion theory is suggested to extract as much useful information as possible from the sample and thus improves the accuracy of system recognition. Meanwhile, an artificial neural network model-BP neural network is used to map multi-dimensional space of disaster situation to one-dimensional disaster situation and to raise the grade resolution of flood disaster loss. Furthermore, its application is verified in the flood risk analysis in Henan Province, China, and the risks of different flood grades are obtained. The results indicate that the methods are effective and practical and therefore the model is considered to have a good application prospect in disaster risk assessment.

Keywords: information diffusion; neural network; flood; risk assessment.

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1 Introduction

Flood disasters occur frequently in China, and about two-thirds of its area are facing the threat of different types and degrees of floods which is the result of natural and unnatural reasons such as social, economic factors. As severe floods occurring frequently, flood risk assessment and management play an important role in guiding the government take timely and correct decision for disaster rescue and relief. It's an inevitable choice in the historical development of China to change from flood control to flood management which is an important contemporary strategy on flood control. Risk assessment, one of the main subjects of flood management which consists of risk identification, risk assessment, and risk control is a challenging task at the present.

The analysis methods of flood risk have shown a progress from direct integral method, Monte Carlo method, mean first-order-second-moment method, to advanced first-order-second-moment method, second-order-method and JC method. Since the beginning of 20th century, flood frequency had been taken into account in some researches. The theory and method of flood risk analysis was established according to the studied by the authors (Ang, & Tang, 1984; Todorovic, & Zelenhasic, 1970; Todorovic, & Rousselle 1971; Wood, 1975; Ashkar, & Rousselle, 1981; Kuczera, 1982; Stedinger, & Taylor, 1982; Diaz, 1984). But because of too much stress on frequency analysis, risk analysis was neglected. The risk analysis expands the definition of probability, and it treats not only the various inherent uncertainties such as the stochastic characteristics but also much additional subjective deviation or error because of the incompleteness of data information. In 1989, Rasmussen and Rosbjerg studied risk estimation problem of design flood in case of lacking of flood data , the concept of expected risk was put forward and its application was verified by MC method (Rasmussen, & Rosbjerg, 1989). Xu ZX et al. considered the flood process as a kind of stochastic point process, since 1988 they had successively discussed the flood risk models compound with Poisson process, Renewal process, Neyman-Scott process and other random point processes (Xu, 1989; Xu, & Ye, 1988; Xu, & Deng, 1989; Xu, & Zeng, 1992). Sen investigated the effect of dependence on the simple risks involved in any engineering design on the basis of the lag-one Markov process (Sen, 1999). Mei YD and Tan GM took the effect of hydrological and hydraulic uncertainties on dam safety into account, a stochastic simulation approach-MC method to calculate the overall risk of flood prevention and safety of dam is developed (Mei, & Tan, 2002).

As previously mentioned, scholars have made a deep research on the flood's random characteristics as well as its related risk analysis, but the study on some aspects such as its fuzziness (Chen, 1998), gray characteristic (Xia, 2000), unascertained characteristic (Liu, et al. 1994), fractal dimension characteristic and chaos characteristic of the flood is relatively weak, so the researches on the correspondingly risk analysis need to be developed further.

In traditional flood risk assessment, probability statistics method is usually used to estimate hydrological variables' exceedance probability. This method has the advantage of its mature basic theory and easy application. But when it comes to practical issues, problems exist in the feasibility and reliability without considering its fuzzy uncertainty. In the case of small sample issues, results based on the classical statistical methods are very unreliable sometimes. In fact, it is rather difficult to collect long sequence flood data and the sample is usually small. Information diffusion theory helps to extract as much useful underlying data as possible from the sample and thus improves the accuracy of system recognition (Huang, 2002; Palm, 2007). Information diffusion is just a fuzzy mathematic set-value method for samples, considering optimizing the use of fuzzy information of samples in order to offset the information deficiency. So we can use this fuzzy mathematical method for comprehensively disaster risk assessment.

Meanwhile, in order to map multi-dimensional space of disaster situation to one-dimensional disaster situation nonlinearly ,to test the grade criterions of flood disaster loss and resolve the non-uniformity problem of evaluation results of disaster loss indexes, and to raise the grade resolution of flood disaster loss, an artificial neural network model-BP neural network is suggested for evaluating the degree of flood disaster, where the disaster loss degree is a more reasonable continuous real number.

In this study we establish a composite model based on information diffusion method and artificial neural network with a small number of measured samples and it is then applied to the flood risk analysis in Henan province successfully.

2 model introducing

The essential of the risk analysis is to estimate the probability density of an index. Because of the incompleteness of the data, the application of traditional statistical methods can not guarantee a high precision, and information diffusion method is an effective treatment for small sample size. We train the neural network with the observed sample and get their degree values, and then convert the degree values into fuzzy sets by information diffusion method, and finally get the risk estimations with the composite model. It is tested by a case showing that the composite model is superior to traditional probability statistics method and improves the accuracy of the probability estimation.

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2.1 information diffusion

Information diffusion is a fuzzy mathematic set-value method for samples, considering optimizing the use of fuzzy information of samples in order to offset the information deficiency. The method can turn an observed sample into a fuzzy set, that is, turn a single point sample into a set-value sample. The simplest model of information diffusion is normal diffusion model.

Information diffusion: Let X be a set of samples, and V be a subset of the universe, $\mu : X \times V \to [0,1]$ is a mapping from $X \times V$ to [0, 1]. $\forall (x,v) \in X \times V$ is called a kind of information diffusion of X on V. And it satisfies three conditions as follows.

(1)It is decreasing. $\forall x \in X$, $\forall \upsilon', \upsilon'' \in V$, if $\|\upsilon' - x\| \le \|\upsilon'' - x\|$, then $\mu(x,\upsilon') \ge \mu(x,\upsilon'')$. μ becomes a diffusion function.

(2) $\forall x \in X$, Let υ^* be observed value of x , then $\mu(x,\upsilon^*) = \max_{\upsilon \in V} \mu(x,\upsilon)$.

(3) $\mu(x,\upsilon)$ is conservative, if and only if $\forall x \in X$, its Integral value on the universe is 1. $\int_U \mu(x,u)du = 1$

If the random variables' domain is discrete, suppose it is $U = \{u_1, u_2, \cdots, u_m\}$,the conservation condition is $\sum_{j=1}^{m} \mu(x,u_j) = 1$, $\forall x \in X$.

Let $X = \{x_1, x_2, \cdots, x_n\}$ be a sample, and $U = \{u_1, u_2, \cdots, u_m\}$ be the discrete universe of X. x_i and u_j are called a sample point and a monitoring point, respectively. $\forall x_i \in X$, $\forall u_j \in U$, we diffuse the information carried by x_i to u_j at gain $f_i(u_j)$ by using the normal information diffusion shown in Eq. (1).

$$f_i(u_j) = \exp\left[-\frac{(x_i - u_j)^2}{2h^2} \right], \quad u_j \in U \tag{1}$$

Where h is called normal diffusion coefficient, calculated by Eq. (2).

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$$h = \begin{cases} 0.8146(b-a), & n=5; \\ 0.5690(b-a), & n=6; \\ 0.4560(b-a), & n=7; \\ 0.3860(b-a), & n=8; \\ 0.3362(b-a), & n=9; \\ 0.2986(b-a), & n=10; \\ 0.6851(b-a)/(n-1), & n \geq 11. \end{cases} \tag{2}$$

Where $b = \max_{1 \leq i \leq n}\{x_i\}; a = \min_{1 \leq i \leq n}\{x_i\}$

Let $$C_i = \sum_{j=1}^{m} f_i(u_j) \tag{3}$$

We obtain a normalized information distribution on U determined by x_i, shown in Eq. (4).

$$\mu_{x_i}(u_j) = \frac{f_i(u_j)}{C_i} \tag{4}$$

For each monitoring point u_j, summing all normalized information, we obtain the information gain at u_j, which came from the given sample X. The information gain is shown in Eq. (5).

$$q(u_j) = \sum_{i=1}^{n} \mu_{x_i}(u_j) \tag{5}$$

$q(u_j)$ means that, with the information diffusion technique we infer that there are $q(u_j)$ (generally is not an integer) sample points in terms of statistic averaging at the monitoring point u_j.Obviously $q(u_j)$ is not usually a positive integer, but is certainly a number not less than zero. And assumption $Q = \sum_{j=1}^{m} q(u_j)$ (6), where Q is the sum of the sample size of all $q(u_j)$, theoretically, there will be Q = n, but due to the numerical calculation error, there is a slight difference between Q and n. Therefore, we can employ Eq. (7) to estimate the frequency value of a sample falling at u_j.

$$p(u_j) = \frac{q(u_j)}{Q} \tag{7}$$

The frequency value can be taken as the estimation value of its probability. Apparently, the probability value of transcending u_j should be $P(u_j) = \sum_{k=j}^{m} p(u_j)$ (8), $P(u_j)$ is the required risk estimation value.

2.2 Basic principle of BP neural network

Artificial Neural Network (ANN) are massively parallel interconnected networks of simple (usually adaptive) nodes which are intended to interact with objects of the real world in the same way as biological nervous systems do(Simon, 2009). It was proposed based on modern biology research concerning human brain tissue, and can be used to simulate neural activity in the human brain (Markopoulos1, Manolakos, & Vaxevanidis, 2008). ANN has the topological structures of information processing, distributing parallel. The mappings of input and output estimation responses are obtained via combinations of nonlinear functions (Chat, & Abdullah, 2002).

In terms of their structures, neural networks can be divided into two types: feedforward networks and recurrent networks. In a feedforward network, the neurons are generally grouped into layers. Signals flow from the input layer through to the output layer via unidirectional connections, the neurons being connected from one layer to the next, but not within the same layer. The multi-layer perceptron (MLP) is perhaps the best known type of feedforward networks. For the typical multi-layer perceptron of the feed-forward mode neural network, it consists of the input layer, output layer, and hidden layer. Neurons in the input layer only act as buffers for distributing the input signals x_j to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_j after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum,viz.

$$y_j = f(\sum w_{ji} x_i) \qquad (9)$$

In which f can be a simple threshold function or sigmoidal, hyperbolic tangent or radial basis function. The output of neurons in the output layer is computed similarly.

The backpropagation (BP) algorithm, a gradient descent algorithm, is the most commonly adopted MLP training algorithm. It gives the change Δw_{ji} the weight of a connection between neurons i and j as follows:

$$\Delta w_{ji} = \eta \delta_j x_i \tag{10}$$

Where η is a parameter called the learning rate and δ_j is a factor depending on whether neuron j is an output neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)(y_j^{(t)} - y_j) \tag{11}$$

And for hidden neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\sum_q w_{qj}\delta_q \tag{12}$$

In Equation (11), net j is the total weighted sum of input signals to neuron j and $y_j^{(t)}$ is the target output for neuron j.

The neural cell of each layer only affects the status of the next neural cell. If the expected output signals cannot be obtained in the output layer, the weight values of each layer of the neural cells must be modified. Erroneous output signals will be backward from the source. Finally, the signal error will arrive in certain areas with repeated propagation. After the neural networks' training procedure is complete we can start to analyze the forecast information with weight values and thresholds.

3 Flood risk assessment composite model based on neutral network and information diffusion

3.1 Flood disaster index and the BP neural networks' training

According to the 41 years' practical series material from 1950 to 1990 in henna province, we take inundated area and direct economic loss as the indexes of disaster degree and by frequency analysis the disaster grading standards of the area are seen in table 1.

Table 1: Henan flood disaster rating standard

Disaster level	Inundated area (hm^2)	Direct economic losses (Billion Yuan)	Degree value
Small flood	0~46.7	0~9.5	0~1
Medium flood	46.7~136.7	9.5~31.0	1~2
Large flood	136.7~283.3	31.0~85.0	2~3
Extreme flood	283.3~2833	85.0~255	3~4

In order to map multi-dimentional space of disaster situation to one-dimensional disaster situation, a relationship between the disaster degree and the degree indexes is needed. But it is impossible to describe the relationship using a related function. Therefore, we adopt the ‘‘simulation” and ‘‘memory” of the neural networks in flood degree evaluation. This is because the advantages of neural networks can be used to simulate and record the relationship of the input variables and output variables in the complex ‘‘function” through training and learning without any mathematical models.

We take the inundated area data and direct economic loss data as input variables and disaster grading value as an output variable, and then we set the nodes of the input as 2 and of the output layers as 1. It follows on from Kolmogorov’s theorem that the number of nodes in the hidden layer is at least 2n + 1, where n is the number of nodes in the input layer. Since n = 2, the number of nodes in the hidden layer is at least 5. Considering the accuracy, we determine that the number of nodes in the hidden layer is 6. Thus, we can obtain the topology structure (2, 6, and 1) of the neural networks for flood degree forecasting.

The four flood grades are small, medium, large and extreme flood, whose degree value are in the interval [0,1]、[1,2]、[2,3]、[3,4]; We use the disaster grading standard boundary values (table 1) as 5 two-dimensional training samples for training and learning in the BP neural network. Meanwhile initial parameters of BP model weights and biases are randomly assigned before the commencement of training. With 100,000 cycles of training and learning in the training samples, the global error of the networks was set $E=10^{-6}$. Learning rate and impulse parameter of the network are changed adaptive, and function trainlm is used for fast training.

Table 2: Expected output & actual output of floods evaluation standard limits

Expected output	0.0000	1.0000	2.0000	3.0000	4,0000
Actual output	0.0000	0.9995	2.0000	3.0000	4.0000

The calculated output values are compared with the expected values in Table 2 where the mean square error is 5.94387*exp(-8) and the gradient 4.46355*exp(-3), indicating a good fitting. Thus the BP neural network has completed the training procedure. So we can use the BP network to forecast disaster degrees of all the samples with the weighting coefficients and the thresholds modified. The flood degree estimations are list in Table 3.

Table 3: Disaster degree estimations based on the BP network evaluation

Number	Inundated area (hm^2)	Direct economic loss(Billion Yuan)	Output degree value	Number	Inundated area(hm^2)	Direct economic loss(Billion Yuan)	Output degree value
i			x_i	i			x_i
1	38.70	7.900	0.3814	17	157.30	38.600	2.8297
2	38.50	7.800	0.3704	18	283.30	85.000	3.4817
3	32.10	6.500	0.1333	19	556.90	67.100	4.0000
4	24.20	4.900	0.0636	20	649.50	194.900	4.0000
5	36.40	7.400	0.2877	21	602.30	180.700	4.0000
6	46.70	9.500	0.6989	22	446.50	134.000	3.9996
7	97.60	21.700	1.3560	23	694.90	208.500	4.0000
8	60.40	12.800	1.0214	24	72.92	9.900	1.0858
9	112.60	25.200	1.6815	25	148.13	20.656	2.4734
10	56.20	11.800	0.9590	26	203.92	27.521	2.9919
11	80.60	17.600	1.1714	27	179.10	24.858	2.9029
12	136.70	31.000	2.4142	28	375.46	94.927	3.9854
13	259.10	76.100	3.2234	29	301.24	47.836	3.6167
14	200.10	54.400	3.0076	30	141.97	116.439	2.9900
15	280.10	83.800	3.4432	31	279.84	121.127	3.5082
16	236.10	67.600	3.0856	32	172.06	51.619	2.9598

3.2 Flood risk assessment based on information diffusion

Based on the disaster degree values of the 32 samples (see Table 3), that is the sample points set $X=\{x_1,x_2,\cdots,x_{32}\}$. The universe discourse of the disaster degree values namely the monitoring points set is taken as $U=\{u_1,u_2,\cdots,u_{41}\}=\{0,0.1,0.2,\cdots 4.0\}$. The normalized information distribution of each x_i ,that is, $\mu_{x_i}(u_j)$, can be obtained according to equation (1),(2),(3)and(4)，then based on equation (5),(6),(7)and(8), disaster risk estimate namely probability risk value in Henan province is calculated out. The relationship between the recurrence interval N and probability p can be expressed as $N = 1/p$, and then the probability density curve and the exceedance probability curve of flood to disaster degree value are shown as Figure 1 and Figure 2.

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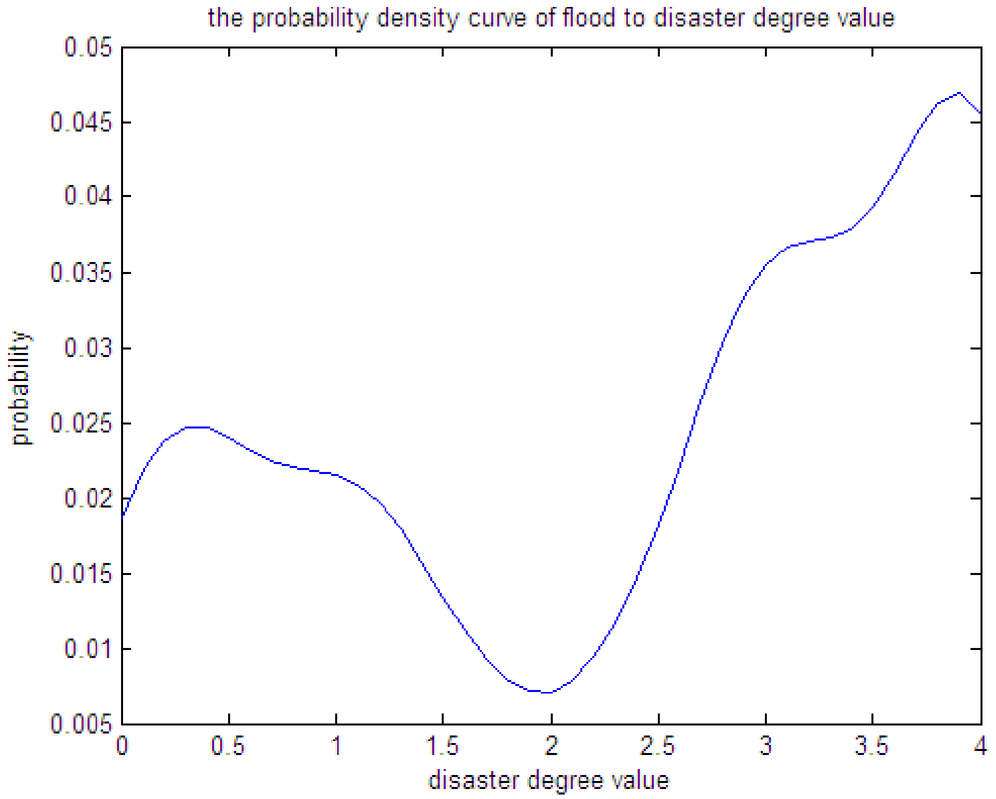

Figure 1: The probability density curve of flood to disaster degree value

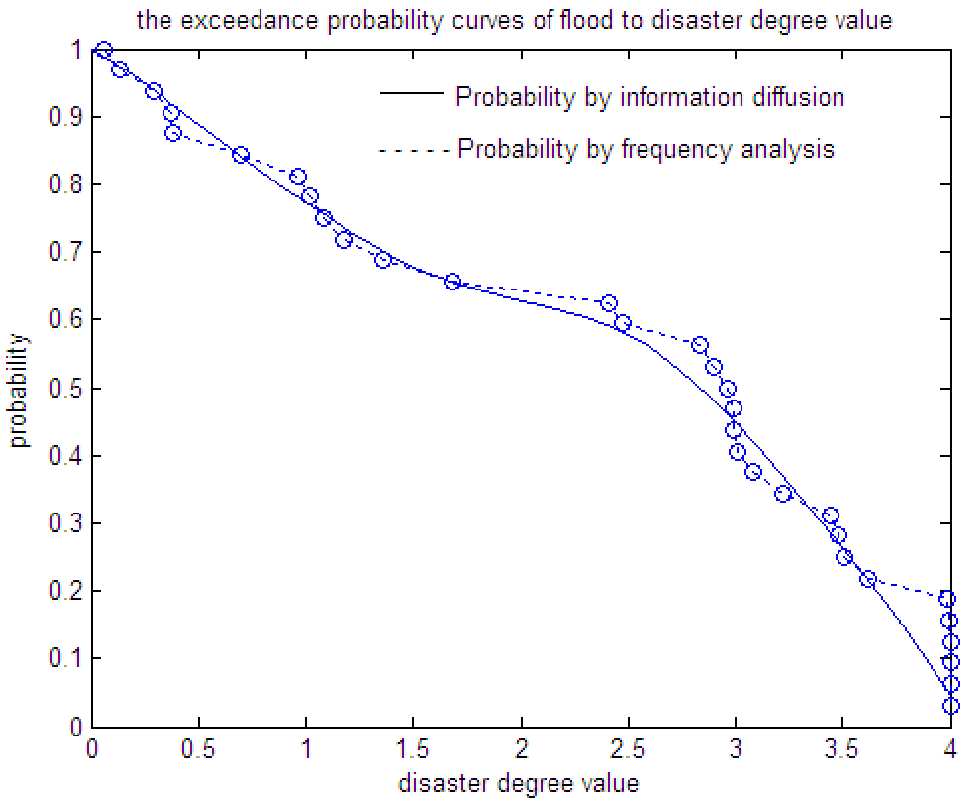

Figure 2: The exceedance probability curves of flood to disaster degree value based on information diffusion and frequency analysis

Figure 1 illustrates the probability distribution in the whole interval and the probability values on different disaster levels in Henan Province. From the probability density curve of flood we can see a maximum probability of 4.7*exp(-2) occurs with 3.9 disaster degree and a minimum probability of 7.1*exp(-3) occurs with 2.0 disaster degree.

Due to the standard of four grades, so we have:

(a) If $0 \le x_i \le 1$, then flood degree belongs to small.

(b) If $1 < x_i \le 2$, then it belongs to medium.

(c) If $2 < x_i \le 3$, then it belongs to large.

(d) If $3 < x_i \le 4$, then it belongs to extreme.

The result in Figure 2 illustrates the risk estimation i.e. the probability of exceeding the disaster degree value. From Figure 2 we know the risk estimation is 0.4478 when the disaster index is 3, in other words, in Henan Province, floods exceeding 3 degree value (extreme floods) occur every 2.23 years. Similarly, the probability of floods exceeding 2 degree (large floods) is 0.6286, namely Henan Province suffers the floods exceeding that intensity every 1.59 years. This indicates the serious situation of floods in Henan Province whether on the aspect of frequency or intensity. In Figure 2 the curve so estimated is compared to the result by frequency analysis which shows that our results are consistent with those of frequency analysis. It also means that normal information diffusion is useful to analyze probability risk of flood disaster. Because the flood disaster belong to the fuzzy events with incomplete data, therefore, the method proposed is better than traditional frequency method to analyze the risk of the flood disaster. The methods of information diffusion are more fit to estimate the risks of natural disasters and to smooth the patterns which are employed to train neural networks.

Obviously, the estimator by this composite model is also better than the linear-regression estimator and conventional BP neural-network estimator, because this estimator is more precise than the linear-regression estimator, and more stable than the conventional BP-neural network estimator.

The frequency and the recurrence interval of the floods of the four grades are shown in Table 4. Compared with traditional probabilistic method, the risk values obtained by this composite method can provide more characteristics of risk system when we analyze the risk of system. The result could help in strategic decision making to manage flood disasters.

Table 4: Flood disaster risk assessment values in Henan province

Disasters level	Small flood	Medium flood	Large flood	Extreme flood
Exceedance probability risk	1.0000	0.7733	0.6286	0.4478
Recurrence interval(year)	1.00	1.29	1.59	2.23

4 Conclusions

Floods occur frequently in China and cause significant property losses and casualties. In order to implement a compensation and disaster reduction plan, the losses caused by flood disasters are among critically important information to flood disaster managers. This study develops a method of flood risk assessment disasters based on BP neural network and information diffusion technique, and it can be generalized as an integration of techniques. It has been tested that the method is reliable and the results are consistent with the real values.

In view of the facts that the theoretic system of flood risk assessment has not been perfect enough so far, and the observed series of flood disaster are quite short or even unavailable, the method based on information diffusion adopted in the paper is indisputably an effective and practical method. In short, information diffusion is a data treatment process that can transform data from a point in a traditional data sample to a fuzzy data set. The methods of information diffusion are more fit to estimate the risks of natural disasters and to smooth the patterns which are employed to train neural networks.

Our method is based on a general modeling framework and the techniques used are applicable for other natural disasters. Thus, our method can be easily extended to other natural disasters if relevant domain knowledge is incorporated in this framework and relevant data are available.

In the future, we will consider the following aspects as the extension of this work:

(1) Further studies are needed such as the flood disaster index selection and the index calculation strategy etc to ensure the estimation is more close to the practical situation.

(2) In terms of the form and adaptive condition of information diffusion and the determination of diffusion

coefficients, further in-depth research should be conducted in order to ensure the estimation probability values get much closer to the real happening values.

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