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Risk Assessment on Drought Disaster in China Based on Integrative Cloud Model

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Abstract: This study promotes cloud model for risk assessment of drought disaster. Cloud model is an effective tool in uncertain transforming between qualitative concepts and their quantitative expressions. Cloud is expressed by a concept with three quantitative characteristics of expectation, entropy and hyper entropy and the mapping between qualitative and quantitative is realized. In this study, considering the fuzziness and uncertainty of drought disaster, we established the comprehensive cloudy model based on entropy weight method for evaluating the risk of drought disaster. The disaster-affected rate and disaster-damaged rate are selected as the evaluation indices of drought degree. The model is applied to assess the drought disaster risk in China. The BP neural network, hard division method and integrative cloud model are compared, and the integrative cloud model is shown better for evaluating drought risk. This study shows that risk assessment of drought disaster based on cloud model is feasible and effective and can provide decision-making for the risk assessment of drought disaster.

Key words: Cloud model, drought disaster, index system, risk assessment

INTRODUCTION

Climate change and its impacts have been well recognized, especially on droughts. The synthesis report of the IPCC Fourth Assessment Report (AR4) was launched in Spain in 2007. The report indicates whether the negative impacts of climate change could be minimized largely depends upon the efforts and investment in Global Green House Gas (GHG) emission control in the future 20 to 30 years. It is urgent for us to take prompt actions in reducing the GHG emission and strengthen the international negotiation regarding climate change (IPCC, 2007 a,b). The global climate change anticipated to have threatening consequences on our water resources and environment at both the global level and at local/regional levels. The current state of our water resources and the climate change problem is reviewed and the strategies in dealing with the potential impacts of climate change on our water resources are proposed (Sivakumar, 2010). Drought disaster is still a serious problem in the Asian and Pacific region due to global warming and human activity. Countries in South-West and Central Asia faced more challenges for drought mitigation than other countries in Asia due to severe drought combined with the effects of protracted socio-political disruption (UNESCAP, 2007). For water resources management in south Florida, a sensitivity analysis using a regional-scale hydrologic and water management model is conducted and the results suggest that projected climate change has potentials to reduce the effectiveness of water supply and flood control operations for all water sectors (Obeysekera, 2010). These findings emphasize the potential impacts of climate change need to be investigated with particular attention (Obeysekera, 2010). In southeast Australia, given the current prolonged drought and predictions of a generally drier future, Chiew *et al*. (2010) suggested that the future climate will be drier than those experienced in the long-term historical climate and the recent climate should be considered as one possible scenario for short-term and medium-term planning because the drought will continue for some time yet. Rosenzweig *et al*. (2001) discussed the effects of climate variability and change on food production, risk of malnutrition, and incidence of weeds, insects and diseases. It focuses on the effects of extreme weather events on agriculture, looking at examples from the recent past and to future projections and projected scenarios of future climate change impacts on crop production and risk of hunger in major agricultural regions are presented. Burke *et al*. (2010) evaluated the likelihood of drought

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over the UK by extreme value analysis of drought indices during the 20th century and potential future changes due to increase atmospheric greenhouse gas.

In recent years, drought disaster has been occurred frequently in China, seriously affecting agriculture, industrial production, urban water supply and ecological environment. Furthermore, the continuous accumulation of drought will degrade land resources and restrict sustainable development. It is shown that drought and water shortage crisis is increasing with the rapid economic development and population growth and directly enlarge the arid areas. Drought problem has become the focus in China. According to statistics, 95.3 thousand km^2 of wheat in Henan, Anhui, Shandong, Hebei, Shanxi, Gansu and other main producing areas suffered drought in China in February, 2009 (Chen, 2009). Since 2010, five provinces and cities in Southwest China sustained drought which has seriously threatened people's daily life and economic production activities. In the literature, an evaluation model of the drought degree is developed by identification of the drought phenomenon using the artificial neural network, and the model has been widely used through empirical analysis (Feng *et al*., 2000). Information diffusion theory was used to establish the fuzzy relationship between the sample and its relevant domain, and the model was applied to the period of year 2000-2006 in Gansu province of China. The result showed that the risk of both agricultural damage area and disaster area increases (Chang and Liang, 2009). Wang *et al*. (2001) established the measuring method and forecasting model about soil water content for north of the Huaihe River and the model was used in similar regions and arid and semi-arid regions.

Because of the uncertainty between qualitative language and quantitative expression in assessment drought degree, a new model is established to transform qualitative language and quantitative measures. Cloud model is proposed by (Li *et al*., 1995, 1998a, b) based on traditional fuzzy set theory, and statistics & probability, which can express the uncertainty between qualitative language and quantitative measures. The cloud model mainly reflects fuzziness and randomness of the object and fully integrates both fuzziness and randomness together by forming a mapping of qualitative and quantitative aspects (Li and Du, 2005). Cloud model has been applied to many fields. Zhang *et al*. (2009) used cloud model to evaluate urban air quality and establish the assessment standard, and concluded that the proposed approach was efficient. Li *et al*. (2010) introduced a comprehensive assessment model which adopted the trapezium-cloud model to get concept partition of the safety, and the concepts gained by this way can reflect the characteristics of data distribution more obviously. Cao *et al*. (2007) used cloud model and the uncertain illation based on the cloud model to translate the qualitative appraisal of the factors level into quantitative scores, and further merged gray relationship theory to appraise the comprehensive level of the objects. The prediction issue of water resource supply and demand was studied by using the cloud model and the result showed that the precision of this method was excellent (Shao and Liang, 2008). A risk evaluation method based on the cloud theory was put forward for evaluating project risk. It realized the transformation between qualitative concepts and their quantitative expression for the project risk assessment (Liu and Qiu, 2008). A model for reliability assessment of combat aircraft based on the cloud theory is proposed and the model can solve the transition problem between qualitative and quantitative in reliability assessment. The result of assessment can reflect the distribution of data and mode of our thinking while keeping the qualitative boundaries (Liao *et al*., 2005). Li and Guo (2011) proposed a piecewise cloud approximation method to reduce the dimensionality of time series and measure the similarity between time series.

At present, the use of cloud model to assess drought disaster is still new. In this paper, we promote the cloud theory in this field and establish a new model for drought disaster assessment based on integrative cloud model. An example of drought disaster in China from 1978 to 2009 is used for demonstration. We also compared BP neural network, hard division method with cloud model for demonstration the effectiveness of the model.

COMPREHENSIVE EVALUATION METHOD BASED ON THEORY OF CLOUD

Conception of cloud: Cloud model is an uncertainty transition model between some qualitative concepts and its quantitative expression. For example, how can we express the phenomenon, such as degree of drought, degree of pollution, the temperature of weather. Generally, we can express the phenomenon by qualitative language. For example, the degree of drought is light drought, severe drought, extreme drought; The temperature of weather is "high", "middle", "low", and so on. This method can realize the transition between precise value and qualitative concept (Shi *et al*., 2008; Gao, 2009). A brief introduction is given below.

Let X be a universal set described by precise numbers, $X = \{x\}$, as the universe of discourse. $\tilde{A}$ is the qualitative concepts associated with X. If there is a quantitative value $x \in X$ which is the randomly realization of the concept $\tilde{A}$, $y = u_{\tilde{A}}(x) \in [0,1]$ is a random value with stabilization tendency for $x \in X$. Then, the distribution of x on X is called membership cloud, in short for cloud.

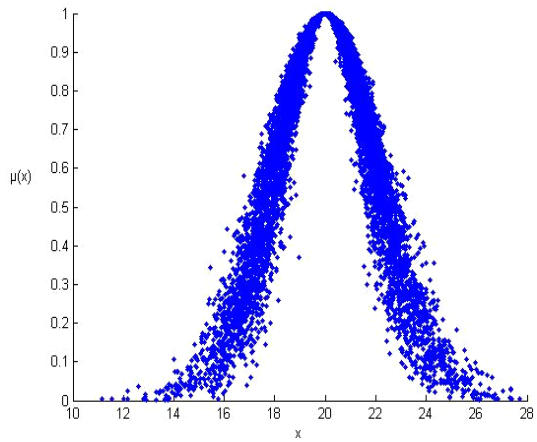


Fig. 1: Cloud model C(20,2,0.3,1000), the cloud model with parameters Ex = 20, En = 2, Hye = 0.3 and n = 10000. x-axis expresses x and y-axis expresses $\mu_{\tilde{A}}(x)$

Each (x,y) is defined as a cloud drop, represented as (x,y) or(x,$u_{\tilde{A}}$(x)).

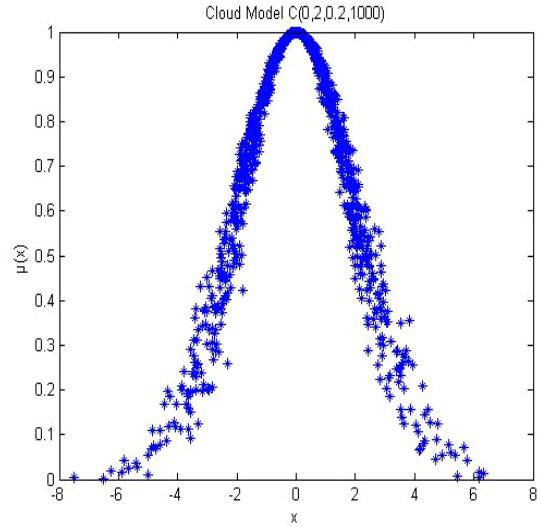
The quantitative features of the cloud can be represented with the three parameters, namely, Ex (Expectation Value), En (Entropy) and Hye (Hyper Entropy), and be expressed as C(Ex,En,Hye), as shown in Fig. 1 .

Ex is the expectation value of cloud-drops. Generally speaking, Ex is a most representative drop for the qualitative concept, that is the center value of qualitative concept Ã.

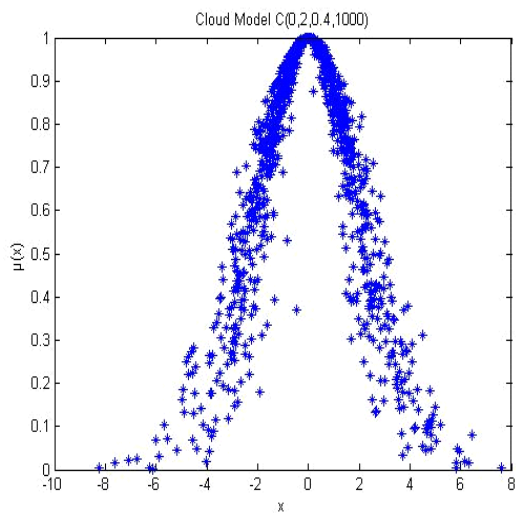
En reflects the fuzziness of qualitative concept. On the one hand, En reflects the cloud-drops range which can be accepted by this concept in the number field, and represents the fuzziness. On the other hand, En reflects the probability which cloud-drops represent the qualitative concept in the number field, and is the measure of the randomness of the cloud-drop. In addition, En also shows the connection of fuzziness and randomness, and can be used to represent the size of one qualitative concept. Usually, the larger the En is, the larger fuzziness and randomness of the concepts are. In risk assessment of drought disaster, En represents the value range of degree classification.

Hye is the degree of the randomness of membership function, and is a tool to measure the uncertainty of En. Hye reflects the dispersion of the cloud-drops and its value can determine the thickness of the cloud indirectly. The larger the Hye is, the larger the randomness of membership degree and the thickness of the cloud are. Therefore, Hye is codetermined by the randomness and fuzziness of En.

There are many kinds of cloud model, such as normal cloud model, trapezium-cloud model, half-down cloud



(a)



(b)

Fig. 2: (a) Cloud Model C(0, 2, 0.2, 1000), the cloud model with parameters Ex = 0, En = 2, Hye = 0.2 and n = 1000. x-axis expresses x and y-axis expresses $\mu_{\tilde{A}}(x)$, (b) Cloud Model C(0, 2, 0.4, 1000), the cloud model with parameters Ex = 0, En = 2, Hye = 0.4 and n = 1000. x-axis expresses x and y-axis expresses $\mu_{\tilde{A}}(x)$

model and half-up cloud model, which are formed by choosing different probability distribution function. Li *et al*. (2006) has proved the universality of normal cloud model, and the cloud expectation curves of qualitative knowledge approximately obey the normal or half-normal distribution in many natural and social sciences. The normal cloud model is the most important and powerful tool to express the linguistic atom. Therefore, the normal

cloud model is used to estimate drought disaster. Ex and En of drought disaster can determine the cloud expectation curve of normal distribution, and its equation is as follows.

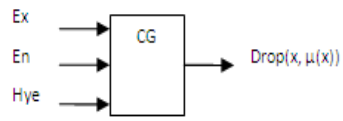
$$y = \mu(x) = e^{-\frac{(x-Ex)^2}{2En^2}} \quad (1)$$

Figure 1 shows the cloud model with parameters Ex = 20, En = 2, Hye = 0.3 and n = 10000. It can be seen that in normal cloud model, the contribution of cloud-drops to qualitative concepts is mainly focused on [Ex-3En, Ex+3En], that is [14, 26] for the example, and the other contribution beyond the interval is negligible. The interval is called "3 En criterion" which means that the elements beyond [Ex-3En, Ex+3En] in the universe of discourse can be neglected.

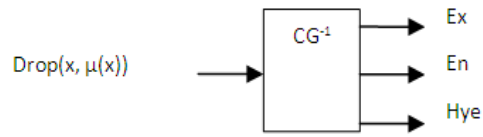
When the value of Ex and of En are set, along with the increase of Hye, cloud-drops become discrete, and change into the fog, as shown in Fig. 2.

Clouds Generator (CG): Cloud generator establishes the mapping relationship between qualitative concept and quantitative characteristic, including forward cloud generator, backward cloud generator, condition X cloud generator and condition Y cloud generator (Huang, 2008), as shown in Fig. 3. Forward cloud generator maps qualitative concept to quantitative characteristic. When the three quantitative characteristics (Ex, En, Hye) and the required number of cloud-drops are given, the generator can produce as many cloud-drops as required. The inputs are the parameter values of (Ex, En, Hye) and number of cloud-drops n. The output is the quantitative value of cloud-drops and the membership degree μ(x), as shown in Fig. 3a. Backward cloud generator is contrary to forward cloud generator, mapping quantitative characteristic to qualitative concept. The three quantitative characteristics of (Ex, En, Hye) can be produced to represent the corresponding qualitative concept, as shown in Fig. 3b. When the parameter values of (Ex, En, Hye) and the value of x are given, the cloud generator is called condition X cloud generator. Figure 3c shows the generator producing drops under a given numerical value x in the universe X. Figure 3d shows the generator under the condition of a given membership degree μ(x), from which we can obtain the quantitative value x. This kind of generators are called condition Y cloud generator. In this paper, cloud model of drought assessment is established based on forward cloud generator and condition X cloud generator, as shown in Fig. 4.

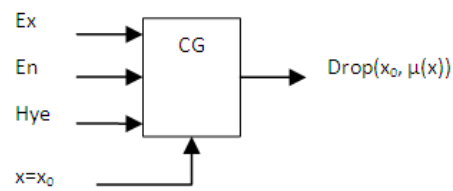
Each cloud generator has different algorithm. We take the forward cloud generator as an example. The input: the parameter values of (Ex, En, Hye) and number



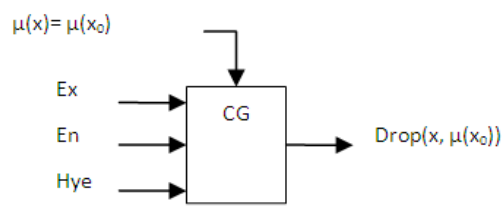
(a) Forward cloud generator



(b) Backward cloud generator



(c) Condition X cloud generator



(d) Condition Y cloud generator

Fig. 3: Cloud generator, (a) Forward cloud generator, (b) Backward cloud generator, (c) Condition X cloud generator, (d) Condition Y cloud generator

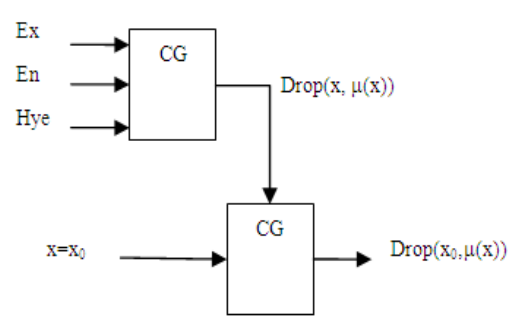


Fig. 4: Comprehensive cloud generator based on forward cloud generator and condition X cloud generator

of cloud-drops n. The output: the position of cloud-drops and the membership degree μ of every cloud-drops, i.e. (x,μ). The algorithm of forward cloud generator is described as follows.

Step 1: Generate a normally distributed random number En´ with mean En and standard deviation Hye;

Step 2: Generate a normally distributed random number x with mean Ex and standard deviation En

Step 3: Let x be a specific quantitative value of qualitative concept Ã, named cloud-drop

Step 4: Calculate $\mu = \mu(x) = e^{-\frac{(x-Ex)^2}{2(En')^2}}$

Step 5: Repeat Step 1 to Step 4 until n cloud drops are generated.

Assessment model based on cloud: Suppose there are n indexes which reflect the drought degree and the number of evaluation samples is m. Let x_{ij}(i = 1, 2, ..., n; j = 1, 2, ..., m) be the original data of each sample, so we can get the primal evaluation matrix $X = (x_{ij})_{n\times m}$.

Index weight: The index weight is the quantitative measure of each index importance in the whole index system. Whether the index weight is reasonable or not will affect the comprehensive evaluation results. In this paper, the information entropy method is used to compute the weights of evaluation indexes. The information entropy method emphases on objective information of the system and can be better able to reflect the actual situation (Yelshin, 1996; Zhang, 2006; Wang *et al*., 2009). The step of computing the entropy weight is as follows.

Step 1: Normalization index data, that is:

$$v_{ij}' = \frac{x_{ij} - x_{ij\min}}{x_{ij\max} - x_{ij\min}} \times 10 \quad (2)$$

where v_{ij} is the standardized value of index; x_{ij} is the original data of index; x_{ijmax} and x_{ijmin} is maximum and minimum of the original data of each index.

Step 2: Calculating the information entropy H_i of each evaluation index:

$$H_i = -\frac{1}{\ln m \sum_{j=1}^{m} f_{ij} \ln f_{ij}} \quad (3)$$

where, $f_{ij} = v_{ij} \Big/ \sum_{j=1}^{m} v_{ij}, H_i \in [0,1]$

Step 3: Calculating the difference coefficient g_i of the ith index.

$$g_i = 1 - H_i \quad (4)$$

For a given index, the smaller difference of v_{ij}, the larger H_i and vice versa. The larger the value of g_i, the stronger importance of the ith index in comprehensive evaluation , when all the value of v_{ij} are equal, $H_i = H_{max} = 1$.

Step 4: Calculating the entropy weight w_i of each index:

$$w_i = \frac{g_i}{\sum_{i=1}^{n} g_i} \quad (5)$$

Then, we obtain the weight vector:
$W = (w_1, w_2, ..., w_n)$

and $\sum_{i=1}^{n} w_i = 1$

Integrative membership computation: When the cloud membership matrix of index vector U is calculated by cloud model and the weight vector W is calculated by entropy weight method, we can do synthetic operation in order to obtain the assessment vector B of drought degree. That is:

$$B = W \bullet U = (w_1, w_2, ..., w_n) \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1p} \\ u_{21} & u_{22} & \dots & u_{2p} \\ \dots & \dots & \dots & \dots \\ u_{n1} & u_{n2} & \dots & u_{np} \end{bmatrix} = (b_1, ..., b_p) \quad (6)$$

where, $B = (b_1, ..., b_p)$ is integrative membership vector of evaluation sample. p is the grade number of drought classification standard. $u_i = (u_{i1}, u_{i2}, ..., u_{ip})^T$ is the ith index's cloud membership for i = 1,2,...,n . "•" is ordinary multiplication operation.

According to the principle of maximum integrative membership degree, set $b_k = \max\{b_1, ..., b_p\}$, then the drought grade of evaluation sample is k grade.

Case study: In this study, the problems of Chinese agricultural drought as a case are studied. In recent years, drought disasters continuously happen and cause serious impact to people's production and life in China (Song *et al*., 2003). For example, the southwest five province of China happened serious droughts during 2009 to 2010 and the Chinese Northern region suffered severe drought in 2011. Therefore, it is significant to reduce drought risk by drought risk assessment, and adopt effective disaster prevention measures.

The disaster-affected rate and disaster-damaged rate are selected as the evaluation indices of drought risk. The disaster-affected rate and disaster-damaged rate are defined as follows:

$$I_s = \frac{A_s}{A_b} \times 100\% \tag{7}$$

$$I_c = \frac{A_c}{A_b} \times 100\% \tag{8}$$

where I_S is the disaster-affected rate and I_c is the disaster-damaged rate (in percentage %), A_s is the disaster-affected area (khm^2) and A_c is the disaster-damaged area (khm^2), A_b is the planting area (khm^2).

We use four-category classification for agricultural drought (Huang, 2008): normal (disaster-affected rate <10% or disaster-damaged rate <5%), light drought (10%≤ disaster-affected rate < 20% or 5% ≤ disaster-damaged rate < 10%), severe drought (20% ≤ disaster-affected rate ≤ 30% or 10% ≤ disaster-damaged rate≤20%), extreme drought (disaster-affected rate > 30% or disaster-damaged rate >20%). The indicators of agricultural drought classification are given in Table 1, in which four degrees interval of disaster-affected rate I_s are denoted as I (0,10), II[10, 20), III [20, 30], IV (30, +∞) and disaster-damaged rate I_c are denoted as I (0, 5), II [5, 10), III [10, 20], IV (20, +∞). Three quantitative characteristics of cloud model are achieved, as shown in Table 2. Set He = 0.1, Ex and En are given as follows:

- **Grade 1**

$$Ex1_s = 0, En1_s = \left(Ex2_s - Ex1_s\right)/3;\ Ex1_c = 0, En1_c = \left(Ex2_c - Ex1_c\right)/3;$$

- **Grade II**

$$Ex2_s = (10+20)/2 = 15, En2_s = (Ex2_s - Ex1_s)/3 = 5$$

that is $Enl_s = 5$

$$Ex2_c = (5+10)/2 = 7.5, En2_c = (Ex2_c - Ex1_c)/3 = 2.5$$

that is $En1_c = 2.5$

Table 1: Index grade of drought classification

Index drought degree	Disaster-affected rate (%)	Disaster-damaged rate (%)
I: Normal	$10<I_s$	$I_c<5$
II: Light drought	$10\le I_s<20$	$5\le I_c<10$
III: Severe drought	$20\le I_s\le 30$	$10\le I_c\le 20$
IV: Extreme drought	$I_s>30$	$I_c>20$

Table 2: Quantitative characteristics of C(Ex,En,Hye)

Cloud	Ex_s	Ex_c	En_s	En_c	$H_{es} = H_{ec}$
C1,I	0	0	5	2.5	0.1
C2,II	15	7.5	5	2.5	0.1
C3,III	25	15	3.3	2.5	0.1
C4,IV	30	20	1.7	1.7	0.1

- **Grade III**

$Ex3_s = (20+30)/2 = 25$, $En3_s = (Ex3_s - Ex2_s)/3 = 3.3$

$Ex3_c = (10+20)/2 = 15$, $En3_c = (Ex3_c - Ex2_c)/3 = 2.5$

- **Grade IV**

$Ex4_s = 30$, $En4_s = (Ex4_s - Ex3_s)/3 = 1.7$; $Ex4_c = 20$, $En4_c = (Ex4_c - Ex3_c)/3 = 1.7$

Forward cloud generator algorithm is used to generate the comprehensive cloud model, as shown in Fig. 5 and 6. The transverse axis is division of disaster-affected rate or disaster-damaged rate and the longitudinal axis is degree of membership, from left to right, the first half-down cloud represents conception of grade I, by parity of reasoning, there are cloud model of grade I, II, II and.

The index data of disaster-affected rate and disaster-damaged rate are obtained from China Statistical Yearbook, as shown in Fig. 7. The disaster-affected rate and disaster-damaged rate of each year subjects to the membership of four levels is calculated, as shown in Table 3. As a compare, we computer the drought risk grade by hard division method which evaluates the drought risk according to the four-category classification grade division, as shown in Table 3. For example, when we use hard division, the drought degree of 1984 is grade II by disaster-affected rate I_{s1984} = 10.97%, but grade I by disaster-damaged rate I_{c1984} = 4.86%. Therefore, hard division method can not solve the multiple index problems. We can see that, when using the different index, we will get different risk level, so that it isn't benefit for us to do risk assessment. Then, we analyze the

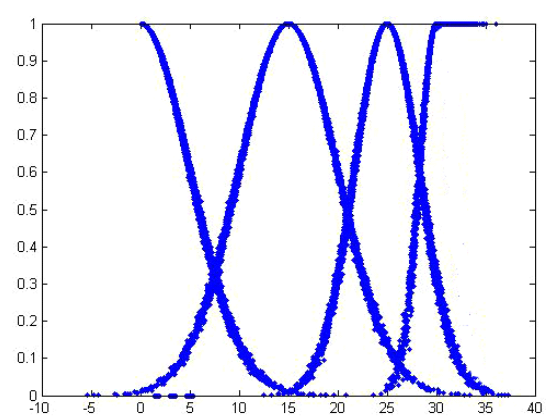


Fig. 5: Disaster-affected rate subjects to the comprehensive cloud model of drought degree concept, x-axis expresses the index value of drought degree and y-axis expresses $\mu_{\tilde{A}}(x)$

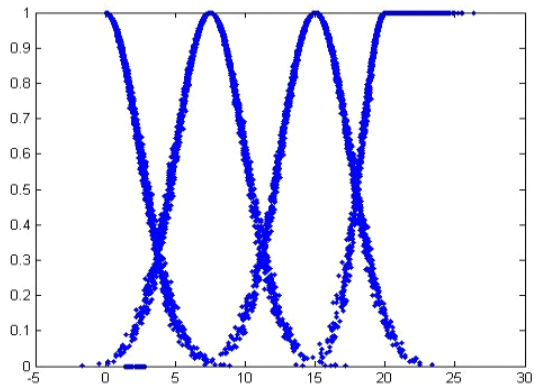


Fig. 6: Disaster-damaged rate subjects to the comprehensive cloud model of drought degree concept, x-axis expresses the index value of drought degree and y-axis expresses $\mu_{\tilde{A}}(x)$

results computed by single index cloud model and we can also find the same problem. For example, the drought degree of 1978 is grade III by disaster-affected rate according to the membership degree, but grade II by disaster-damaged rate. Therefore, facing the multiple index problems, we need to determine the weight of each index before doing risk assessment.

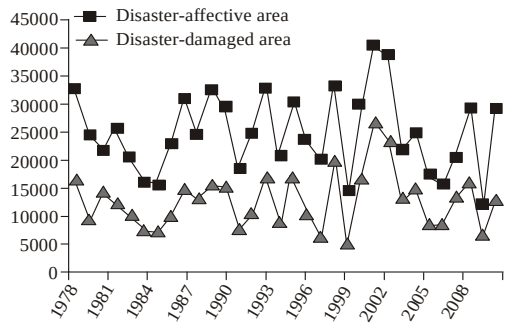


Fig. 7: Statistical graph of disaster-affected area and disaster-damaged area in China from 1978 to 2009, x-axis expresses the year and y-axis expresses disaster-affected area and disaster-damaged area

The weights of the disaster-affected rate and disaster-damaged rate are calculated by entropy weight method, according to formula (2) to (5), we can calculate the information entropy H, difference coefficient g and Table 4. From Table 4, we draw a conclusion that the weight of disaster-damaged rate is greater than disaster-affected rate, which means the disaster-damaged area plays more important role in risk assessment of drought disaster.

Table 3: Membership degree of disaster rate and hazard rate of drought in China from 1978 to 2009

Year	Disaster-affected area (khm^2)	Disaster-damage area (khm^2)	Planting area (khm^2)	Membership $\mu_S(x)$ affected rate)				Grade by cloud model (disaster-damaged rate)	Hard division (disaster-	Membership $\mu_c(x)$				Grade by cloud model (disaster-affected rate)	Hard division (disaster-damaged rate)
1978	32641	16564	150104	0.00008	0.40250	0.61491	0.00001	III	III	0.00006	0.36799	0.28431	0.00000	II	III
1979	24646	9316	148477	0.00404	0.95014	0.03915	0.00000	II	II	0.04288	0.88677	0.00226	0.00000	II	II
1980	21901	14174	146380	0.01137	0.99997	0.00979	0.00000	II	II	0.00055	0.68301	0.10418	0.00000	II	II
1981	25693	12134	145157	0.00190	0.86432	0.08658	0.00000	II	II	0.00373	0.94265	0.02936	0.00000	II	II
1982	20697	9972	144755	0.01676	0.99019	0.00520	0.00000	II	II	0.02245	0.97056	0.00518	0.00000	II	II
1983	16089	7586	143993	0.08234	0.74614	0.00015	0.00000	II	II	0.10856	0.67137	0.00051	0.00000	II	II
1984	15819	7015	144221	0.09016	0.72249	0.00012	0.00000	II	II	0.15066	0.57358	0.00027	0.00000	II	I
1985	22989	10063	143626	0.00595	0.97996	0.02438	0.00000	II	II	0.01970	0.98070	0.00603	0.00000	II	II
1986	31042	14765	144204	0.00009	0.42661	0.57466	0.00000	III	III	0.00023	0.54873	0.16310	0.00000	II	III
1987	24920	13033	144957	0.00271	0.90843	0.06083	0.00000	II	II	0.00155	0.83708	0.05565	0.00000	II	II
1988	32904	15303	144869	0.00003	0.30429	0.78650	0.00010	III	III	0.00013	0.47203	0.20707	0.00000	II	III
1989	29358	15262	146554	0.00033	0.60262	0.32203	0.00000	II	III	0.00017	0.50699	0.18589	0.00000	II	III
1990	18175	7805	148362	0.04971	0.85967	0.00057	0.00000	II	II	0.10926	0.66956	0.00051	0.00000	II	II
1991	24914	10559	149586	0.00390	0.94667	0.04088	0.00000	II	II	0.01857	0.98455	0.00644	0.00000	II	II
1992	32981	17047	149007	0.00006	0.36138	0.68580	0.00002	III	III	0.00003	0.28877	0.36289	0.00000	III	III
1993	21097	8656	147741	0.01694	0.98968	0.00511	0.00000	II	II	0.06418	0.80617	0.00125	0.00000	II	II
1994	30423	17050	148241	0.00022	0.54335	0.39836	0.00000	II	II	0.00003	0.27776	0.37564	0.00000	III	III
1995	23455	10402	149879	0.00746	0.99160	0.01805	0.00000	II	II	0.02121	0.97525	0.00553	0.00000	II	II
1996	20152	6247	152381	0.03026	0.93891	0.00172	0.00000	II	II	0.26066	0.39652	0.00007	0.00000	II	I
1997	33516	20012	153969	0.00008	0.40007	0.61903	0.00001	III	III	0.00000	0.08912	0.72555	0.00021	III	III
1998	14236	5060	155706	0.18790	0.50353	0.00001	0.00000	II	I	0.42962	0.23570	0.00002	0.00000	I	I
1999	30156	16614.3	156373	0.00059	0.69269	0.22318	0.00000	II	II	0.00012	0.45788	0.21623	0.00000	II	III
2000	40541	26784	156300	0.00000	0.09138	0.96041	0.05757	III	III	0.00000	0.00059	0.69413	0.24199	III	III
2001	38472	23698	155708	0.00000	0.15186	0.99609	0.00786	III	III	0.00000	0.00850	0.99615	0.01918	III	III
2002	22124	13174	154636	0.01667	0.99045	0.00525	0.00000	II	II	0.00301	0.92023	0.03474	0.00000	II	II
2003	24852	14470	152415	0.00491	0.96649	0.03109	0.00000	II	II	0.00074	0.72759	0.08844	0.00000	II	II
2004	17253	8481.6	153553	0.08007	0.75324	0.00017	0.00000	II	II	0.08709	0.73161	0.00076	0.00000	II	II
2005	16028	8479.2	155488	0.11941	0.64387	0.00005	0.00000	II	II	0.09264	0.71525	0.00068	0.00000	II	II
2006	20738	13411.34	152149	0.02434	0.96316	0.00264	0.00000	II	II	0.00200	0.87088	0.04685	0.00000	II	II
2007	29386	16169.93	153464	0.00065	0.70879	0.20761	0.00000	II	II	0.00014	0.47822	0.20317	0.00000	II	III
2008	12137	6798	156266	0.29925	0.35121	0.00000	0.00000	II	I	0.22003	0.45219	0.00011	0.00000	II	I
2009	29259	13197	158639	0.00111	0.78884	0.13896	0.00000	II	II	0.00394	0.94777	0.02813	0.00000	II	II

Table 4: Weight of drought evaluation index by entropy method

Coefficient index	H	g	w
Disaster-affected rate	0.9558	0.0442	0.4390
Disaster-damaged rate	0.9435	0.0565	0.5610

According to the results by comprehensive cloud model, the disaster rate of 1984 is I_{s1984} = 10.97% and the hazard rate is I_{c1984} = 4.86%, then the membership of each degree is: $\mu_{s1984}(I)$ = 0.09016, $\mu_{s1984}(II)$ = 0.72249, $\mu_{s1984}(III)$ = 0.00012, $\mu_{s1984}(IV)$ = 0.00000, $\mu_{c1984}(I)$ = 0.15066, $\mu c_{1984}(II)$ = 0.57358, $\mu_{c1984}(III)$ = 0.00027, $\mu_{c1984}(IV)$ = 0.00000. So, we can obtain the comprehensive membership degree value I_{1984}, that is $\mu_{1984}(I)$ = 0.12410,$\mu_{1984}(II)$ = 0.63895,$\mu_{1984}(III)$ = 0.00020,$\mu_{1984}(IV)$ = 0.00000, according to the principle of maximum membership degree, we can conclude that the risk grade of 1984 is grade II. Consequently, the comprehensive membership of drought disaster from 1978 to 2009 is obtained based on formula (6), as shown in Table 5 Then, according to the principle of maximum membership degree, the drought degree of each year is obtained when the defined value is given, we can determine the degree of drought clearly.

In order to prove the effectiveness of the cloud model, we compare the results of cloud model with BP neural network. The comparison results are shown in Table 5. When we use BP neural network model, the drought disaster for 1978, 1984, 1986, 1988, 1989, 1994, 1996, 1998, 1999, 2007 and 2008, respectively are regarded as testing samples, and the rest as training samples. The network structure is (2, 4, 4). Selecting learning rate as 0.01 and allowable error 0.001, the training process is shown in Fig. 8. The 11 testing samples included all of the different grades of disaster which are disagreed between the comprehensive cloud model and cloud model or hard division method of single training process is shown in Fig. 8. The 11 testing samples included all of the different grades of disaster which are disagreed between the comprehensive cloud model and cloud model or hard division method of single

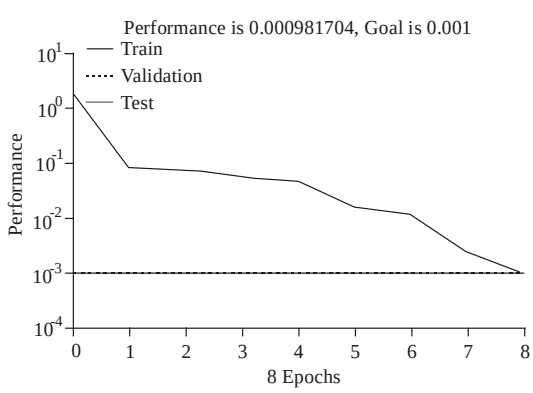


Fig. 8: Training process of BP neural network

Table 5: Risk level of drought disaster in China from 1978 to 2009

Year	Comprehensive membership μ(x)				Grade by cloud model	Grade by neural network
1978	0.00007	0.38314	0.42944	0.00000	III	III
1979	0.02583	0.91459	0.01846	0.00000	II	II
1980	0.00530	0.82216	0.06274	0.00000	II	II
1981	0.00293	0.90826	0.05448	0.00000	II	II
1982	0.01995	0.97918	0.00519	0.00000	II	II
1983	0.09705	0.70419	0.00036	0.00000	II	II
1984	0.12410	0.63895	0.00020	0.00000	II	II
1985	0.01366	0.98037	0.01408	0.00000	II	II
1986	0.00017	0.49512	0.34378	0.00000	II	III
1987	0.00206	0.86840	0.05792	0.00000	II	II
1988	0.00009	0.39839	0.46144	0.00005	III	III
1989	0.00024	0.54897	0.24566	0.00000	II	II
1990	0.08312	0.75302	0.00054	0.00000	II	II
1991	0.01213	0.96792	0.02156	0.00000	II	II
1992	0.00004	0.32064	0.50465	0.00001	III	III
1993	0.04344	0.88673	0.00294	0.00000	II	II
1994	0.00011	0.39436	0.38561	0.00000	II	II
1995	0.01517	0.98243	0.01103	0.00000	II	II
1996	0.15952	0.63463	0.00080	0.00000	II	II
1997	0.00003	0.22563	0.67879	0.00012	III	III
1998	0.32351	0.35328	0.00001	0.00000	II	II
1999	0.00033	0.56096	0.21928	0.00000	II	II
2000	0.00000	0.04045	0.81103	0.16103	III	III
2001	0.00000	0.07144	0.99612	0.01421	III	III
2002	0.00901	0.95106	0.02179	0.00000	II	II
2003	0.00257	0.83246	0.06326	0.00000	II	II
2004	0.08401	0.74111	0.00050	0.00000	II	II
2005	0.10439	0.68391	0.00040	0.00000	II	II
2006	0.01181	0.91139	0.02745	0.00000	II	II
2007	0.00036	0.57944	0.20512	0.00000	II	II
2008	0.25481	0.40786	0.00006	0.00000	II	II
2009	0.00270	0.87800	0.07678	0.00000	II	II

index. So we can say that they are more representative and can prove the applicability of cloud model.

From Table 5, the results of cloud model have only one difference from BP neural network. That is, there are 96.875% identical points between cloud model and BP neural network, only 3.125% of different points. The different point is 1986, as we know the disaster rate is 21.53% and the hazard rate is 10.24%. Through cloud model, I_{1986} subjects to the membership of each degree are calculated as $\mu_{1986}(I)$ = 0.00017, μ1986(II) = 0.49512, μ1986(III) = 0.34378, μ1986(IV) = 0.00000, so μ(II)>μ(III)>μ(I)>μ(IV). It shows that I_{1986} has the possibility of 49.512% being degree II, 34.378% being degree III, with small possibilities of grade I and grade IV, which is closer to the fact. In this case, it shows that risk assessment of drought disaster based on cloud model is promising.

CONCLUSION AND DISCUSSION

Climate change causes extreme climate happen more frequently. This study describes current work on the risk assessment of drought disaster under the background of climate change. In this study, an assessment model of drought disaster risk is proposed based on cloud model.

Cloud model considers the fuzziness and uncertainty of drought disaster. The resulted of the disaster-affected rate and disaster-damaged rate are associated with degree concept reasonably. Forward cloud generator is used to obtain the disaster-affected rate and disaster-damaged rate subjects to the comprehensive cloud model of drought degree concept, combined with condition X cloud generator to calculate the disaster-affected rate and disaster-damaged of each year subjects to the membership of four levels. The model was applied to evaluate the drought disaster in China from 1978 to 2009 and the results show that drought disaster assessment based on cloud model is suitable for risk assessment. The results of drought degree assessment are the same as the real understanding. The result shows that it is feasible the comprehensive evaluation of drought disasters risk by cloud model. Cloud model can deal with the problem of the fuzziness and the randomness of the drought index data, and can handle multi-index risk evaluation which hard division can't handle. Meanwhile, the cloud model based on entropy weight methods can give the membership degree of drought grade, so it can more reasonable reflect the final drought disaster risk assessment results. But the reliability of evaluation results is dependent on the choice of a number of factors such as super entropy, indices weight etc, so it is necessary for personnel's practical experience and repeatedly test and how to determine the more reasonable, accurate parameters is worth further research work. Due to the complexity of risk evaluation of drought disaster coupled with the climate change and the geographical environment of area, the evaluation index system is complicated. The methods used in this paper can be improved by using more multiple index risk evaluation of drought disaster. The problem of risk evaluation of drought disaster in this direction will be developed in the future.

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