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Paper:

Terrain Hazard Risk Analysis for Flood Disaster Management in Chaohu Basin, China, Based on Two-Dimensional Cloud

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Terrain analysis is essential to flood disaster risk evaluation. It is a complicated evaluation process, involving both quantitative and qualitative data analysis. However, quantitative and qualitative data cannot be put into operation directly. Based on stochastic and fuzzy mathematics, cloud models allow interchange between qualitative and quantitative data, dealing with randomness and ambiguity. Two- or multi-dimensional cloud models can solve the problem of multivariable analysis. This study used absolute elevation and neighborhood elevation standard deviation as main factors. Using the model, it demonstrated the construction of qualitative conditions and risk evaluation clouds and established a set of two-dimensional cloud reasoning rules to calculate the joint certainties with all the grids in reasoning rules. By selecting the highest certainty of cloud reasoning, preliminary evaluation results were obtained. For more accurate results, the model algorithm was improved, and further iterations were performed. The results of two-dimensional cloud reasoning showed better dispersion and precision than traditional methods did. The terrain risk distribution of Chaohu Basin, China, agreed with reality with great detail. A new method regarding the risk assessment of flood disaster was also proposed.

Keywords: cloud model, risk assessment, terrain hazard, two-dimensional cloud reasoning, Chaohu Basin

1. Introduction

Recent natural disasters have threatened the survival and sustainable development of humans. Among the 14 major natural disasters, floods occur most frequently, causing massive damage and loss of life [1]. The frequency of floods is predicted to increase as a result of climate change [2, 3]. Globally, flood risk depends on the cumulative effect of (a) the hazard risk of a flooded area, (b) the exposure and vulnerability of the disaster-bearing body, and (c) the disaster prevention and mitigation ability [4, 5]. Analysis of these factors along with associated flood risk distribution maps [6–8] can provide strong support for (a) the development of disaster precaution policy before disasters occur, (b) the decision-making procedures of the disaster prevention command, and (c) the improvement of post-disaster relief programs.

To reflect human cognitive habits, many studies on flood hazard risk assessment have used a qualitative categorized list such as "high, medium, and low" for the expression of risk [5, 9]. Evaluation factors in the risk assessment process comprise both quantitative data and qualitative expressions [10, 11], and the two types of data cannot easily be combined directly. Furthermore, the evaluation calculation results need to be converted into qualitative descriptions [12]. Therefore, qualitative and quantitative conversion is a basic and important task in flood disaster risk assessment.

Many researchers have used a variety of conversion methods to bridge the gap between qualitative and quantitative data in risk assessment, e.g., equal interval [13, 14], standard deviation [15], natural breakpoint [16, 17], and similar clustering classification [18] methods. The general premise of these methods is to convert qualitative data into a certain numerical interval according to mathematical or statistical theory. However, the intervals between the qualitative categories can be cut directly so that the upper and lower bounds of the interval could not represent the randomness and uncertainty of the qualitative concept itself. As the qualitative results contain a certain degree of ambiguity and randomness, it is difficult to objectively classify the findings. This also happens in flood risk assessment: The exact values often fail to convey the full meaning of qualitative concepts from the three categories mentioned above. Thus, it is difficult to accurately analyze and quantify these concepts.

To address this problem, this study used a cloud model to analyze the terrain risk of flood disasters. The cloud model is a tool that can convert qualitative and quantitative data better than other methods can [19]. This model transforms a "blunt" edge ("either this or that") into a "smooth" edge ("both this and that"). It allows proper conversion between the concepts from qualitative data and the values from quantitative data. This study applied the cloud model to flood risk assessment in Chaohu Basin, China, and obtained valuable results.

2. Cloud Model

2.1. Concept of Cloud Model

The cloud model is a model of uncertainty conversion between a qualitative description and its quantitative representation, based on traditional fuzzy mathematics and probability statistics. It mainly reflects the randomness and ambiguity of concepts in human cognition or objective things and combines the two to form a map between qualitative and quantitative results [20].

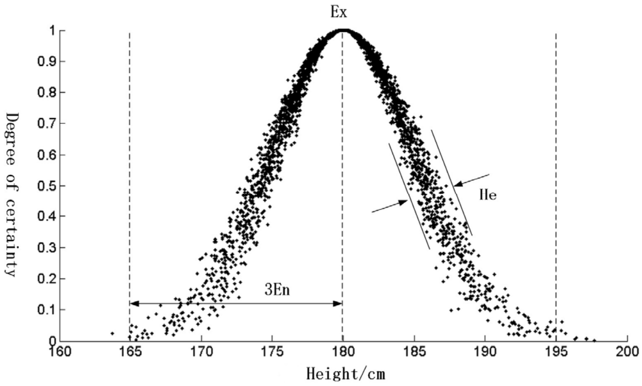
If U is a quantitative domain represented by exact values $U = \{x\}$, then C is a qualitative concept in domain U. If x is a random implementation of the concept C, and $\mu(x) \in [0,1]$, the degree of certainty of x to C is a random number with a stable tendency, that is, $\mu(x)$: $U \to [0,1]$, $\forall x \in U$. The distribution in the domain is called the cloud model, referred to simply as "the cloud" [21]. The cloud is composed of many "cloud drops." Each cloud drop is a quantitative conversion of a qualitative concept. A single cloud drop cannot reflect the content, and the overall shape of the cloud reflects the basic characteristics of the qualitative concept. This model has been used in data mining, knowledge discovery, system evaluation, and decision support [22–24].

$$C_T(x)\colon U \to [0,1], \quad \forall x \in X(X \subseteq U),$$
$$x \to C_T(x) \quad \text{. . . . . (1)}$$

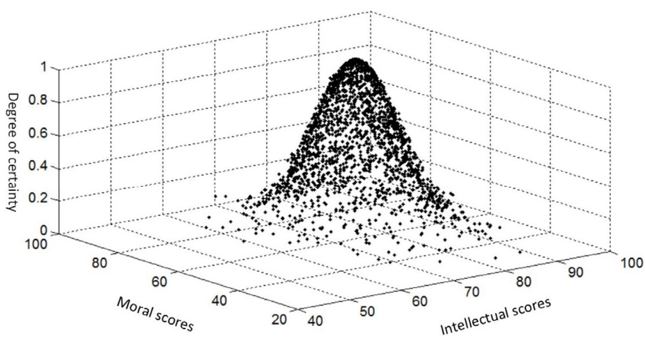
The digital characteristics of the cloud are characterized by the expected value (Ex), entropy (En), and hyperentropy (He). Ex is the closest to the qualitative concept in the domain, En represents the acceptable range within the domain, and He reflects the dispersion degree. The cloud model builds forms of clouds with a large number of cloud drops using the above three digital characteristics. It can integrate the randomness and fuzziness of the qualitative concepts. For example, **Fig. 1(a)** depicts a one-dimensional cloud diagram showing the qualitative concept of "height." The three digital characteristics (Ex, En, and He) of the cloud model are also shown in the diagram.

When the qualitative concept of the corresponding domain is expanded to two or even multiple dimensions, the one-dimensional cloud model can be extended to a two- or multi-dimensional cloud model, which is an important tool for representing and solving multivariate complex systems. **Fig. 1(b)** shows a two-dimensional cloud chart of the evaluation of a student's comprehensive performance, including their intellectual and moral scores.

In the cloud model, the specific tool used in this study to achieve qualitative and quantitative conversion was the cloud generator. It was categorized into forward and backward cloud generators. Specifically, assuming that the three digital characteristics (Ex, En, and He) of the cloud



(a) One-dimensional cloud model



(b) Two-dimensional cloud model

Fig. 1. Examples of cloud models.

are given, a number of cloud drops can be generated with the forward cloud generator algorithm. For a group of samples with a normal distribution, the backward cloud generator algorithm can be used to calculate the digital characteristics (Ex, En, and He) of the cloud.

2.2. Reasoning Course Based on Cloud Model

Humans can process information and analyze it to draw logical conclusions. For example, humans can process a statement "if A happens, B will occur as well," where A and B are qualitative concepts described in natural language [25]. In this case, A is called the antecedent of the rule (referred to as the condition), and B is the consequent of the rule (referred to as the result). For example, the statement "if it is summer, the temperature will be high" is a single-condition-single-rule reasoning process, where "summer" and "high temperature" are the antecedent and consequent, respectively. In the real world, any reasoning process is the result of multiple factors, and complicated rules, such as double-condition-single-rule (if A_1, A_2 then B) and multi-condition-single-rule (if A_1, A_2, ..., A_n then B) can be generalized. The cloud reasoning process is composed of one or more antecedent-cloud and one consequent-cloud combinations. **Fig. 2** shows a diagram of the single-condition-single-rule and double-condition-single-rule cloud reasoning. The two algorithms of the cloud reasoning process are as follows:

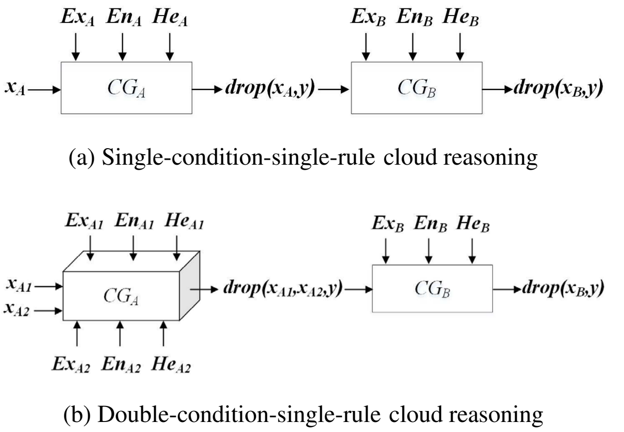


Fig. 2. Diagram of cloud reasoning rules.

Algorithm 1: Single-condition-single-rule generator. The input is the digital characteristics of the antecedent cloud (Ex_A, En_A, and He_A), the given value x_A, and the digital characteristics of the consequent cloud (Ex_B, En_B, and He_B). The output is the result value x_B, which satisfies the consequent concept, and the degree y, which is concluded by the antecedent concept and x_A.

Step 1: Generate a random number ${En_A}'$ that satisfies the normal distribution $Norm(En_A, {He_A}^2)$.

Step 2: Calculate the degree of certainty y.

$$y = \exp\left\{-\frac{(x_A - Ex_A)^2}{2\left({En_A}'\right)^2}\right\} \quad . \; . \; . \; . \; . \; . \; . \; . \; . \quad (2)$$

Step 3: Generate a random number ${En_B}'$ that satisfies the normal distribution $Norm(En_B, {He_B}^2)$.

Step 4: Calculate the value of x_B based on the value of x_A.

$$x_B = \begin{cases} Ex_B - {En_B}' \times \sqrt{-2\ln y} & (x_A \leq Ex_A) \\ Ex_B + {En_B}' \times \sqrt{-2\ln y} & (x_A > Ex_A) \end{cases} \quad (3)$$

In the algorithm, the single-condition-single-rule generator contains two layers of uncertainty reasoning. A membership degree of uncertain y is obtained from the given value of x_A and the antecedent cloud on the one hand. On the other hand, the value of x_B is calculated based on the consequent cloud and uncertain degree y. Therefore, the transfer of uncertainty from simple cloud reasoning can be realized. However, when the domain of the antecedent cloud is extended to two dimensions, a two-dimensional antecedent cloud and one-dimensional consequent cloud connection form a dual-condition-single-rule cloud generator.

Algorithm 2: Dual-condition-single-rule generator. The input is the digital characteristics of two antecedent clouds, namely Ex_{A1}, En_{A1}, and He_{A1} and Ex_{A2}, En_{A2}, and He_{A2}, the given values of x_{A1} and x_{A2}, and the digital characteristics of the consequent cloud (Ex_B, En_B, and He_B). The output is the result of x_B that satisfies the consequent concept, and the degree y can be concluded by the two antecedent concepts and two given values of x_{A1} and x_{A2}.

Step 1: Generate random numbers ${En_{A1}}'$ and ${En_{A2}}'$ that satisfy the normal distributions $Norm(En_{A1}, (He_{A1})^2)$ and $Norm(En_{A2}, (He_{A2})^2)$, respectively.

Step 2: Calculate the joint degree of certainty y.

$$y = \exp\left\{-\frac{(x_{A1} - Ex_{A1})^2}{2({En_{A1}}')^2} - \frac{(x_{A2} - Ex_{A2})^2}{2({En_{A2}}')^2}\right\} \quad . \quad (4)$$

Step 3: Generate a random number ${En_B}'$ that satisfies the normal distribution $Norm(En_B, {He_B}^2)$.

Step 4: Calculate the value of x_B based on x_{A1} and x_{A2}.

(1) If $x_{A1} \leq Ex_{A1}$ and $x_{A2} \leq Ex_{A2}$, then $x_B = Ex_B + {En_B}' \times (\sqrt{-2\ln y})/2$;

(2) If $x_{A1} > Ex_{A1}$ and $x_{A2} > Ex_{A2}$, then $x_B = Ex_B - {En_B}' \times (\sqrt{-2\ln y})/2$;

(3) If $x_{A1} \leq Ex_{A1}$ and $x_{A2} > Ex_{A2}$, then
$y_1 = \exp\{-(x_{A1} - Ex_{A1})^2/2({En_{A1}}')^2\}$,
$y_2 = \exp\{-(x_{A2} - Ex_{A2})^2/2({En_{A2}}')^2\}$,
$x_B = Ex_B + {En_B}' \times (\sqrt{-2\ln y_1} - \sqrt{-2\ln y_2})/2$;

(4) If $x_{A1} > Ex_{A1}$ and $x_{A2} \leq Ex_{A2}$, then
$y_1 = \exp\{-(x_{A1} - Ex_{A1})^2/2({En_{A1}}')^2\}$,
$y_2 = \exp\{-(x_{A2} - Ex_{A2})^2/2({En_{A2}}')^2\}$,
$x_B = Ex_B + {En_B}' \times (\sqrt{-2\ln y_2} - \sqrt{-2\ln y_1})/2$.

3. Study Area and Data Source

3.1. Study Area

Chaohu Basin lies between the Yangtze and Huaihe Rivers in central Anhui Province, China (**Fig. 3**). It is located on the left bank of the lower reaches of the Yangtze River. The total area of the basin is about 13,350 km^2, including Shucheng County, Feixi County, Hefei City, Feidong County, Chaohu City, Shucheng County, Wuwei County, Hanshan County, and He County. Chaohu Basin has a humid monsoon climate in the northern subtropical zone, and heavy rainstorms often occur around Chaohu Lake in summer and autumn. The Chaohu water system originates from the Dabie Mountains and flows from west to east. It passes through Chaohu Lake and enters the Yangtze River from the Yuxi River. The surrounding rivers are radially injected around Chaohu Lake.

Chaohu Basin surrounds Chaohu Lake and is divided into two areas by the Yinping and Phoenix Mountains as well as other mountains to the east. The eastern area of the basin comprises an alluvial plain along the Yangtze River and is mainly composed of sandbars, river floodplains, and terraces. The terrain is flat and open with an average elevation of 5–20 m and a low standard deviation of elevation. However, in the west of the basin, except for the low terrain of Chaohu Lake, it is basically hilly terrain, especially the Dabie Mountains in the southwest is higher in altitude, with an average elevation above 300 m.

The topography of Chaohu Basin contributes to its frequent flooding. Nonetheless, the basin is an important

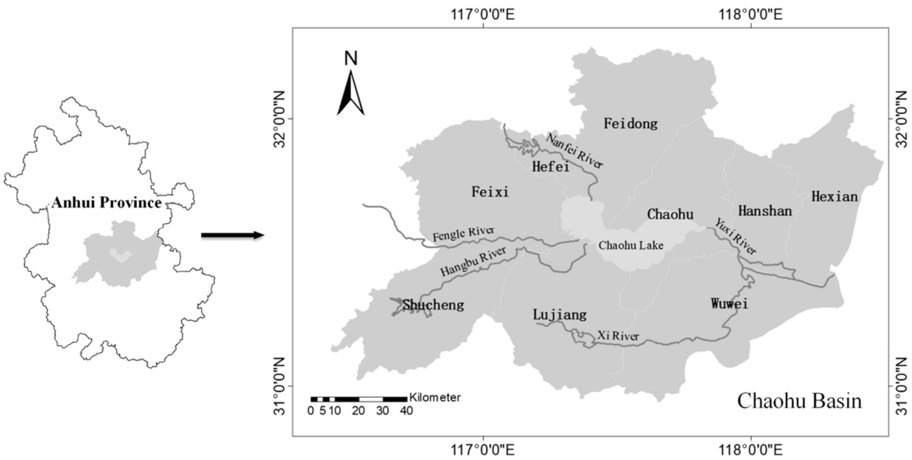


Fig. 3. Location of Chaohu Basin, China.

grain-producing area and a key industrial region with a large population. Flood disasters therefore have far-reaching impacts on the local economy.

3.2. Data Source

Many factors affect flood hazard risk analysis. For example, the underlying earth surface attributes, such as terrain factors, are essential to the assessment of flood risk. These effects of terrain altitude and topographic variation are often combined to determine flood danger levels.

Topographic data of the Chaohu Basin were mainly derived from the ASTER Global Digital Elevation Model V2 30 m digital elevation model dataset, obtained from the Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences (http://www.gscloud.cn).

The criteria for judging the flood risk terrain are usually described as qualitative concepts, such as "the higher the elevation and the flatter the terrain is, the higher risk of flooding will be." The absolute elevation and neighborhood elevation standard deviation (NESD) of grid units were considered reliable quantitative data. The terrain absolute elevation data were obtained directly through the digital elevation model data. By using ArcMap statistical functions to generate the standard deviation of 25 grid elevation in a 5 by 5 square areas, NESD was calculated and analyzed based on the absolute elevation data of the terrain.

4. Development of Cloud Model

4.1. Data Preprocessing

A cloud model was used in this study, and the cloud reasoning method was used to integrate elevation and NESD data to more accurately convert qualitative concepts to quantitative values. Before formal cloud reasoning ensued, three main steps needed to be carried out.

4.1.1. Qualitative Condition Clouds

The "3En rule" of the normal cloud indicated that the vast majority (99.74%) of the quantitative values contributed to the qualitative concept in the domain fall in the range $[Ex-3En, Ex+3En]$ [26]. For these values with bilateral constraints $[C_{min}, C_{max}]$, the following algorithm could be used to construct qualitative cloud [24]:

Algorithm 3: Cloud construction method for qualitative values with bilateral constraints:

(1) Ex is the midpoint of the range, i.e., $Ex = (C_{min}+C_{max})/2$.

(2) En is one-sixth of the range, i.e., $En = (C_{max}-C_{min})/6$.

(3) He is usually a constant value that is an order of magnitude less than En. It can be adjusted according to the physical meaning of the concept.

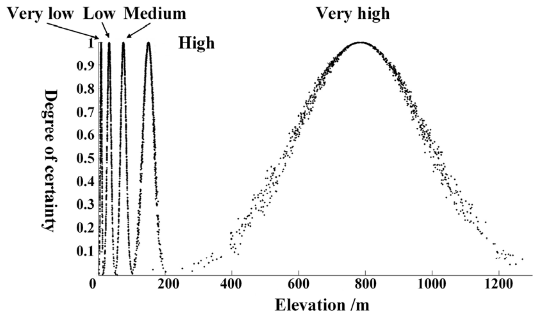
Based on the distribution of the terrain in Chaohu Basin [27], the terrain elevation and NESD were divided into five qualitative ranges, and corresponding condition clouds were generated according to Algorithm 3 (**Table 1**). For areas with moderate altitude and flat terrain, the altitude was 50–100 m, and the NESD was within 10 m. By using Algorithm 3, the corresponding absolute elevation and NESD condition clouds were $C(75, 8.3, 0.1)$ and $C(5, 1.7, 0.1)$, indicating that the values of the two terrain parameters in this area were in the range of these two conditional clouds (**Fig. 4**).

4.1.2. Cloud Reasoning Rules Set

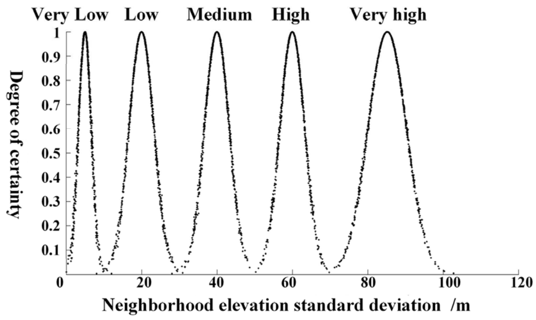
During floods, river currents concentrate on the low-lying flat areas. Therefore, the lower the altitude is, the more likely water is to converge, and the greater the likelihood of flooding becomes. If the terrain is flat and not conducive to a flood receding, the danger of flooding is even larger. The correspondence between elevation and NESD and risk from relevant sources have been extracted.

Table 1. Grading table of altitude and neighborhood elevation standard deviation (NESD).

	Impact factor		Condition cloud	
	Absolute elevation [m]	***NESD [m]***	***Absolute eleveation cloud***	***NESD cloud***
Very low	<15	<10	$C(8.3, 2.2, 0.1)$	$C(5, 1.7, 0.1)$
Low	15–50	10–30	$C(32.5, 5.8, 0.1)$	$C(20, 3.3, 0.1)$
Medium	50–100	30–50	$C(75, 8.3, 0.1)$	$C(40, 3.3, 0.1)$
High	100–200	50–70	$C(150, 16.7, 1)$	$C(60, 3.3, 0.1)$
Very high	>200	>70	$C(784.2, 194.7, 10)$	$C(85.2, 5.1, 0.1)$



(a) Cloud of absolute elevation



(b) Cloud of neighborhood elevation standard deviation

Fig. 4. Qualitative condition clouds.

Nine reasoning rules were used based on the analysis of all 25 qualitative concept combinations (**Table 2**).

Rule 1: If the elevation is very low, and the NESD is moderate, the risk is very high.

Rule 2: If the elevation is moderate, and the NESD is very low, the risk is slightly higher.

Rule 3: If the elevation is low, and the NESD is low, the risk is high.

Rule 4: If the elevation is low, and the NESD is high, the risk is slightly higher.

Rule 5: If the elevation is moderate, and NESD is moderate, the risk is moderate.

Rule 6: If the elevation is high, and the NESD is low, the risk is slightly lower.

Rule 7: If the elevation is high, and the NESD is high, the risk is low.

Rule 8: If the elevation is very high, and the NESD is medium, the risk is very low.

Rule 9: If the elevation is moderate, and the NESD is very high, the risk is very low.

These rules are dual-condition-single-rule examples.

4.1.3. Risk Comment Clouds

Intuitive understanding and description of the risk level is usually qualitative. It requires the establishment of a qualitative and quantitative relationship between risk concepts and values so that an accurate risk diagram can be constructed. In this study, the risk was divided into seven levels corresponding to different risk values (**Table 3**). In addition, seven comment clouds were generated based on Algorithm 3 (**Fig. 5**). Thus, based on the condition cloud and reasoning rules discussed above, nine reasoning rules with digital characteristics were generated (**Table 4**).

4.2. Single Grid Assessment of Terrain Hazard Risk

To clarify the algorithm process, two grids were randomly selected from the Chaohu Basin digital elevation model diagram (**Table 5**). The steps for the assessment for Grid 1 are as follows:

(1) In line with the nine abovementioned rules (**Table 4**), calculate random numbers En_{A1}' and En_{A2}' that satisfy normal distributions $Norm(En_{A1}, He_{A1}^2)$ and $Norm(En_{A2}, He_{A2}^2)$, based on each rule.

(2) Substitute $x_{A1} = 1.831$ and $x_{A2} = 4.324$ into all nine rules, and calculate the certainty value y of every rule according to Eq. (2).

(3) Choose the maximum value y in Rule 3 as the current reasoning rule.

(4) Generate a random value $En_B' = 0.3370$, which satisfies the normal distribution $Norm(En_B, He_B^2)$ in Rule 3.

(5) If $x_{A1} < Ex_{A1}$ and $x_{A2} < Ex_{A2}$, according to Algorithm 2, step 4(1), calculate x_B as $x_B = Ex_B + En_B' \times (\sqrt{-2\ln y})/2$ to obtain $x_B = 0.9179$.

The steps for assessment with Grid 2 are as follows:

(1) In line with the nine rules, calculate random numbers En_{A1}' and En_{A2}' that satisfy normal distributions $Norm(En_{A1}, He_{A1}^2)$ and $Norm(En_{A2}, He_{A2}^2)$ based on every rule.

(2) Substitute $x_{A1} = 78.287$ and $x_{A2} = 30.092$ into all nine rules, and calculate the certainty value y of every rule according to Eq. (2).

(3) Choose the maximum value y in Rule 5 as the current reasoning rule.

(4) Generate a random value $En_B' = 0.3376$, which satisfies the normal distribution $Norm(En_B, He_B^2)$ in Rule 5.

(5) If $x_{A1} > Ex_{A1}$ and $x_{A2} < Ex_{A2}$, according to Algorithm 2, Step 4-(4), calculate $y_1 = 0.9575$ and $y_2 = 0.0068$, based on the equation $x_B = Ex_B + En_B' \times (\sqrt{-2\ln y_2} - \sqrt{-2\ln y_1})/2$, to obtain $x_B = 0.5483$.

Table 2. Reasoning rule set.

		Neighborhood elevation standard deviation				
		Very low	Low	Medium	High	Very high
Elevation	Very low			Rule 1 Very high risk		
	Low		Rule 3 High risk		Rule 4 Slightly higher risk	
	Medium	Rule 2 Slightly higher risk		Rule 5 Slightly higher risk		Rule 9 Very low risk
	High		Rule 6 Slightly lower risk		Rule 7 Low risk	
	Very high			Rule 8 Very low risk		

Table 3. Grading of risk comment.

Qualitative comments	Range of risk value	Risk comment cloud
Very low	$[0, 0.1]$	$C(0.05, 0.0167, 0.001)$
Low	$[0.1, 0.3]$	$C(0.2, 0.0333, 0.001)$
Slightly lower	$[0.3, 0.4]$	$C(0.35, 0.0167, 0.001)$
Medium	$[0.4, 0.6]$	$C(0.5, 0.0333, 0.001)$
Slightly higher	$[0.6, 0.7]$	$C(0.65, 0.0167, 0.001)$
High	$[0.7, 0.9]$	$C(0.8, 0.333, 0.001)$
Very high	$[0.9, 1]$	$C(0.95, 0.0167, 0.001)$

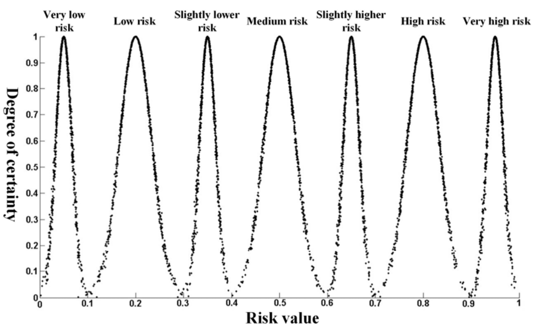


Fig. 5. Grading cloud of cloud reasoning.

4.3. Overall Hazard Risk Analysis Process

Based on single grid calculation, this method of cloud reasoning could be extended to every grid in the entire study area. All the data were analyzed in MATLAB, and the original elevation and NESD were converted into floating-point arrays and implemented in the cloud reasoning algorithm in MATLAB. The results were then converted back to the grid file in ArcGIS (**Fig. 6**).

5. Results and Analysis

5.1. Terrain Risk Analysis

Chaohu Basin is surrounded by mountains and hilly areas, with the Dabie, Fucuo, and Phoenix and Yinping Mountains to the southwest, north, and east, respectively. These mountains are generally higher than 400 m above sea level, comprising typical moderate cutting tectonic erosion landforms with a high NESD. Fanghu Hill west of Chaohu Lake, Baba Hill to the southeast, and Yefu Hill to the south are categorized as hilly areas with an elevation of 200–300 m. Some low hills are distributed along the exterior of the hilly areas and are about 100 m above sea level. Most of these hills have medium NESD since they are located in the middle and upper reaches of the river. Mounds (50–100 m above sea level) occur between the hills and alluvial plains, with gentle wavy distribution (**Fig. 7**).

Figure 8(a) shows the result of cloud reasoning. Firstly, the alluvial plains of rivers and lakes, along which Hexian County, Wuwei County, and Chaohu City occur, are depicted. The absolute elevation is low, and the land is flat. Therefore, this area is the most susceptible to floods during the flood season given its location in the immediate vicinity of the Yangtze River and Chaohu Lake.

Secondly, southeastern Hefei City and Feixi County and eastern Shucheng and Lujiang Counties are located between the hills and alluvial plains. The elevation of these locations is higher than that of the plains. The terrain has some slopes. Thus, the flood risk is relatively low. However, as this area is highly populated and the economic loss and casualties during flood events are likely to be high, potential flood disasters cannot be disregarded. Feidong County, central Shucheng County, and most of Feixi County are located in hilly areas, with an average elevation of about 50 m and high NESD. Therefore, the risk of flood disaster is moderate.

Lastly, the Dabie Mountains in southwestern Shucheng County and the mountainous areas of Chaohu and Hanshan Counties have an average elevation of above 400 m, varying terrain, and high NESD. Therefore, the flood hazard is relatively low, and this area is not susceptible to floods. However, this region contains steep mountains, and precipitation may concentrate during flood season. Precautions are thus needed to prevent other geological disasters.

Table 4. Reasoning rule set.

Rules	Cloud of elevation			Cloud of NESD			Risk comment cloud		
	Ex	En	He	Ex	En	He	Ex	En	He
Rule 1	8	2.2	0.1	40	3.3	0.1	0.95	0.0167	0.001
Rule 2	75.8	8.3	0.1	5	1.7	0.1	0.65	0.0167	0.001
Rule 3	32.5	5.8	0.1	20	3.3	0.1	0.8	0.0333	0.001
Rule 4	32.5	5.8	0.1	60	3.3	0.1	0.65	0.0167	0.001
Rule 5	75.8	8.3	0.1	40	3.3	0.1	0.5	0.0333	0.001
Rule 6	150	16.7	1	20	3.3	0.1	0.35	0.0167	0.001
Rule 7	150	16.7	1	60	3.3	0.1	0.2	0.0333	0.001
Rule 8	784.2	194.7	10	40	3.3	0.1	0.5	0.0167	0.001
Rule 9	75.8	8.3	0.1	95	8.3	0.1	0.05	0.0167	0.001

Table 5. Grading table of risk comments.

	Grid 1	Grid 2
Longitude	117°42′54.108″E	117°53′03.268″E
Latitude	31°38′47.04″N	31° 50′43.914″N
Elevation [m]	1.831	78.287
Neighborhood elevation standard deviation [m]	4.324	30.092
Reasoning result	0.9179	0.5483

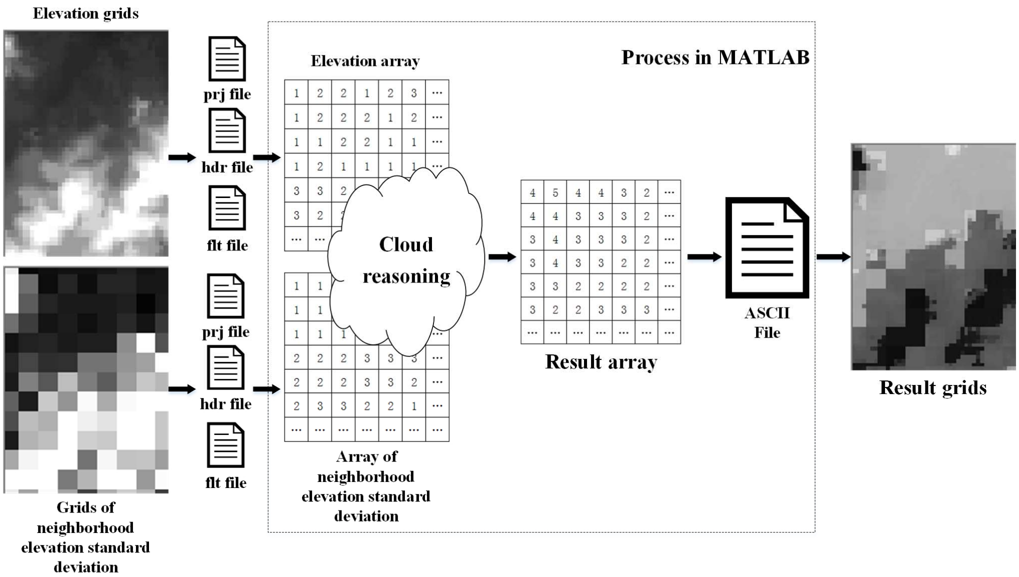


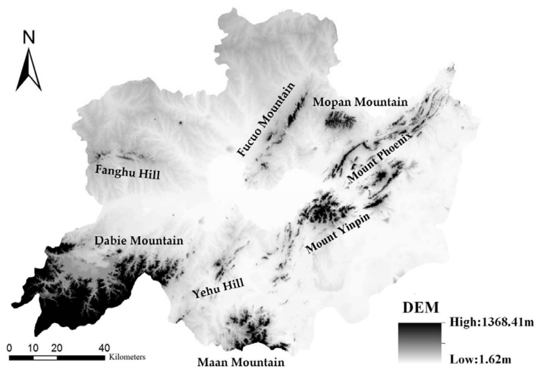
Fig. 6. Flowchart of terrain hazard risk analysis of flood disaster based on cloud reasoning.

5.2. Comparative Analysis of Results

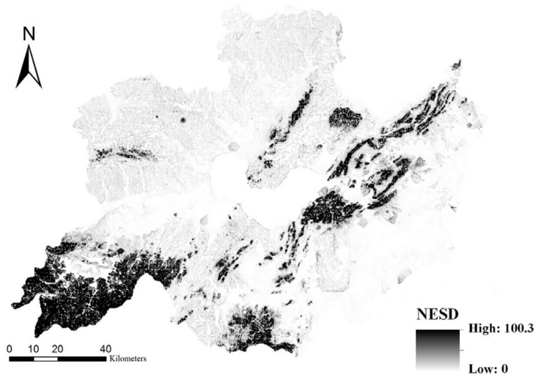
The most commonly used method in flood risk assessment depends on traditional mathematical methods: constructing a two-dimensional terrain hazard table based on actual absolute elevations and NESD (or slope) and then converting qualitative concepts to quantitative data [28, 29]. The advantages of this method are intuitiveness, simple construction, and fewer calculations. However, this method does not consider the subjectivity and randomness of qualitative concepts and lacks reasonable "soft" transitions among the qualitative concepts.

To illustrate the advantages of cloud reasoning in assessing the terrain risk of flood, a two-dimensional terrain hazard determination table (**Table 6**) was constructed by using previous research methods and results [27]. The risk of terrain hazard in Chaohu Basin was evaluated, and the terrain hazard map based on the two-dimensional table is shown in **Fig. 8(b)**.

Table 7 shows the statistical results of the whole study area and individual counties using the cloud reasoning



(a) Digital elevation model diagram



(b) Neighborhood elevation standard deviation (NESD) diagram

Fig. 7. Underlying surface of Chaohu Basin.

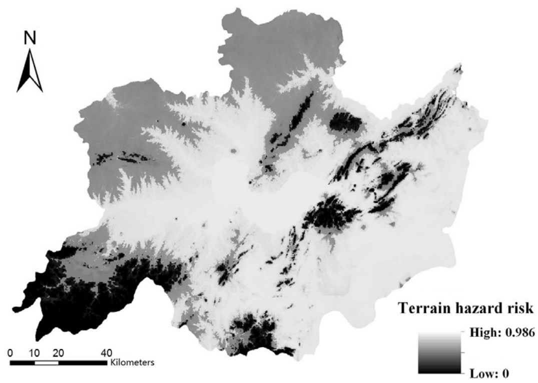
method. The findings showed a higher standard deviation and degree of dispersion than the two-dimensional table method did. This means that the results of cloud modeling had a greater dispersion degree (**Fig. 9(a)–(c)**).

When the risk range $[0,1]$ interval was divided into equal parts of 10, 10^2, 10^3, and 10^4, the cloud reasoning method results covered 100, 100, 99.68, and 97.43% respectively, and were much higher than those of the two-dimensional table method (**Fig. 9(d)**). This indicated that cloud reasoning had a more accurate coverage than the two-dimensional table method did. Compared to the table method, the cloud reasoning terrain risk distribution map was much clearer and more detailed, with richer layers, and the transition was more natural.

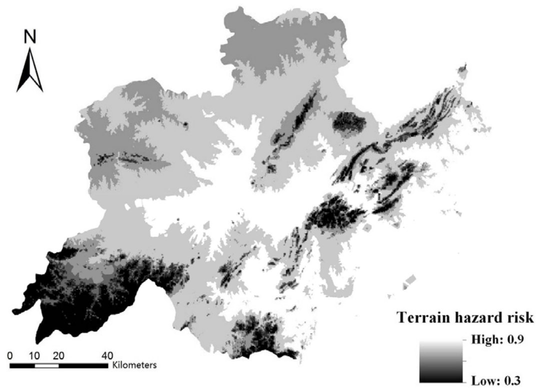
5.3. Improved Cloud Reasoning Method

When some regions of the results of single terrain risk cloud reasoning were amplified during the experiment, rough "noise" around the local transition zone was found. This was due to the existence of randomness and uncertainty in the process of cloud reasoning. Despite the differences in cloud reasoning values, the overall trend was consistent and did not affect the final assessment. This finding was consistent with the basic characteristics of the cloud model.

To reduce the noise, the cloud reasoning results were iterated several times and average-weighted before the final



(a) Result of cloud model



(b) Result of two-dimensional table

Fig. 8. Distribution of terrain hazard risk assessment of flood disaster in Chaohu Basin.

Table 6. Two-dimensional table of terrain hazard risk judgment. NESD: neighborhood elevation standard deviation.

NESD [m] / Elevation [m]	< 12	12–36	>36
<15	0.9	0.8	0.7
15–50	0.8	0.7	0.6
50–100	0.7	0.6	0.5
100–200	0.6	0.5	0.4
>200	0.5	0.4	0.3

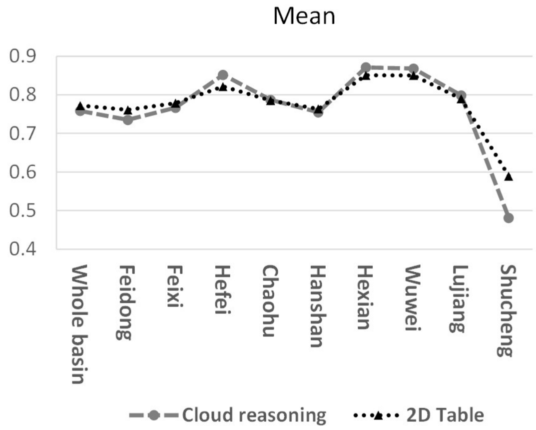
results were obtained. Thus, we used the same grid data to produce cloud reasoning results (x_{Bn}, y_n) by the algorithm. If the results were not inconsistent, these results could be substituted into Eq. (5) to calculate the weighted average as the final result:

$$(x_B, y) = \frac{\sum_{i=1}^{n} x_{B_i} \times y_i}{\sum_{i=1}^{n} y_i} \quad (1 \le i \le n) \quad . \; . \; . \; . \; . \quad (5)$$

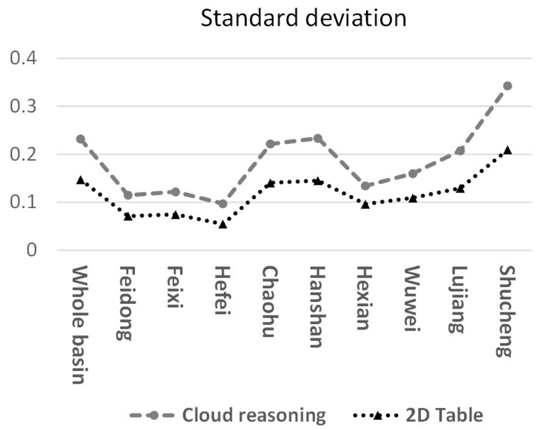
For example, (x_B, y_i) is one result of Algorithm 2. **Fig. 10(a)** shows a section image of one-time cloud reasoning, and **Fig. 10(b)** shows the result with 10 iterations

Table 7. Reasoning rule set.

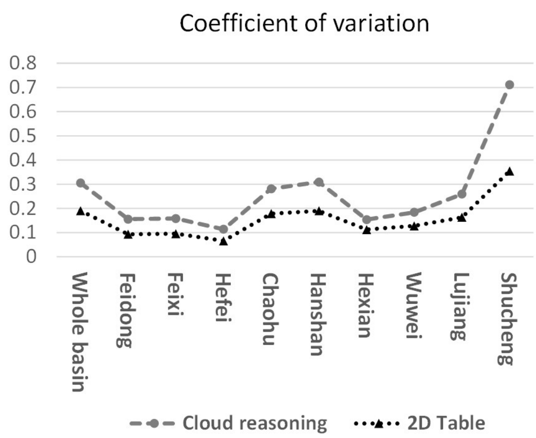
	Risk result of cloud model method			Risk result of two-dimensional table method		
	Mean	*Standard deviation*	*Coefficient of variation*	*Mean*	*Standard deviation*	*Coefficient of variation*
Whole basin	0.7583	0.2315	0.3053	0.7722	0.1471	0.1905
Feidong	0.7351	0.1144	0.1557	0.7610	0.0711	0.0934
Feixi	0.7666	0.1214	0.1583	0.7786	0.0744	0.0955
Hefei	0.8517	0.0969	0.1138	0.8213	0.0544	0.0662
Chaohu	0.7866	0.2213	0.2814	0.7852	0.1403	0.1787
Hanshan	0.7546	0.2332	0.309	0.7633	0.1451	0.1901
Hexian	0.8711	0.1339	0.1538	0.8506	0.0958	0.1126
Wuwei	0.8678	0.1595	0.1838	0.8504	0.1089	0.1281
Lujiang	0.7984	0.2070	0.2592	0.7897	0.1291	0.1634
Shucheng	0.4811	0.3423	0.7115	0.5895	0.2092	0.3549



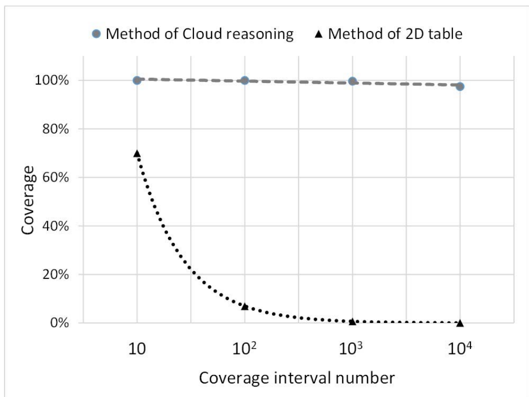
(a) Mean comparison



(b) Standard deviation comparison



(c) Comparison of coefficient of variation



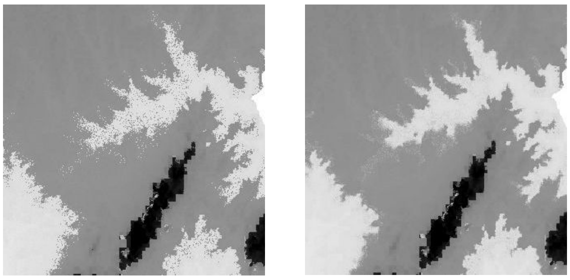
(d) Coverage accuracy

Fig. 9. Comparison of statistical indicators between two methods.

average-weighted in the same section. **Fig. 11** shows a modified cloud reasoning result. After processing, the cloud reasoning results were clearer and more accurate than before.

6. Conclusion

This study developed a cloud model that used three variables, namely expectation, entropy, and hyper-entropy, to describe qualitative concepts in natural language and with some universality [30]. This solves the problem of conversion between qualitative concepts and



(a) Result of one iteration (b) Result after 10 iterations

Fig. 10. Enlarged images comparing local details.

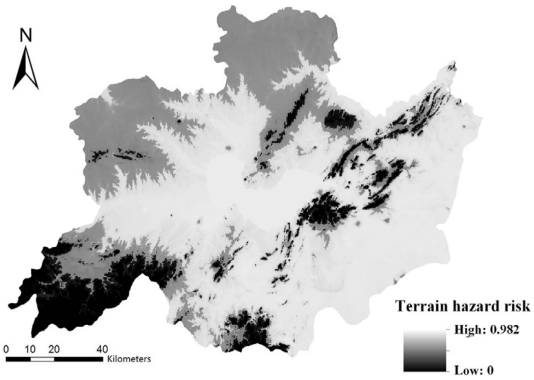


Fig. 11. Improved distribution of terrain hazard risk assessment of flood disaster in Chaohu Basin.

quantitative values. Based on the cloud model, a rule generator was applied to rule derivation, and qualitative concept reasoning was performed.

This study combined two elements of terrain risk in risk assessment, namely elevation and NESD, to establish a cloud model. The condition and risk comment clouds were generated by constructing algorithms. Cloud reasoning rule sets were created and joint certainty values were calculated according to each rule. The rule with the highest degree of certainty was selected. Reasoning was subsequently calculated, and the corresponding risk assessment value was obtained.

In contrast to the traditional two-dimensional table method for flood risk assessment, the cloud model reasoning method optimized the situation dealing with the "blunt" boundary. Using this model, the boundaries of risk evaluation elements were "softened" to address the lack of ambiguity and randomness in traditional methods. This study improved terrain risk estimation in flood hazard assessment. The boundary of qualitative concept quantification was softened, and the vagueness and uncertainty of the qualitative concept were reduced. The cloud model had advantages regarding qualitative and quantitative conversion, and it generated analysis maps more clearly and accurately, with richer layers and more natural transitions.

This study nonetheless had limitations. As flood risk assessment involves numerous contributing factors, the selection of only elevation and NESD as two major factors cannot be used to accurately assess any fold risk. Thus, for future studies, other risk factors, such as precipitation and river reservoir distance, should be considered in cloud reasoning operation for a more comprehensive assessment. Furthermore, a degree of uncertainty existed in a single deduction of the cloud reasoning algorithm. The reasoning result was slightly flawed, and the algorithm therefore needs to be further optimized in future research.

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