Sensors and Materials, Vol. 34, No. 12 (2022) 4405–4424
MYU Tokyo

S & M 3118

Constructive Method for Calculating Entropy of Comprehensive Feature Information of Map Area Objects for Disaster Severity Analysis

Beibei Wu,[1] Longhao Wang,[1] Ziyuan Zhu,[1] Liping Guo,[2] and Qing Xu[1*]

[1]College of Geospatial Information, Information Engineering University,
62 Science Avenue, High-tech District, Zhengzhou 450001, China
[2]61175 Troops, Qixia District, Nanjing 210000, China

(Received October 18, 2022; accepted November 16, 2022; online published December 8, 2022)

Keywords: emergency mapping, comprehensive feature information entropy, map area object, disaster severity, visualization

Maps possess prominent advantages in expressing geographic information data in general and in displaying spatial information about events of natural disasters in particular. With the recent enhancement of geographic information acquisition capabilities, the demand for thematic mapping of multitype disaster emergency response has dramatically increased. To solve the problems of insufficient information transmission and lack of combination of features of objects in emergency mapping, we introduce the concept of information entropy, an important indicator of artificial intelligence in the field of maps, and proposes a constructive method for calculating the entropy of comprehensive feature information of map area objects, aimed at the analysis of problems of disaster severity. Through the quantitative description of indicators of the geometry, spatial distribution, and disaster type of an area object, a comprehensive information entropy calculation model of the area object is constructed, through which the comprehensive feature information entropy of the area object is calculated and visualized. The experimental results obtained for typical case analyses show that the comprehensive feature information entropy model is superior to competing methods as it is more suitable for the requirements of human cognition and judgment. Moreover, this model improves the effectiveness of disaster thematic map information transmission and enriches the traditional emergency mapping information transmission theory.

1. Introduction

The People's Republic of China is a vast country with a variety of landscapes and a high incidence of natural disasters. Flooding, drought, earthquakes, and other disasters cause large human and financial losses every year, and the numbers of various disasters are increasing year by year.[1] Disasters are notorious for their adverse effects on almost all aspects of human life. Only by correctly understanding disasters, analyzing their severity, and taking decisive and

*Corresponding author: e-mail: xq1982_no.1@163.com
https://doi.org/10.18494/SAM4178

ISSN 0914-4935

reasonable measures can we reduce disaster losses. In the modern era of artificial intelligence, and in the social context of frequent occurrences of various public emergencies, disaster events tend to have strong spatiotemporal attributes. With the extensive application of geographic information data, the use of maps as a carrier to express disaster events is becoming increasingly common and is oriented toward multiple types of disaster events, wherein emergency mapping has become more urgent. As a model of the objective world, maps are the main tool for the transmission of spatial information.(2) Taking earthquakes as an example, we can collect a large amount of current data after a disaster occurs, such as satellite image data, vector terrain data, and disaster attribute data. How to quickly and accurately grasp earthquake and post-earthquake information, analyze earthquake severity, and enact decision-making for post-earthquake rescue has become the main focus and a source of difficulty in current research. Liu(1) analyzed the attributes and severity of disasters, indicating that it is important to understand the severity of disasters and effectively avoid them as much as possible. Liu *et al.*(3) proposed the use of the Lorentz curve and Gini coefficient as indicators to measure the unevenness of the spatial distribution of precipitation to express the degree of regional drought and waterlogging, so as to judge whether there is a possibility of a flood disaster. Post-disaster emergency mapping to understand the damage of buildings and other features in the disaster area in real time, quickly locate emergency rescue areas, and provide a reference for rescue, forecasting and decision-making, which require rapid and accurate positioning of key areas as well as quantitative measurement of map information, have also become an urgent key problem. However, the map information theory and the method of disaster severity analysis have been insufficiently studied, thus, new theories are needed to solve this problem.

In the 1960s, the Czech cartographer Kolácný(4) introduced the concept of information into map cartography, and subsequently, the information transmission function of maps began to have a major impact on cartography. A new field of modern cartography emerged in terms of the theory of map information transmission, and the map information transmission constitutes the basic content of modern cartography theory. This field covers cartographic synthesis theory, map information theory, map perception theory, map model theory, and map semiotics.(5) The measurement of map information is the basic problem of map spatial information transmission, map information services, map quality evaluation, and other related technologies and applications. The mathematization of map information transmission theory is an important step in the map representation of spatiotemporal data.(6) With the increasingly extensive application of emergency mapping, many scholars have studied the theory and method of information measurement of map elements. Shannon,(7) a celebrated American mathematician, pioneered the application of information entropy theory to map information measurement based on probability theory and used entropy to measure the content of information, thereby laying a solid foundation for modern information theory. Sukhov(8) and Kirschbaum *et al.*(9) and proposed a measure of information entropy of symbol types, introducing information theory to cartography for the first time, but the entropy they dealt with was still a statistical entropy that did not consider spatial relationships. Knopfli(10) first applied the measurement of map spatial information to cartographic generalization, but his calculation method based on the entropy of Shannon information required improvement. Later, He(11) used information theory to measure specific types of indirect information such as location information and color information. Ou and Yao[12] considered advanced cartographic elements, such as diversity and complexity, and proposed a "comprehensive eigenvalue measurement method", but their analysis of the relationship between diversity, complexity, and difference of symbols required further improvement. On the basis of the above contributions, Li and Huang[13,14] proposed the novel concept that the map information should include not only statistical information, but also spatial relationship information, geometric information, and thematic information. Deng and colleagues[15–18] conducted a systematic study on the information measurement of area features. Throughout existing research theories and methods, the information of map features has mostly been measured solely as mathematical probability and statistics, a paradigm that does not combine with the characteristics of area features and the support of objective models in mapping. Therefore, the aim of this paper is to maximize the use of the characteristics of various types of information of map area features and to combine these features with factors that affect the amount of information. We calculate the geometric feature information entropy of area objects through the size, irregularity, and quantity of map area objects, calculate the spatial distribution feature information entropy of area objects through the topological relationship, distance relationship, and distribution relationship of area objects, and calculate the type feature information entropy through the color difference of area objects. The comprehensive feature information entropy of map area objects is calculated from the three features of size, irregularity, and quantity, and the influence of different features on the information entropy is visualized and compared, which enriches the traditional map information transmission theory and provides a theoretical reference for emergency mapping.

2. Measurement Model of Map Information

2.1 Shannon information entropy measurement model

Shannon information entropy is a measure of information that is based on probability and statistics, which is governed by the earliest mathematical theory applied in the field of map information measurement. Shannon proposes that each map element appears with a specific probability. The content of map information is judged by the uncertainty of the element symbols on the map. The greater the uncertainty, the greater the content of map information. That is, the content of map information is closely related to the frequency of map symbols,[19] i.e., the more frequent the map symbols, the richer the content of map information.

Shannon information entropy deals with the information associated with a variable X assumed to be a random variable with n possible values, each with a specific probability. The set of probabilities for the n possible values is depicted as $\{P_1, P_2, \ldots, P_{n-1}, P_n\}$. Then the information entropy $H(X)$ of the random variable X is

$$H(X) = H(P_1, P_2, \ldots, P_n) = -\sum_{i=1}^{n} P_i \log(P_i). \tag{1}$$

The quantity in Eq. (1) represents the average number of binary digits (bits) required to represent or transmit the random variable X, and hence the “bit” is considered the unit for this quantity.

The frequency of a feature on a map is not necessarily equal to that of another feature. In spatial cognition of people, a map with a greater content difference, more element diversity, and a more widely spread distribution density appears more informative. Therefore, the entropy method does not conform to people’s spatial cognition of a map. It can describe the statistical information on the map, but not the characteristics of the features or the spatial information, and hence there are certain limitations in the measurement of map information by the entropy method.

2.2 Measurement model of feature information entropy

Gao[20] proposed that “map space cognition is the study of the environment on which people understand their existence, including the relevant positions, dependences, changes, and regularity of various things and phenomena”. The process of human cognition of map space is that of distinguishing the differences in map features. The greater the map contents and the greater the differences within these contents, the greater the amount of information obtained. Therefore, a feature based on a map information measurement model is more accurate than Shannon information entropy in measuring map information.[12] The information entropy is therefore calculated as

$$I = \sum_{i=1}^{n} \log_2 \left(V_i + 1 \right), \tag{2}$$

where V_i represents the standardized index describing the spatial and nonspatial features in the map, and the unit of information is again the bit.

The feature based on the information entropy measurement model considers the diversity and the differences within the map content. The greater the diversity and the differences, the greater the amount of information entropy, a rule that conforms to the map space cognitive rules of people, and is suitable for map information measurement. Therefore, we use the feature based on the information entropy measurement model combined with the geometric and spatial distribution characteristics of map area objects to build an index that quantitatively describes the map area object features as well as to build a calculation model of the map area object information entropy; this is a novel paradigm that solves the problem of measuring map information only using mathematical probability.

3. Calculation Method of Comprehensive Feature Information Entropy of Disaster Map Area Objects

Disaster map geometric information includes the location, quantity, size, and shape of map features. By contrast, spatial relationship information includes the topology, direction, distance, and distribution of map features, while thematic information includes the type and importance of map features.[2] Depending on the information characteristics of disaster map area objects, different features are expected to generate different types of information. For convenience, we select seven prominent aspects of information: quantity, size, shape, topology, distance, distribution, and type. We next use the feature information entropy measurement model to establish a quantitative description of the features, and build an area object information entropy calculation model based on each object feature. Figure 1 shows the basic strategy employed for computing comprehensive feature information entropy.

3.1 Information cognition of map area objects

Map area features are composed of a group of closed boundary lines. The different spatial morphological structures of boundary lines form various morphological structures of area features, thus generating the spatial information of these area features.[5] In terms of the external form, the area object mainly includes the area in a straight-line form and a curve form, where the area in the straight-line form includes residential areas and other similar areas, and the area in the curve form includes faceted water systems, vegetation, and other similar areas, as shown in Fig. 2. In terms of internal filling, area objects include solid areas and imaginary areas. In the map, solid areas refer to area features with clear outlines and clear areas, such as areal waters, residential areas, and other similar features, while imaginary areas refer to areas formed by gathering points and lines or intermittently enclosed points and lines, such as large-area vegetation coverage and other similar features, as shown in Fig. 3. In summary, the information measurement of map area objects requires comprehensive information measurement of the

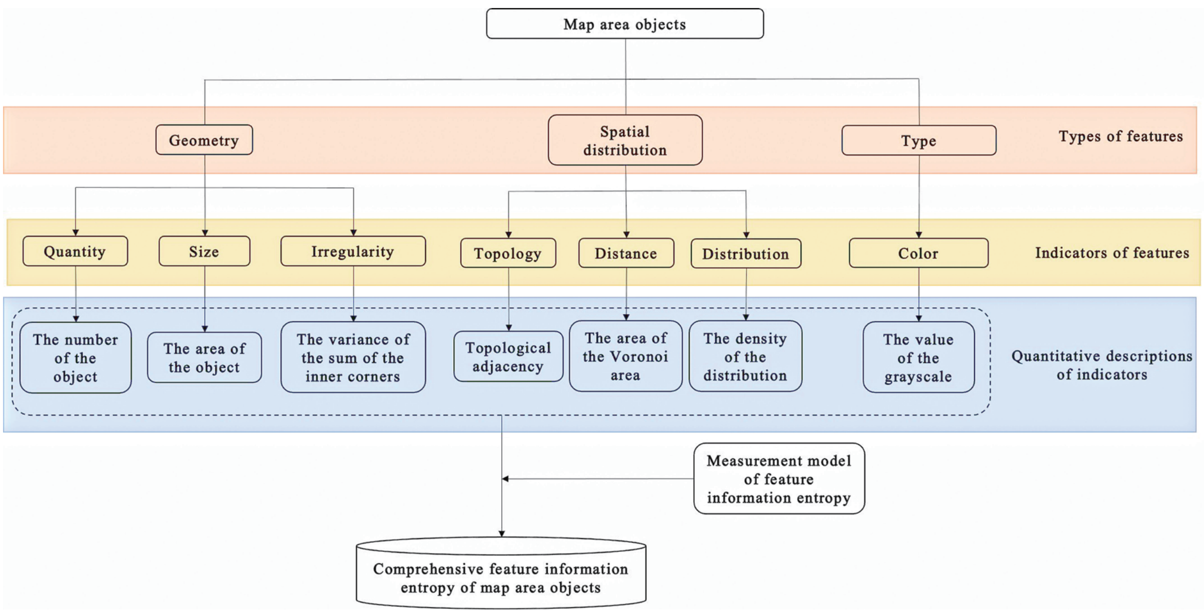
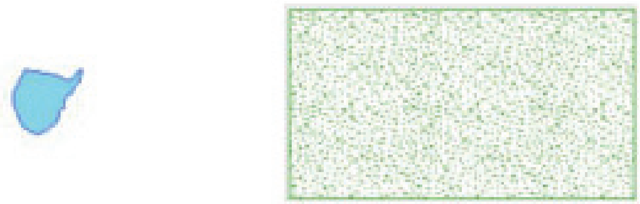


Fig. 1. (Color online) Strategy for computing comprehensive feature information entropy.

(a) (b)

Fig. 2. (Color online) External forms of area objects. (a) Area object with a straight-line form. (b) Area object with a curve form.



(a) (b)

Fig. 3. (Color online) Inner padding of area objects. (a) Solid area. (b) Imaginary area.

geometric, spatial distribution, and type characteristics of the area objects in accordance with their spatial morphology and relationship, combined with the map spatial cognitive characteristics of people.

According to research on the human brain in the field of artificial intelligence, the human visual system does not directly recognize the signal entering the human eye, but it utilizes an internal derivation mechanism to analyze and understand this visual signal.[20,21] According to this internal derivation mechanism, the human brain can model the visual perception signal, separate the relevant and trivial information, and thus measure the importance of various pieces of map information. The measurement model of the comprehensive feature information entropy of area objects uses the information features and the cognition of area objects to select the key factors that affect the information of area objects, and it calculates the information entropy of features of various types and the comprehensive features of area objects.

3.2 Calculation method of feature information entropy of disaster map area objects

Disaster map area objects have various categories of spatial features, including the main categories of geometry, spatial distribution, and type. In terms of geometry, map area objects have different shapes and sizes, which are manifested in the complexity and diversity of geometric forms.[5] In terms of the spatial distribution, the uneven distribution of map area objects constitutes the differences within and diversity of pieces of information on a map. In terms of the type, differently colored objects on a map represent different types of ground objects, which constitute differences among various parts of the map content.

3.2.1 Geometric Feature Information Entropy

The geometric features of a disaster map area object mainly include its shape features, size features, and quantitative features. The size features are quantitatively described by the area of the area object, and the differences within the shape features of the area object can be expressed by the degree of irregularity of the shape. The quantitative features are described by the number of elements of the same type. In a vector map, the boundary of the area object is a polygon obtained through the connection of multiple inflection points. Taking advantage of the connection information of the inflection points, we propose a shape irregularity measurement method based on the standard deviation of the polygon internal angles. Generally, the size of the internal angles can directly represent the shape of the polygon, and the standard deviation of the internal angles can reflect their dispersion degree. The larger the standard deviation, the greater the dispersion degree of the internal angles, and the more irregular the area object. The calculation process of the standard deviation of the internal angles is shown in Fig. 4.

Taking a concave polygon as an example, as shown in Fig. 5, the side length information is calculated using the inflection point coordinates and connection relationship, and then the internal angles of the polygon are calculated by applying the inverse-cosine theorem [Eq. (3)].

$$\angle 2 = \arccos \frac{a^2 + c^2 - b^2}{2ac} \tag{3}$$

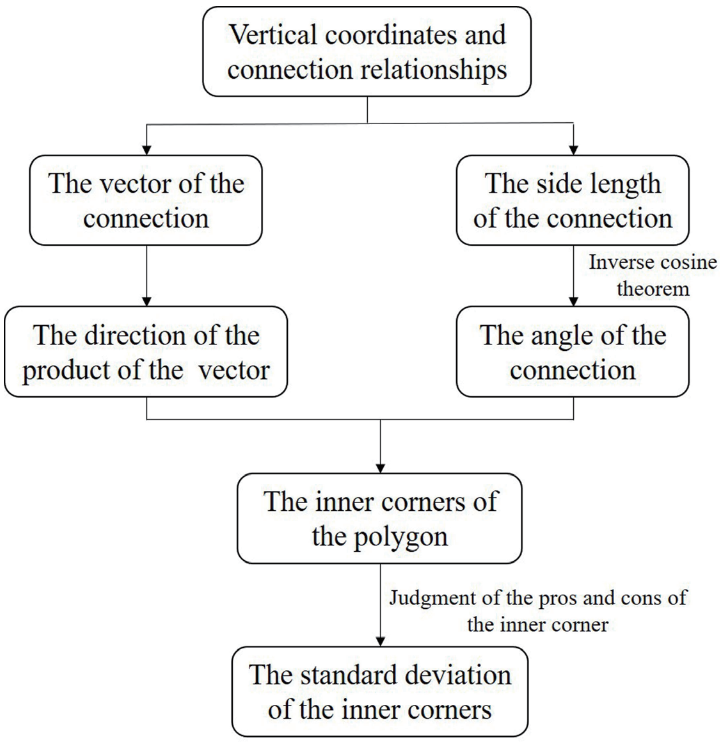


Fig. 4. Calculation process of the standard deviation of the internal angles.

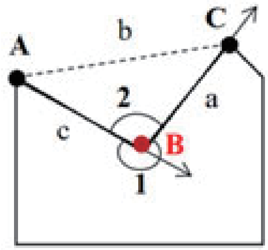


Fig. 5. (Color online) Concave polygon object.

Here, $\angle 2$ is the internal angle corresponding to vertex B in ΔABC, and a, b, and c are the lengths of the sides opposite angles $\angle$BAC, $\angle 2$, and $\angle$ACB, respectively.

However, in the actual calculation, when the internal angle ($\angle 1$) at point B is a superior angle ($180° < \angle 1 < 360°$), since the principal range of the inverse cosine function is [0, π], the calculation result is the size of the external angle (inferior angle, $0 \leq \angle 2 \leq 180°$) of the point, making it necessary to judge the superior and inferior angles of the internal angle of the point. To solve this problem, a method based on the direction of the vector product of two vectors is proposed to determine the admissible and inadmissible angles, as shown by

$$\begin{cases} \text{reflex angle}: \overrightarrow{AB} \times \overrightarrow{BC} < 0 \\ \textit{inferior angle}: \overrightarrow{AB} \times \overrightarrow{BC} > 0 \end{cases} \tag{4}$$

$\overrightarrow{AB}$ and $\overrightarrow{BC}$ are vectors formed by edges AB and BC, respectively, in Eq. (4).

After obtaining all the internal angles of the area object, we calculate their standard deviation s to measure the irregularity of the area object.

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}} \tag{5}$$

Here, n is the number of the internal angles of the polygon, and x_i and $\overline{x}$ respectively represent the size and mean value of the ith ($1 \leq i \leq n$, i is an integer) internal angle.

Using the shape, size, and quantity characteristics of the area object, the geometric information entropy of the area object is expressed via a generalization of Eq. (2) as

$$I_{geometry} = \sum_{i=1}^{n} \log_2\left(\frac{S_i}{\overline{S}} + 1\right) + \sum_{i=1}^{n} \log_2\left(\frac{s_i}{\overline{s}} + 1\right) + \sum_{i=1}^{n} \log_2\left(\frac{m_i}{\overline{m}} + 1\right). \tag{6}$$

Here, n is the total number of objects in the map, S_i and $\overline{S}$ are the area of the ith ($1 \leq i \leq n$, i is an integer) area object and the average area of an object on the map, s_i and $\overline{s}$ are the variance of the sum of the internal angles of the break points of the area object contour and the mean of the sum of the internal angles of the target on the map, respectively, m_i is the number of target element categories of the ith plane, and $\overline{m}$ is the mean value of the element categories given by

$$\overline{m} = \frac{n}{q}. \tag{7}$$

Here, q is the number of types of elements in the map.

3.2.2 Spatial distribution characteristic information entropy

The spatial distribution characteristics of the disaster map area objects mainly include the topological relationship, the distance relationship and the distribution relationship between area objects. The spatial proximity relationship between objects on the map can be described by Voronoi diagrams, wherein the adjacent edges of the Voronoi area represent the topological proximity relationship of objects on the map.(18) The topological relationship can be quantitatively described as the topological adjacency degree, that is, the number of edges in the Voronoi region. The more the number of edges, the more complex the adjacency relationships of the object. In the construction of a Voronoi diagram, it is necessary to consider the range of the region, which reflects the distance relationship between adjacent objects. Therefore, the distance relationship is quantitatively described as the area of the Voronoi regions. The greater the difference in the area of the Voronoi region of different area objects, that is, the greater the difference in the distance relationship, the greater the amount of spatial information generated by the distance. The distribution relationship of objects is quantitatively described by the distribution density, which can be determined as the ratio of the total area of the Voronoi diagram to the number of edges in the Voronoi region. According to the topological relationship, the distance relationship, and the distribution relationship of area objects, the information entropy of area objects in terms of the spatial distribution is expressed as

$$I_{distribution} = \sum_{i=1}^{n} \log_2\left(\frac{A_i}{\overline{A}}+1\right) + \sum_{i=1}^{n} \log_2\left(\frac{\left|S_{Vi}-\overline{S_V}\right|}{\overline{S_V}}+1\right) + \sum_{i=1}^{n} \log_2\left(\frac{D_i}{\overline{D}}+1\right). \tag{8}$$

Here, A_i and $\overline{A}$ are the number of edges in the Voronoi region of the ith area object and the average number of all such edges over all objects, S_{Vi} and $\overline{S_V}$ are the area of the Voronoi region of the ith area object and the average of all such areas, and D_i and $\overline{D}$ are the distribution density of the Voronoi region of the ith area object and its average, respectively. Here, the distribution density D_i is expressed as

$$D_i = -\frac{S_V}{A_i}, \tag{9}$$

where S_V represents the total area of all Voronoi areas in the figure.

3.2.3 Type feature information entropy

The type characteristics of disaster map area objects are mainly reflected in the color difference of area objects. Different colors represent different types of area objects. The color difference can be quantitatively described by a gray-scale value. In a disaster thematic map, different disaster types or different levels of the same disaster type are represented by different colors. Gray-scale is a series of transition colors ranging between pure black and pure white. Each object on the map has a gray-scale value, which can be used to distinguish different ground object types. For example, the four levels of earthquake disasters are severe, major, large, and general, and the affected areas are distinguished by four colors in accordance with the severity of the earthquake, as shown in Fig. 6. By contrast, the red-green-blue (RGB) color model of map symbols is a different way of mapping colors to numerical values. The range of gray-scale values in the gray-scale model is [0, 255], where 0 denotes black and 255 depicts white. The larger the gray-scale value, the closer the color is to white, and the smaller the gray-scale value, the closer the color is to black. This means that the smaller the gray-scale value, the deeper the color, the greater the visual impact on people, and the more information is obtained. In this paper, the floating point method is used to convert RGB values to gray-scale values as follows:

$$g = \mathrm{R}*0.299 + \mathrm{G}*0.587 + \mathrm{B}*0.114, \tag{10}$$

where R, G, and B represent the intensity values of red, green, and blue, respectively, and range from 0 to 255. Note that (R, G, B) = (0, 0, 0) means black and (R, G, B) = (255, 255, 255) means white.

Using the gray level features, the information entropy of the area object in terms of type features is expressed as

$$I_{type} = \sum_{i=1}^{n} \log_2 \left(\frac{G_i}{\bar{G}} + 1 \right), \tag{11}$$

where G_i and $\bar{G}$ are the gray-scale value of the ith area object and the average gray-scale value of the map, respectively.

Fig. 6. (Color online) Symbols for areas with different earthquake severity ratings. (a) General. (b) Large. (c) Major. (d) Severe.

3.2.4 Comprehensive feature information entropy

After calculating the results I of various types of information entropy, we standardize them by the range standardization method, as shown in Eq. (12), and we obtain I' as the processed result, which expresses the information entropy of the disaster map area object.

$$I' = \frac{I - I_{\min}}{I_{\max} - I_{\min}}. \tag{12}$$

Here, $I_{\max}$ and $I_{\min}$ are the maximum and minimum values of I, respectively. Note that the standardization process in Eq. (12) transforms the raw value of I in the range $[I_{\min}, I_{\max}]$ to the processed value of I' in the range [0.0, 1.0].

Combining the geometric, spatial distribution, and type characteristics of the map area objects, we adopt the feature-based map information measurement model, then obtain the information entropy of the disaster map area objects as

$$I = I_{geometry} + I_{distribution} + I_{type} \tag{13}$$

4. Experimental Analysis

4.1 Information entropy measurement of disaster data

As the research objects, we selected and symbolized experimental data from the building-evaluation data of the Haiti earthquake in the certain area, the buildings that collapsed in the earthquake, and areas with high population density in a campus, such as the playground and classrooms. The overlapping parts of the selected areas are the areas with high population density in the campus damaged by the earthquake. After cleaning the missing, redundant, and other abnormal data, a total of 568 objects were selected. A general drawing and a partial display of the study area are shown in Fig. 7.

Among the 568 objects selected, the 386 objects in orange are collapsed buildings. The green area objects denote the data of the high-population-density areas on campus, totaling 182 objects. The area, irregularity, topological relationship, distance relationship, distribution density, and gray-scale value of the two types of elements in Fig. 7 were then calculated. The experimental starting data of the damaged buildings (Damaged_Buildings) are shown in Table 1, and the experimental starting data of the campus areas with high population density (Camp) are shown in Table 2. The unit of area is the SI unit (m^2).

On the basis of the data in Tables 1 and 2, we used the comprehensive feature information entropy model of area objects to calculate the comprehensive information entropy of all area objects in Fig. 6, and then we obtained the comprehensive feature information entropy and the sum of the elements in the area with damaged buildings and campus areas with high population density. To verify the rationality of the construction method of the comprehensive feature

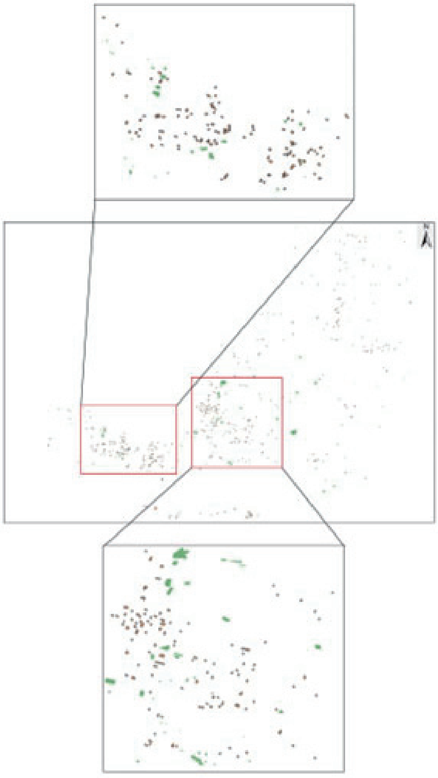


Fig. 7. (Color online) Thumbnail of the study area.

Table 1
Experiment starting data of Damaged_Buildings.

Number	Area	Irregularity	Topological relationship	Distance relationship	Distribution density	Gray value
1	7.06572018	19.24995123	9	7.10999935	0.00331799	170.75200000
2	12.03959982	39.74115749	6	5.95200028	0.00497699	170.75200000
3	12.49130037	46.59011093	7	54.27100035	0.00426599	170.75200000
4	21.46510087	50.73193225	4	3.29549795	0.00746548	170.75200000
5	6.89958005	10.66318401	8	7.05599963	0.00373274	170.75200000
⋮	⋮	⋮	⋮	⋮	⋮	⋮
386	10.23240020	49.11980913	10	45.10000696	0.00298619	170.75200000

Table 2
Experiment starting data of Camp.

Number	Area	Irregularity	Topological relationship	Distance relationship	Distribution density	Gray value
1	68.14420541	37.81222325	10	14.55001203	0.00298619	151.98100000
2	389.71159948	49.60656089	7	12.34997294	0.00426599	151.98100000
3	59.48338643	50.61152312	4	899.99805986	0.00746548	151.98100000
4	43.97865267	57.86997458	8	41.80001072	0.00373274	151.98100000
5	32.96643483	50.00194367	6	18.64999438	0.00497699	151.98100000
⋮	⋮	⋮	⋮	⋮	⋮	⋮
182	11.35639232	4.66880699	6	5.06000244	0.00497699	151.98100000

information entropy model of area objects, we compared this method with the measurement method using Shannon' s information entropy model. The results are shown in Table 3. The unit of information entropy is the binary digit (bit).

By calculating the comprehensive feature information entropy results of each area object in Fig. 7, we select the center of mass of each area object and use nuclear density analysis to visualize the comprehensive information entropy of the two pertinent types of element. At the same time, we visualize the comprehensive feature information entropy results of all area objects, as shown in Fig. 8. We also visualize the measurement results based on Shannon information entropy, as shown in Fig. 9.

In both Figs. 8 and 9, the information entropy of the blue part is smaller than that of the red part. The results of the comprehensive feature information entropy model of the area objects (Fig. 8) show that the comprehensive information entropies of the lower left corner and upper right corner in the figure are large. By contrast, the Shannon information entropy model (Fig. 9) only considers the statistical probability of the area of area objects, thus, the information entropy of the areas with a large area distribution is large, and hence, the results show that only the lower left corner in Fig. 9 has a large comprehensive information entropy, and the part with a large information entropy has a wide range.

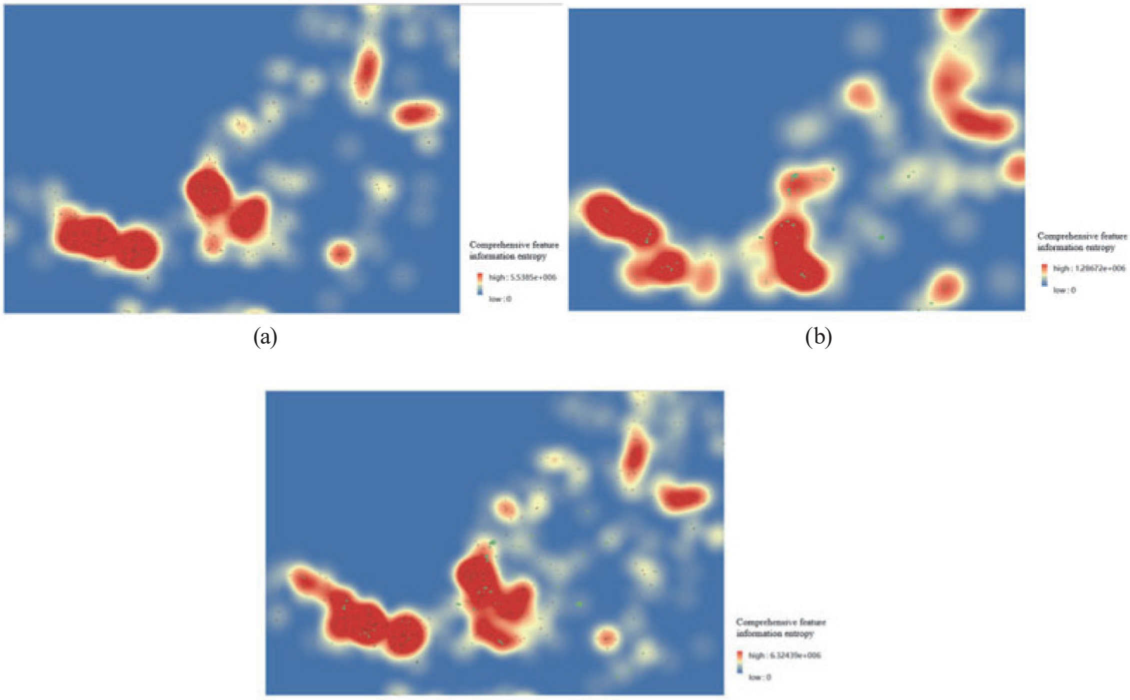
4.2 Comparison of missing characteristic indicators

After we conducted a large number of experiments, we used the control variable method to compare the geometric, spatial distribution, and type features, and we obtained the visualization results of the comprehensive feature information entropy of missing geometric, spatial distribution, and type feature information, as shown in Fig. 10.

By comparing the results of type features, we found that missing spatial distribution features have more influence on the information entropy results of the objects than the missing geometry

Table 3
Measurement results of area object information.

Number	Type of object	Comprehensive feature information entropy	Shannon's information entropy
1	Damaged_Building	13.73589915	0.077153199
2	Damaged_Building	14.46978293	0.072837961
3	Damaged_Building	17.69845317	0.195099289
4	Damaged_Building	15.68958471	0.071145387
5	Damaged_Building	13.55175936	0.073715032
⋮	⋮	⋮	⋮
386	Damaged_Building	14.97442131	0.058965723
387	Camp	15.94397075	0.161664476
388	Camp	18.65095054	0.367711377
389	Camp	16.64663255	0.118526784
390	Camp	15.86938822	0.126554776
391	Camp	15.66842917	0.099327711
⋮	⋮	⋮	⋮
568	Camp	12.8458188	0.102677923
Σ	—	8497.04359	42.60788211



(a) (b)

(c)

Fig. 8. (Color online) Visualization of comprehensive feature information entropy results. (a) Visualization of Damaged_Building comprehensive feature information entropy results. (b) Visualization of Camp comprehensive feature information entropy results. (c) Visualization of combined Damaged_Building and Camp comprehensive feature information entropy results.

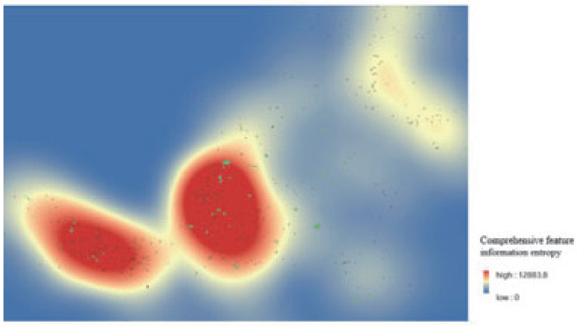


Fig. 9. (Color online) Visualization of Shannon information entropy measurement results.

and type features. We found that after removing the spatial distribution features, the information entropy of all area objects decreased, and the information difference between objects weakened. Figure 10(c) shows the areas with significant changes, and we conclude that the spatial distribution of buildings that collapsed in the earthquake and that of the areas with high population density in the campus have a greater impact on the information entropy results than geometry and type features. The spatial distribution is more important in the preparation and evaluation of the present disaster thematic map.

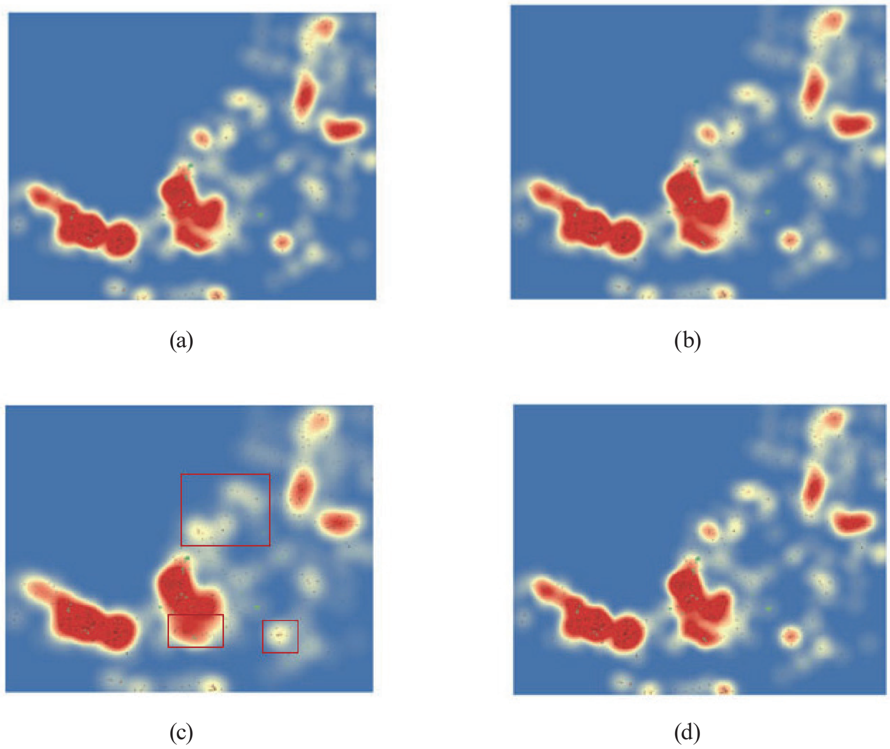


Fig. 10. (Color online) Comparison of missing features. (a) No missing information. (b) Missing geometric feature information. (c) Missing spatial distribution feature information. (d) Missing type feature information.

Considering people's perception of the color of map features, we display a building damaged in the earthquake in orange, indicating that the building has been affected by the disaster. The (R, G, B) value of orange is (222, 158, 102) and its gray-scale value is 170.752. The areas with a high population density on campus are indicated in green, which suggests a large flow of people in such areas and no disaster impact. The (R, G, B) value of green is (115, 178, 115) and its gray-scale value is 151.981. The values of R in the (R, G, B) values of orange and green are markedly different. In this paper, R, G, and B are different in order to represent the two area objects in the experiment, and the control variable method is used to verify the influence of different colors of different elements in the disaster map on the disaster severity analysis. We next discuss several cases of interest.

(1) G-value varies widely

To make the colors of the two area objects highly recognizable, when R and B are both 115, G is set to 0 for the Damaged_Building objects and 255 for the Camp objects. The colors are shown in Fig. 11. Then the gray-scale value of Damaged_Building is 47.495 and that of Camp is 197.18.

(2) B-value varies widely

Here, R and G are both fixed at 115 and B is set to 255 for a Damaged_Building object and 0 for a Camp object. The colors are shown in Fig. 12. Then the gray-scale value of Damaged_Building is 130.96 and that of Camp is 101.89.

(3) R-, G-, and B-values all vary widely

The (R, G, B) value is set to (0, 0, 0) for a Damaged_Building object and (255, 255, 255) for a

(a) (b)

Fig. 11. (Color online) Two area objects with greatly differing G-values. (a) Color of Damaged_Building object. (b) Color of Camp object.

(a) (b)

Fig. 12. (Color online) Two area objects with greatly differing B-values. (a) Color of Damaged_Building object. (b) Color of Camp object.

Camp object. The colors are shown in Fig. 13. Then, the gray-scale value of a Damaged_Building object is 0 and that of a Camp object is 255.

For each of the three cases, the information entropy visualization results are shown in Fig. 14.

Combined with the lack of characteristic indicators, the color difference of the two area objects has little effect on the information entropy results, thus, it has little impact on the results of disaster severity analysis.

4.3 Analysis and discussion of results

By analyzing the information entropy calculation results, we find that the relationship between the amounts of information of various map elements obtained using the model proposed in this paper is plausible and reasonably perceived by a human being, but the amount of information obtained by the Shannon information entropy model does not conform to the spatial cognitive understanding of humans. Specifically, we give a detailed comparison of the two models below.

(1) The visualization results of the comprehensive feature information entropy obtained from the elements in Fig. 7 are shown in Fig. 8, where (c) shows that the comprehensive feature information entropy of the elements in the lower left corner is relatively large, which is mainly for two reasons. The first reason is that there are overlapping parts of Damaged_Building and Camp objects in this area, that is, the area with a high population density in the campus with buildings destroyed in the earthquake, which makes the characteristic information entropy of this area high. The second reason is that the spatial distribution characteristics have a greater impact on the information entropy than geometry and type, while the lower left area has a more intensive distribution of elements and a more complex spatial distribution relationship than other areas, resulting in greater information entropy of

(a) (b)

Fig. 13. (Color online) Two area objects with greatly differing R, G and B values. (a) Color of Damaged_Building object. (b) Color of Camp object.

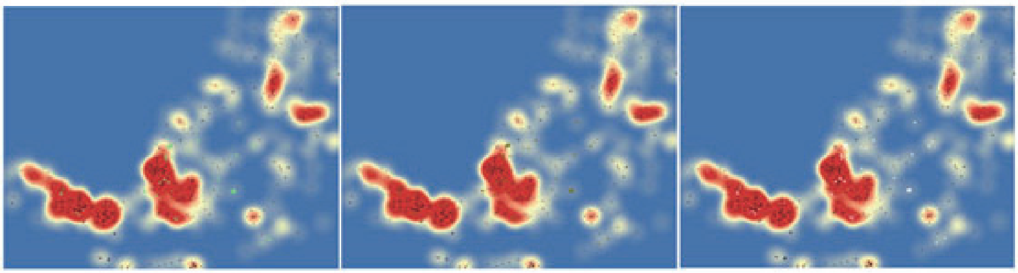
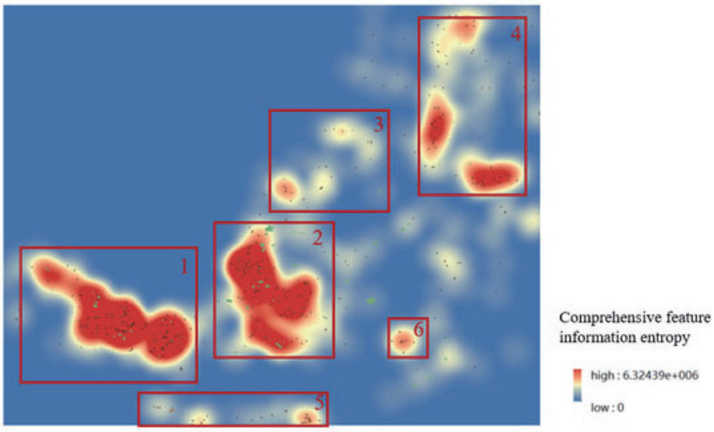


Fig. 14. (Color online) Information entropy visualization results for three cases of interest.

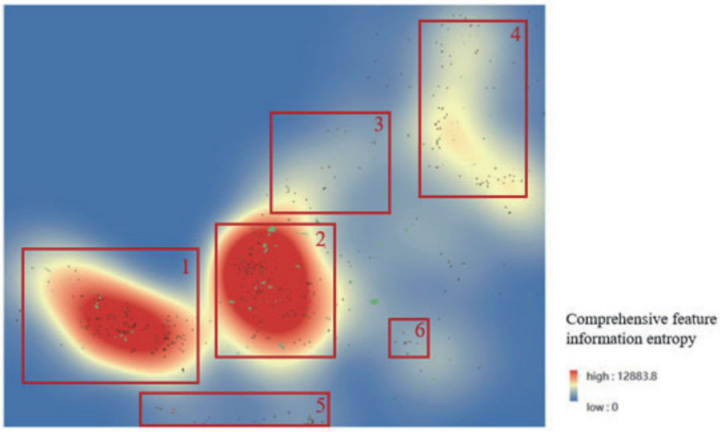
the comprehensive characteristics of this area than in other areas. The calculation of the comprehensive characteristic information entropy of Damaged_Building and Camp elements and the visualization of results are conducive to the rapid identification of areas greatly affected by earthquakes and the implementation of missions for rescue assistance. This calculation also provides a theoretical reference for the design and production of disaster thematic maps.

(2) The comprehensive feature information entropy model of map area objects fully considers the geometric, spatial distribution, and type characteristics of Damaged_Building and Camp features, including their size, irregularity, topological relationship, distance relationship, and color, while the Shannon information entropy model only considers the size of features and the number of adjacent features. Therefore, the information types and influencing factors considered in the area object comprehensive feature information entropy model are relatively complete, and the amount of information obtained is more accurate, resulting in a more effective transmission function for disaster map visualization.

(3) In the experimental data of this study, the Damaged_Building features have more data than the Camp features, and the size relationship between the two types of calculated features is reasonable, conforming to the visual cognition of the human brain, while the amount of information obtained by the Shannon information entropy model does not conform to human cognition, which also verifies the view expressed by Liu *et al.* [15] As shown in Fig. 15, on the whole, the comprehensive feature information entropy model takes into account the spatial relationship between various elements in the map. There is almost no information in the blank area of the map, thus, the information entropy is almost zero, and the information is distributed in the element distribution area. The Shannon information entropy model shows that most of the blank areas in the map have information entropy values, which do not reflect



(a)



(b)

Fig. 15. (Color online) Partial maps of the results of the two models. (a) Result analysis diagram of the comprehensive feature information entropy model. (b) Result analysis diagram of the Shannon information entropy model.

the spatial distribution differences between objects. Locally, as shown by the red areas in Fig. 15, areas 1, 2, and 4 have different information entropy ranges corresponding to the different distributions of the two types of elements. The information entropy range obtained by the comprehensive feature information entropy model is relatively refined, while the visualization results obtained by the Shannon information entropy model are rough and are not conducive to the rapid evaluation of disaster information in earthquakes. There are multiple elements in areas 3, 5, and 6. The information entropy of each area object obtained by the comprehensive feature information entropy model is different from the entropy of its surrounding environment, reflecting the feature difference of the object. However, the entropy of some objects is almost the same as that in the surrounding environment in the Shannon information entropy model calculation results, which does not reflect the characteristics of element information and is not conducive to the timely identification of damaged objects in earthquakes and other disasters.

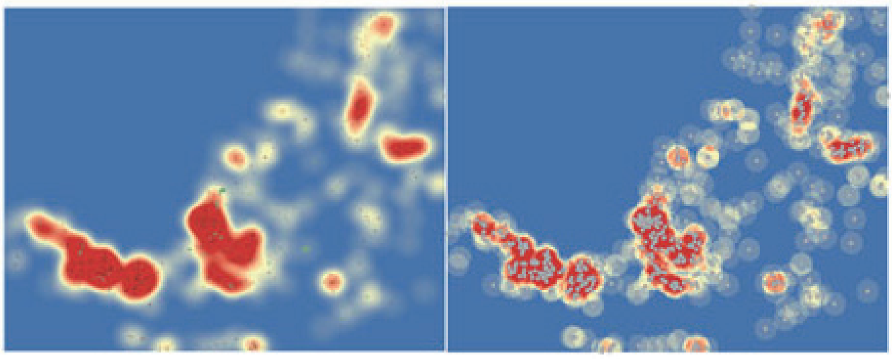


Fig. 16. (Color online) Information entropy visualization results.

(4) The spatial distribution features have a major impact on the comprehensive feature information entropy of the map area objects, as shown in Fig. 10. According to the experimental results, the comprehensive feature information entropy model of area object can evaluate the importance of feature indicators that affect the size of the information entropy, and the spatial distribution characteristics can be used as important indicators that also affect the information entropy, providing theoretical support for the measurement of map information and playing an important role in the design and production of disaster thematic maps.

Xie *et al.* [22] calculated information at each level of each type of impact factor of geological disasters and superimposed the information to obtain a distribution map of the geological disaster susceptibility index. Then, they graded and evaluated the geological disaster susceptibility. The visualization results of the information entropy obtained by their method are shown in Fig. 16.

Xie *et al.* [22] used points to represent disaster assessment, which lacks an association with the surrounding adjacent areas. As can be seen from Fig. 16, if points are used, the spatial relationship between objects cannot be well reflected and lacks continuity. Therefore, we calculated the information entropy of the area and used the centroid of each area object to visualize the results of kernel density analysis. The two studies differ in the selection of the severity analysis factors affecting the disaster map; these can be selected in accordance with the research focus.

5. Conclusions

As an important indicator for monitoring and evaluating changes and complex information in the field of artificial intelligence, an information entropy calculation model is introduced into the area of disaster mapping, which can provide scientific, reasonable, intuitive, and effective data visualization and analysis results useful in post-disaster rescue. In the case of massive map data, the calculation of map information is more complicated and many factors must be considered, and the simple use of probability and statistics as a measurement model ignores the regular characteristics of features. The experimental results show that the comprehensive feature information entropy calculation model of map area objects combines the geometry, spatial distribution, and disaster type characteristics of map elements; quantitatively describes the indicators; calculates the comprehensive information entropy of disaster data using the feature model; and compares the influence of different indicators on the entropy of the map information. Moreover, the results of experiments conducted in this study show that the comprehensive feature information entropy calculation model is rational, can effectively improve information transmission, and will provide theoretical support for emergency mapping oriented toward disaster data. This paper provides a useful exploration of emergency mapping of disaster areas. However, emergency response mapping in the contemporary era of artificial intelligence requires intelligent and dynamic decision-making based on spatial information, and there are many types of data that must be considered for disasters. Moreover, the influence of time factors must also be considered in future work.

Acknowledgments

The authors acknowledge the data support from "National Earth System Science Data Center, National Science & Technology Infrastructure of China. (http://www.geodata.cn)".

References

1 R. F. Liu: Management and Science and Technology of Small and Medium sized Enterprises (First Decade) **2** (2015) 163. https://doi.org/10.3969/j.issn.1673-1069.2015.04.111
2 Z. L. Li, Q. L. Liu, and P. C. Gao: Acta Geodaetica et Cartographica Sinica **45** (2016) 757. https://doi.org/10.11947/j.AGCS.2016.20160235
3 J. M. Liu, Y. G. Ding, and Y. Li: J. Nat. Disasters **5** (2004) 16. https://doi.org/10.3969/j.issn.1004-4574.2004.05.003
4 A. Kolácný: Cartographic J. **6** (1969) 47.
5 H. M. Liu: Research on the measurement method of map spatial information, Central South University (2012).
6 Z. L. Li, W. Z. Xu, and Z. Xu: Acta Geodaetica et Cartographica Sinica **50** (2021) 1033. https://doi.org/10.11947/j.AGCS.20210072
7 C. E. Shannon: The Bell Syst. Tech. J. **27** (1948) 379.
8 V. I. Sukhov: Geod. Aerophotogr. **10** (1967) 212.
9 G. M. Kirschbaum, K. H. Meine, and K. Frenzel: International Yearbook of Cartography, V. I. Sukhov, Ed. (1970) p. 41.
10 R. Knopfli: Communication Theory and Generalization, D. R. Fraser Taylor, Ed. (New York, 1983) pp. 177–218.
11 Z. Y. He: Geomatics Inf. Sci. Wuhan Univ. **12** (1987) 70. https://doi.org/10.13203/j.whugis1987.01.007
12 W. J. Ou and X. L. Yao: Map **4** (1988) 5. https://doi.org/CNKI:SUN:DITU.0.1988-04-001
13 Z. L. Li and P. Z. Huang: Proc. 20th Int. Cartographic Conf. (2001).
14 Z. L. Li and P. Z. Huang: Int. J. Geogr. Inf. Sci. **16** (2002) 699.
15 H. M. Liu, M. Deng, and Z. J. He: J. Earth Inf. Sci. **14** (2012) 744. https://doi.org/10.3724/SP.J.1047.2012.00744
16 H. M. Liu and M. Deng: J. Surv. Mapp. Sci. Technol. **30** (2013) 191. https://doi.org/10.3969/j.issn.1673-6338.2013.02.019
17 J. Chen, M. Deng, and F. Xu: Surv. Mapp. Sci. **35** (2010) 74. https://doi.org/10.16251/j.cnki.1009-2307.2010.01.012
18 H. M. Liu, M. Deng, and Z. D. Fan: Acta Geodaetica et Cartographica Sinica **43** (2014) 1092. https://doi.org/10.13485/j.cnki.11-2089.2014.0154
19 H. L. Liu: J. Surv. Mapp. Sci. Technol. **3** (1992) 49.
20 J. Gao: Spatial Cognition of Maps and Cognitive Cartography (Map of China Publisher, Beijing, 1991) p. 12.
21 J. J. Wu: Xidian University (2014). https://doi.org/CNKI:CDMD:1.1014.324851
22 M. L. Xie, N. P. Ju, J. J. Zhao, Q. Fan, and Z. Y. He. Geomatics Inf. Sci. Wuhan Univ. **46** (2021) 1003. https://doi.org/10.13203/j.whugis20190317