

Land-use regionalization based on landscape pattern indices using rough set theory and catastrophe progression method

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Received: 4 May 2013 / Accepted: 2 July 2014 / Published online: 25 July 2014
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Abstract This study presents the rough set theory and catastrophe progression method to regionalize the land-use change and to analyze the land ecological process. It uses the land-use database of Yixing City of Jiangsu Province, an urbanized and industrialized city in Yangtze River Delta of China, as an exemplification. The study area is divided into six kinds of land-use types according to the national standard of land-use classification. It includes arable land, garden, woodland, urban–rural construction land, water, and unused land. The six kinds of land-use types are formed into their corresponding landscape types in the scale of 1:10,000 by the aid of ArcGIS9.3 software of ESRI. In ArcGIS9.3, the landscape pattern indices are calculated by using Fragstats (raster version 3.3) software. Based on these landscape pattern indices, an integrated indicator system of landscape regionalization of land use in Yixing was established, and land-use regionalization models are set up using the catastrophe theory. Rough set theory is introduced to avoid the subjectivity in the indicator's importance in catastrophe models. The hidden rule among the raw data is acquired by knowledge reduction of the data mining in the rough set theory. In the process, indicators needed to be arranged according to the computed importance of an attribute without

considering the determination of weight function. This greatly avoids the subjectivity in the process of weight factor determination. The zoning of land use based on landscape indices finally is made by the multi-indicator integrated catastrophe progression method. According to these indices, Yixing is divided into four grading land-use zones when the rough set and catastrophe progression methods are combined. The zones include high-, medium-, low-, and weak-intensity zones, indicating that land use primarily varies the landscape pattern. With the increase of water and forest area proportion, the human disturbance to land system wanes; patch fragmentation reduces; patch shape complexity enhances; and landscape diversity decreases. Moreover, it can mostly avoid the subjective evaluation in artificially determining factor weights by using rough set theory. It makes the zoning results more objective and exact.

Keywords Land-use regionalization · Landscape pattern indices · Rough set theory · Catastrophe progression method

Introduction

Land-use change has become a focus globally because of rapid economic-social development and increased human activities (Liu and Deng 2009; Lindemann-Matthies et al. 2010; Munsu et al. 2010). It has varied the structure, the material circulation, and energy flow of the local landscape (Rutherford et al. 2008; Munsu et al. 2010; Sato et al. 2010; Huang et al. 2012). It also has deeply influenced the regional biodiversity and ecological process, an influence that has mainly driven landscape pattern change (Peng et al. 2007; Guan et al. 2008; Houet et al. 2010; Fernandes et al. 2011). A landscape pattern analysis can effectively

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tell the spatial pattern of land-use change if the analysis is based on the geometric characteristics (Lathrop et al. 2007; Zimmermann et al. 2010; Kupfer 2012). This pattern has the spatial heterogeneity and thus represents the mosaic of different land-use patches (Seto and Fragkias 2005; Millington et al. 2007). The performance is mainly due to the interaction result of the land ecological process (Persson et al. 2010; Renetzeder et al. 2010).

Remote Sensing (RS) and Geographic Information System (GIS) have been widely used for the response mechanism, space–time evolution and ecological effects of the land-use landscape pattern (Otto et al. 2007; Porter-Bolland et al. 2007; Guan et al. 2008; Deng et al. 2009; Huang et al. 2009; Zhang et al. 2009; Munsu et al. 2010). Land-use regionalization can analyze and synthesize the spatial information in complicated data. Landscape pattern indices can be used to quantify the spatial pattern of land-cover changes (Long et al. 2010). Therefore, the zoning of land use by landscape pattern indices has been well documented (Hall and Arnberg 2002; Long et al. 2010; Kupfer et al. 2012; Han et al. 2013), with plentiful works concentrated on the selection and development of the division index (Chen et al. 2009, 2012). Recently there has an increasing interest in regionalizing the landscape pattern indices by using multivariate cluster analysis (Long et al. 2010). There is, however, subjectivity in the determinateness of the index's weight. The Rough Sets Theory (Pawlak 1982) is a new-style mathematics tool for dealing with fuzzy and uncertainty issues (Pawlak 1998). The theory uses knowledge reduction to decrease the problem's decision making and classification rules, on the basis of the premise of maintaining the same classification ability (Pawlak 1982, 1998; Ahn et al. 2000). No priori information besides the processed data in rough set theory is required, compared with other fuzzy set theory. It is thus objective to reflect the fuzziness of the knowledge by rough set theory.

This paper selects a developed city Yangtze River Delta, Yixing City as example to analyze the land-use zoning method. The local land use is zoned by using a combination of rough sets and catastrophe progression method, on the basis of selecting the landscape indices of land use. The results of land-use zoning help to understand the degrees of human activities on the different land-use types and are expected to provide a reference for regional sustainable land use and ecological construction.

Materials and methods

Study area

The study area is the Yixing City in the southern part of Jiangsu Province. It is located in the Yangtze River Delta of

China. It extends between east of 111°30' to 120°03' longitude and north of 31°07' to 31°37' latitude (Fig. 1). The City, spreading over an area of 2177.43 km², situates in the west of the Taihu Lake, the second largest freshwater lake of China. The region is surrounded by low hills in the southern part and by plain in the northern part. The climate is of north subtropical monsoon with cold, dry winter and hot, rainy summers. In this region, the average precipitation is about 1,199.8 mm/year and the mean annual temperature is 15.6 °C. The City is one of the most rapidly developing cities in China; it has evolved from a small town to a big modern city because of the rapid industrialization and urbanization of China. In 2010, the city had registered 1,189 industrial enterprises, whose gross product reached to 197 billion Yuan.

Data sources and their processing

Land-cover datasets in 2009 are generated for calculating the landscape pattern metrics. The existing land-cover dataset is updated by using a change detection method, which is based on Landsat Thematic Mapper (TM) and aerial-survey remote-sensing data. According to the regional characteristics, the study area was primarily divided into six kinds of land-use types according to national standard of land-use classification. These types include arable land, garden, woodland, urban–rural construction land, water, and unused land. By using ArcGIS9.3 software of ESRI (Fig. 2), six kinds of land-use types are formed into their corresponding landscape types in the established 1:10,000 land-use database of Yixing City. Supported by the module of spatial analysis in ArcGIS9.3 software, the formed vector data of the land use were transformed into raster data with a cell size of 50 m × 50 m. Landscape pattern indices of six kinds of landscape types were therefore calculated by using Fragstats (raster version 3.3) software to reveal the landscape pattern characteristic of the investigated area. In this study, three major types of landscape pattern characteristic were discussed, including the feature of patch number, patch shape and landscape diversity. Consequently, eight representative landscape indices were selected. They consist of number of patch (NNP), patch density (PPD), average patch area (AAREA-MN), fractal dimension (FFD), shape index (LLIS), diversity index (SSHDI), spread index (CCONT), fragmentation index (FFN) (Huang et al. 2009; Malaviya et al. 2010; Renetzeder et al. 2010).

Taking the administrative town as the evaluation unit, eight landscape indices of each town were described by Fig. 3, respectively.

Establishment of catastrophe models

As a mathematical theory, catastrophe theory is an impactful tool to solve discontinuous sudden issues in the

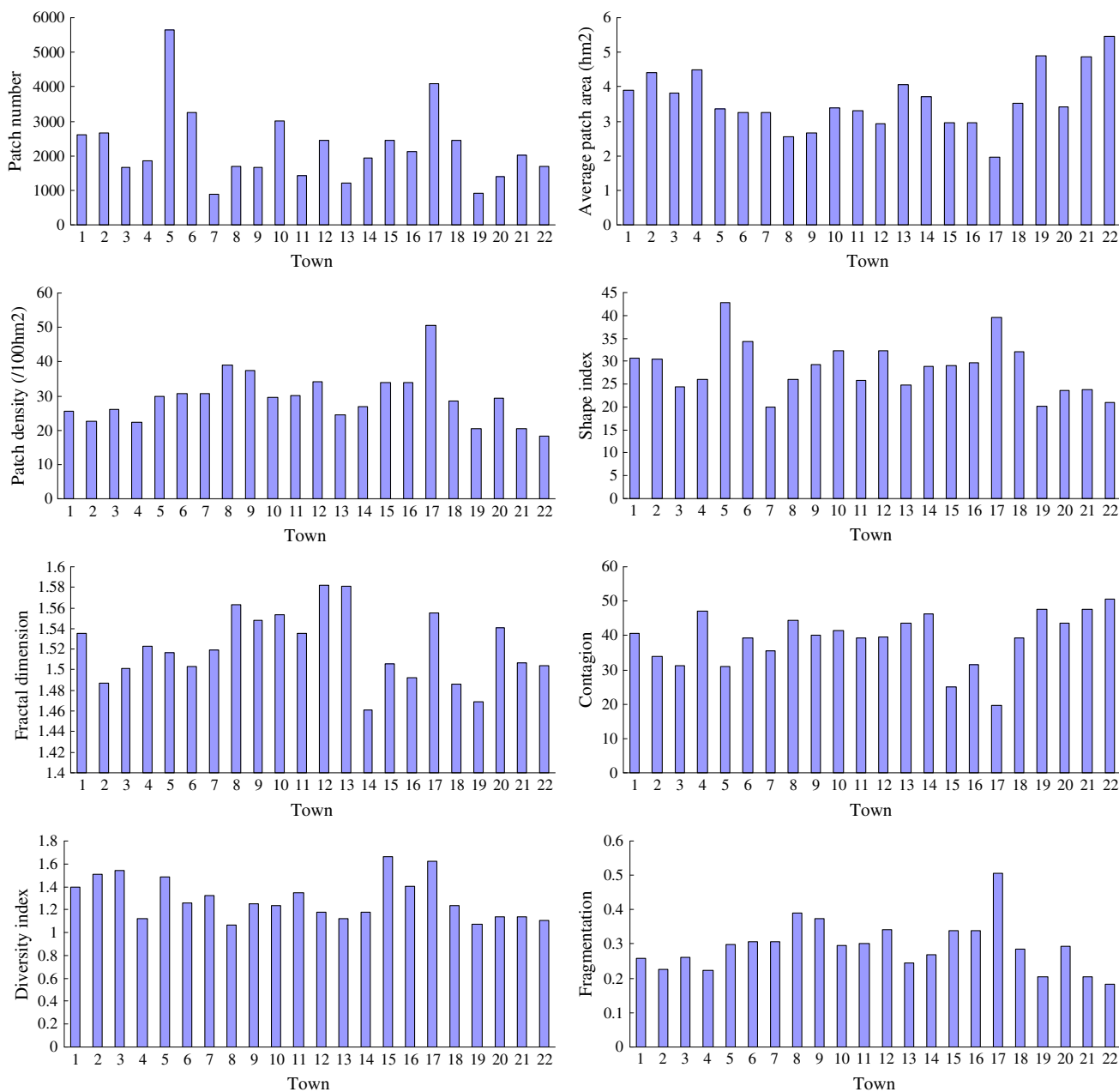


Fig. 3 Landscape pattern indices of land use in Yixing. 1 Yicheng, 2 Dingshu, 3 Environmental Science Park, 4 Gaocheng, 5 Zhangzhu, 6 Guanlin, 7 Qiting, 8 Wanshi, 9 Xinjian, 10 Heqiao, 11 Dapu, 12

Zhoutie, 13 Xinzhuang, 14 Xushe, 15 Xinjie, 16 Jingtang, 17 Xizhu, 18 Yangxiang, 19 Fang zhuang, 20 Fangqiao, 21 Hufu, 22 Taihua

function. The singularity set of the balance curved surface is obtained from the equation $V''(x) = 0$. According to two equations, $V'(x) = 0$ and $V''(x) = 0$, the normalization formulas can be calculated reflecting the relation between state variables and control variables. Table 1 shows common catastrophe models.

According to catastrophe models in Table 1, the zoning of land use based on landscape indices would be evaluated by using catastrophe progression method as follows (Huang and Iwamoto 1995; Schreiber et al. 1997). The

estimation first regarded the zoning of land use as a system. In the system, the zoning of land use (P) is the state variable; while the control variables are three subsystems of the landscape land-use zoning, including the landscape diversity feature, patch shape feature, and patch number feature. In the subsystems, the landscape diversity feature (A), patch shape feature (B), and patch number feature (C) are reconsidered as state variables, and their primary indicators are considered as control variables, respectively. There are three landscape pattern indices in the subsystem of the

Table 1 Catastrophe models in common and their normalization formulas

Catastrophe models	Control variables	State variables	Potential function	Normalization formulas
Folding catastrophe	1	1	$V(x) = x^3 + ux$	$x_u = \sqrt{u}$
Cusp catastrophe	2	1	$V(x) = x^4 + ux^2 + vx$	$x_u = \sqrt{u}, x_v = \sqrt[3]{v}$
Swallowtail catastrophe	3	1	$V(x) = x^5 + ux^3 + vx^2 + wx$	$x_u = \sqrt{u}, x_v = \sqrt[3]{v}, x_w = \sqrt[4]{w}$
Butterfly catastrophe	4	1	$V(x) = x^6 + tx^4 + ux^3 + vx^2 + wx$	$x_t = \sqrt{t}, x_u = \sqrt[3]{u}, x_v = \sqrt[4]{v}, x_w = \sqrt[5]{w}$

t, u, v, w are control variables; x_t, x_u, x_v, x_w are corresponding catastrophe progression values

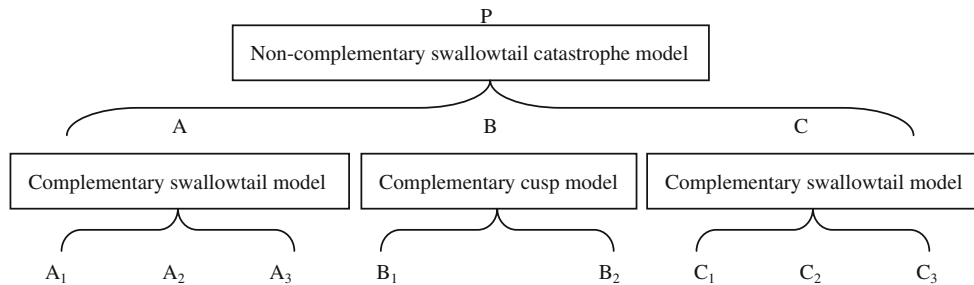


Fig. 4 Catastrophe models of landscape regionalization of land use in Yixing

landscape diversity feature (A), including fragmentation index (A1), diversity index (A2), and spread index (A3). The subsystem of patch shape feature (B) consists of fractal dimension (B1) and shape index (B2). In the subsystem of patch number feature (C), there are three landscape pattern indices, including number of patch (C1), average patch area (C2), and patch density (C3). An integrated indicator system is denoted as a hierarchy system consisting of target-, rule- and indicator layer (Fig. 4).

Although the integrated indicator system was set up in the preceding section, the interrelation among evaluation indicators is fuzzy. Two intrinsic relations among indicators were needed to be defined in the catastrophe progression method. If there is no intrinsic relation among the control variables in a tier, the subsystem would be non-complementary. Otherwise, the subsystem would be complementary. Based on these two intrinsic relations, the catastrophe models of landscape zoning of land use in Yixing were given (Fig. 4) according to correspondence between state variables and control variables in Table 1.

Standardization of data

The indicator data should be normalized to a dimensionless value between 0 and 1 because of the non-uniform of the indicator’s dimension. The normalization is based on the principle of “the bigger, the stronger of anthropogenic interference”.

For positive indicators, the formula is:

$$y_i = (x_i - x_{\min}) / (x_{\max} - x_{\min}) \tag{1}$$

and for negative indicators, the formula is:

$$y_i = (x_{\max} - x_i) / (x_{\max} - x_{\min}) \tag{2}$$

where y_i is the normalized value of each indicator; x_i, x_{\max} and x_{\min} is the initial, maximum, and minimum value of landscape pattern indices in Fig. 3, respectively. Using Eqs. (1) and (2), one can normalize the present values of all eight indicators in Fig. 3.

Therefore, according to Eqs. (1) and (2), the present values of all eight indicators in Fig. 3 are transformed into the normalized values, namely dimensionless values between 0 and 1.

Calculation of the importance of the attributes in rough set theory

Land-use regionalization models are set up using the catastrophe theory. However, the indicator’s weight is easily influenced by man-made factors in the models. The indicators needed to be arranged according to its importance in a system by using the catastrophe progression method. However, the subjectivity in the indicator’s importance is inevitable. In view of this, an attempt is made to determine the indicator’s importance in catastrophe models by using rough set theory.

In rough set theory, “knowledge” is considered as a classification capability—the division of the data (Berger

Table 2 Information table of landscape pattern indices of land use in Yixing

<i>U</i>	<i>A1</i>	<i>A2</i>	<i>A3</i>	<i>B1</i>	<i>B2</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>
<i>R1</i>	2	2	1	3	2	2	3	1
<i>R2</i>	2	2	1	3	4	3	3	1
<i>R3</i>	1	2	1	4	3	3	4	1
<i>R4</i>	1	1	1	3	2	1	1	1
<i>R5</i>	4	3	2	1	3	3	3	2
<i>R6</i>	2	3	2	2	3	2	2	2
<i>R7</i>	1	3	2	4	3	2	2	2
<i>R8</i>	1	4	3	3	1	1	1	3
<i>R9</i>	1	4	3	3	2	2	2	3
<i>R10</i>	2	3	2	2	1	2	2	2
<i>R11</i>	1	3	2	3	2	2	2	2
<i>R12</i>	2	3	2	2	1	2	1	2
<i>R13</i>	1	2	1	4	1	1	1	1
<i>R14</i>	1	3	2	3	4	1	1	2
<i>R15</i>	2	3	2	3	3	4	4	2
<i>R16</i>	2	3	2	3	3	3	3	2
<i>R17</i>	3	4	4	1	1	4	4	4
<i>R18</i>	2	3	2	2	4	2	2	2
<i>R19</i>	1	1	1	4	4	1	1	1
<i>R20</i>	1	3	2	4	2	1	1	2
<i>R21</i>	1	1	1	4	3	1	1	1
<i>R22</i>	1	1	1	4	3	1	1	1

2004). In general, it describes a knowledge representation system by a two-dimensional information table. Each row and each column describe an object and its attribute in the information form. In the study, administrative towns are considered as the objects, and eight landscape indices are seen as their attributes, which will be included in a two-dimensional table. After that, the non-dimensional data in this table are partitioned into four grades (1, 2, 3, and 4) by the equidistant division method. According to the method, the range from 0.00 to 1.00 is equably divided into four 4 sections. These grades represent the range from 0.00 to 0.25, 0.25 to 0.50, 0.50 to 0.75, and 0.75 to 1.00. These data make up of an information table of landscape pattern indices of the land use in Yixing (Table 2).

In Table 2, all 22 samples are considered as the setting *U*. As the subsystems *A* in Fig. 4, the setting *U* can be classified and assorted by the three various conditional attribute *A1*, *A2*, *A3* and the knowledge {*A1*, *A2*, *A3*}. In rough set theory, when an information table is deleted a conditional attribute, if it is the same sort of the setting *U* classified by the remaining conditional attribute as the knowledge, the deleted conditional attribute will be unnecessary and otherwise, necessary. According to this classification, the conditional attribute *A1*, *A2*, *A3* is deleted one after the other in Table 2, and the classified

results to the setting *U* by another conditional attributes are compared with by the knowledge. Therefore, the core of the knowledge {*A1*, *A2*, *A3*}, all necessary conditional attributes, can be calculated by the above-mentioned method. Based on this operation, a new setting can be formed, including the calculated core of the knowledge. If it is the different sort of the setting *U* classified by all conditional attributes with the new setting; this setting is called as one knowledge reduction. Therefore, the important degree of the attribute can be measured by the classified ability to the information system after deleting one attribute. According to the knowledge of information theory (Miao and Li 2008), the information entropy of knowledge *X* can be denoted by the formula as follows:

$$H(X) = - \sum_{i=1}^n p(X_i) \ln p(X_i) \quad (3)$$

where $H(X)$ is the information entropy of knowledge *X*; $p(X_i)$ denotes probability distributing; *X* represents the knowledge; *n* is the sample number. The importance degree of the attribute is calculated by the following equation:

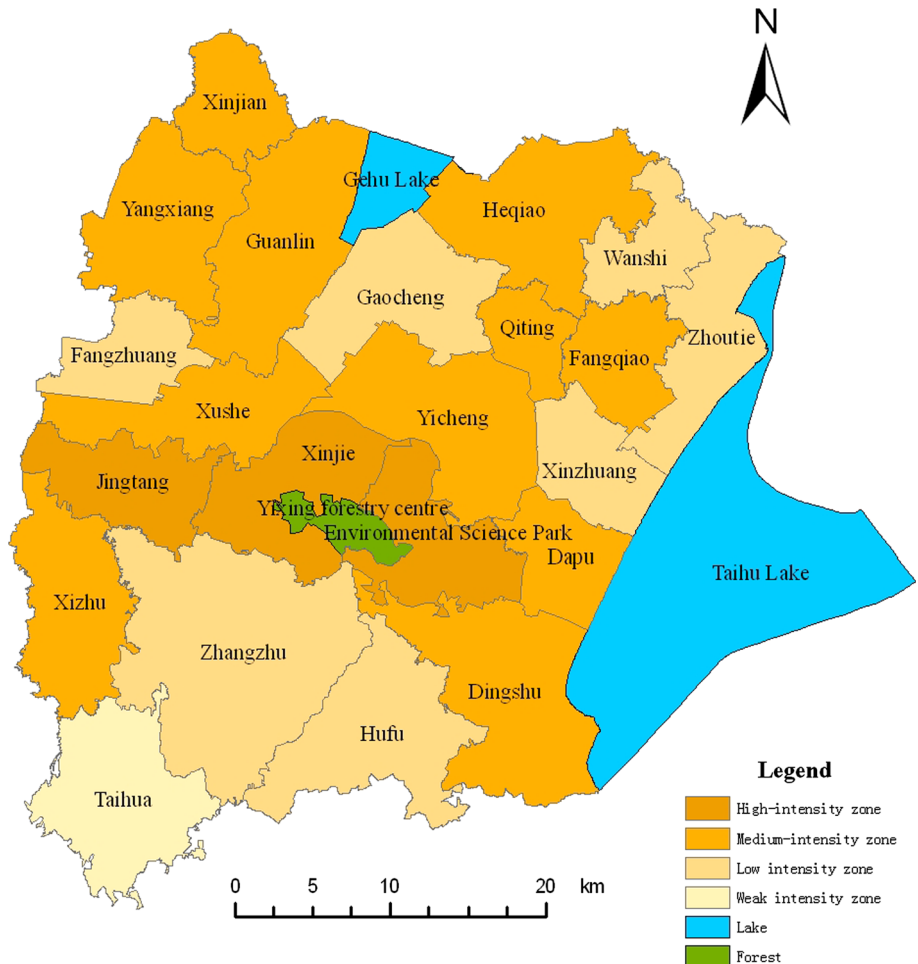
$$S(x) = |H(X - \{x\}) - H(X)| \quad (4)$$

where $S(x)$ denotes the importance degree; $H(X)$ is the information entropy of knowledge *X*; *x* represents the attribute. The larger the numerical value, the more important the attribute *x* is in the attribute setting (knowledge) *X*. Thus, the weightiness of each attribute in knowledge reduction can be computed by the before-mentioned expressions. According to the calculated results, the importance order of three attributes in subsystem is ultimately described in Fig. 4. The importance degree ordinarily weakens from the left to the right. According to the same method, the attributes' weightiness order of other subsystems is also illustrated in Fig. 4.

Establishment of catastrophe progression value

The primary or secondary factor of the system control variables was firstly determined by estimating the attribute importance of each evaluation index. Then, the status variable values in mutation are calculated according to the normalization formula of the catastrophe models in Table 2. Catastrophe progression method follows the principle of "complementary" and "non-complementary". If there is no obvious interrelatedness between all the control variables, it should take the minimum value in all state variables as the system's catastrophe progression value. It is called the "minima criterion" of "non-complementary". Otherwise, it should take the average value of all state variables as the system's catastrophe progression value according to the principle of "complementary".

Fig. 5 The regionalization of land use in Yixing



Ultimately, the total mutation membership function value is determined by the above-mentioned principle.

Division of the land-use zone based on landscape indices

According to the total mutation membership function value of different evaluation units, the zoning of land use based on landscape indices is divided by a clustering analysis.

Results and discussions

According to above-mentioned method, the results of land-use regionalization are illustrated in Fig. 5. Yixing is divided into four grading zones of land use, including high-, medium-, low-, and weak-intensity areas. Four grades used for analyzing the present land use are categorized as follow:

(1) High-intensity zone of land use: This area includes Xinjie Town, Jingtang Town, and Yixing ESTIP (Environmental Science and Technology Industrial Park). As

shown in Fig. 5, the area is located on the urban fringe, encircling the downtown of the city (Yicheng and Dingshu town). Therefore, the strongest human disturbance induces the most changes in local land-use patterns. In addition, the terrain of this area is in the transition zone from western low-lying polder to southern hilly area; therefore, this zone is the main place of human industrial and agricultural production. It has a high degree of land use. At the same time, patch density of this zone is larger according to the landscape pattern index of land use in Fig. 2. The number of patches in Xinjie Town and Jingtang Town reaches to 33.847/100 hm² and 33.795/100 hm², respectively. The patch density not only reflects the differentiation degree of overall landscape element but also reflects the spatial heterogeneity degree of landscape. Therefore, the greater density patch indicates that there are more heterogeneity patches of the landscape elements in a certain area. A small-size patch and a high heterogeneity landscape indicate that the degree of landscape fragmentation is more serious in the region. In this zone, Xinjie Town is adjacent to the center of the City (Yicheng Town), being the urban expansion area. Because this town has undertaken the

industrial transfer from the center of Yixing City in recent years, the interference degree of human activities on land is the most. Jingtang Town is located in the western low-lying polder, which is the modern agricultural production base in Yixing City. In this town, the high proportion in the vegetable land area shows that the land system stability is seriously interfered by anthropogenic activities. As illustrated in Fig. 2, the proportion of urban–rural construction land reaches to 34.43 % in Yixing ESTIP. Especially, a large number of enterprises uniformly distribute in the industrial park and the industrial plots show mostly rectangle (or square). So the patch shape in this industrial park tends to be the rule under the intensively interference of human activities; and it leads to the low shape index of the patch, only 24.354 (Fig. 3). Moreover, the diversity index of three before-mentioned towns is 1.663, 1.406 and 1.540, respectively. These large indices show that because of the interference of human activities, the land-use type of this area is various and the land is in a high degree of fragmentation. Take for example Xinjie Town, the proportion of farmland, orchard, woodland, urban–rural construction land, water area, and unused land is 23.28, 12.30, 26.52, 16.42, 17.99, and 2.86, respectively. It means that affected by strongly anthropogenic activities, the proportion difference of each land-use type is small and landscape diversity index is large in this town.

(2) Medium-intensity zone of land use: This area mainly consists of Xinjian Town, Qiting Town, Dapu Town, Dingshu Town, Guanlin Town, Yicheng Town, Yangxiang Town, Heqiao Town, Xizhu Town, Fangqiao Town, and Xushe Town. As shown in Fig. 5, the majority of the district is located in the Taige plains area. Due to convenient traffic conditions, the intense human activities lead to a high degree of land use. Especially, Yicheng and Dingshu Towns are the centers of Yixing City. Their proportions of urban–rural construction land reach to 29.82 and 28.92 %, respectively (Fig. 2). Figure 3 illustrates that the landscape of this region presents the characteristic of less proportion difference in land-use types, more patch numbers, and higher diversity index. These characteristics indicate the larger fragmentation degree, the higher degree of land use and the more intense human activities in this strip. Moreover, Yicheng Town is situated in the eastern Taihu ditch district, in which the proportion of water area reaches up to 22.71 %. And Dingshu Town is located in the southern hilly areas, in which the proportion of woodland area reaches up to 33.44 %. In addition to the urban construction land, the contribution of river network or woodland to landscape types is more than other landscape elements in these two towns. The water area and woodland play the sub-background role in all landscape elements of the towns; thus these landscapes limit human activities in space. Simultaneously, as the downtown of Yixing City,

the two towns have maturely developed in economic construction and modern industry after 20 years. Thus, land-use degree in this zone is relatively weaker than the high-intensity landscape zone of land use. There are a large number of patches in Guanlin Town and Heqiao Town, the developed industrial towns of Yixing City. Figure 3 shows that the average patch areas of the two towns are 3.248 and 3.379, which is at a lower level. Undoubtedly, the average patch area is the key indicator to reflect landscape heterogeneity, species diversity and landscape productivity; it also can represent the fragmentation degree of the landscape types. The smaller the average patch area, the more fragmented the landscape of this region is disturbed by human activities. In addition, the two towns are located in the northern plains with dense river network and the proportion of water area is 38.92 and 40.66 %, respectively (Fig. 2). Therefore, increasing the proportion of the water landscape elements decreases the land disturbed degree in human activities. Xizhu, Xushe, Yangxiang, Fangqiao, and Dapu towns are the major grain producing areas in Yixing City. The area of arable land in the region is significantly higher than other towns. Especially, the proportions of arable land in Xuse and Fangqiao towns reach up to 44.68 and 58.88 %, respectively (Fig. 2). As shown in Fig. 3, it is on the high level in patch density, mean patch size, diversity index, and fragmentation degree of Xizhu town, while the spread degree of landscape is low. The fractal numbers of Xushe and Yangxiang Towns are relatively small, and the shape indices of Fangqiao and Dapu Towns are smaller. These show that although the area is the base of agricultural production, there is lack of large-scale agricultural operation. Strong human interference on land ecosystems induces a higher fragmentation degree of patch in this area, and the shape of arable land tends to be inerratic. Thus the patch's fractal number and the shape index are partially small. In a word, the background element of regional landscape is not obvious in this zone, and natural landscape elements markedly increase in proportion, including water area and woodland. Various landscape elements mutually influence and enclose in this zone. Due to the complexity of landscape material circulation and energy flow mechanism, the disturbance degree of land ecosystems decreases by human activities.

(3) Low-intensity zone of land use: The region principally includes Xinzhuang Town, Zhoutie Town, Zhangzhu Town, Wanshi Town, Gaocheng Town, Hufu Town, and Fang zhuang Town. In Fig. 5, this zone is located in the Taihu ditch area and southern hilly area. So the water area and woodland area gradually increase, while the degree of land use depresses. Extraordinarily, the proportion of water area accounts for up to 52.30 % in Gaocheng Town and the proportions of woodland area reach up to 44.22 and 63.42 % in Zhangzhu and Hufu Towns, respectively

(Fig. 2). Water area and woodland dominate the regional landscape types; therefore, the ecosystem remains stable under a weak anthropogenic interference. As illustrated in Fig. 3, the shape index of Zhangzhu Town is the most, up to 42.788. The patch's fractal numbers are largest in Zhoutie Town, 1.582 and Xinzhuang, 1.581. Diversity indices and fragmentation degrees are relatively low in four towns (Xinzhuang, Gaocheng, Hufu, and Fangzhuang), while the contagion degrees are higher. Especially, the diversity index of Wanshi Town is the lowest, only 1.066. These indicate that the patch's geometry shape is complex and irregular; thus shape index and fractal number are larger. It means that the alteration of human activities on land ecosystems is weak. A single type of land-use structure and preferable patch connectivity cause the lower degree of fragmentation.

(4) Weak-intensity zone of land use: It consists of Taihua Town. In Fig. 5, the district is located in the southern hilly area, mainly covered by single woodland. The proportion of woodland in all land-use types accounts for up to 66.29 % (Fig. 2). As the background element of the region, the woodland dominates the type of land landscape and other landscape elements embed in a woodland landscape. Therefore, the entire land ecosystem is the most stable and the ability to resisting anthropogenic interference is the strongest. The single structure of land-use type leads to the weakest anthropogenic interference. As can be seen from Fig. 3, Taihua Town is at the station with the smallest patch density, the most average patch area, the smaller diversity index, the most contagion degree, and the smallest fragmentation degree, which is 18.303/100 hm², 5.464 hm², 1.103, 50.710, and 0.183, respectively. These show that the lesser interference of human activities, the better is patch connectivity, the lower is the fragmentation degree, the larger is the difference in each type of land use and the minor landscape diversity index in the region.

Conclusion

1. Land-use patterns affected by the regional geomorphic characteristics are the main factors of landscape pattern variation in land use. It reflects the interference degree of human activities. With the increase in water area and woodland, in particular the woodland area, humanity's transformation on the land system gradually becomes less important due to the limit of human activities in space. As a result, the fragmentation degree and landscape diversity will reduce, and the complexity degree of patch shape and the stability of land ecosystems will enhance.
2. According to the interference degree of human activities, Yixing is divided into four grading landscape

zones of land use, including high-, medium-, low-, and weak-intensity zones. The zoning results not only can reflect the current land use under the interference of human activities to solve the problem of land use, but also is conducive to a better grasp of the future direction of land-use change. In rough set theory, it mines the implied intrinsic rules in data through knowledge reduction; therefore, there is no need to determine the weight according to the order of attribute importance of the evaluation factors. Eventually, landscape zones of land use are divided by catastrophe progression method with integrating multiple indicators. It largely can avoid the subjective evaluation in artificially determining factor weights. In catastrophe progression method, the number of system control variables can not be more than four, and thus it will have a certain impact for the multi-index comprehensive evaluation.

Acknowledgments The authors are grateful for valuable comments and suggestions from two anonymous referees. Useful suggestions given by Dr. Qin Yinghong of Michigan Technological University are also acknowledged.

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