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Investigating landscape pattern and its dynamics in Daqing, China

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The landscape pattern of Daqing city, China has undergone a significant change in 1990–2000 as a result of the rapid urbanization process. The focus of this paper is to quantitatively capture landscape pattern and its spatial dynamics of Daqing city at the landscape level over the 10 years span. A traditional supervised classification (maximum likelihood classification) was carried out on Daqing region using three sets of Landsat Thematic Mapper (TM) imagery, respectively acquired in 1990, 1996, and 2000, and the classification results were transformed to polygon layers and input into geographic information system (GIS) software. In order to facilitate our examination of landscape pattern and its dynamics in Daqing, we chose two categories of landscape indices with supplementary ecological meanings. They are patch-based indices and spatial heterogeneity-based indices. Specifically, for the first category, three representative indices (Patch size coefficient variation, Landscape shape index, and Area-weighted mean patch fractal dimension) were calculated. For the latter category, Shannon's diversity index, Contagion index, Proximity index, and Fragment index were chosen and computed. Based on the derived indices, a general trend of landscape change was revealed: wetland was degraded into grassland resulting in a more fragmented pattern, whereas grassland was cultivated and taken over by agriculture. Forest coverage decreased with the small patch replaced by grassland and agriculture, while city was sprawling by merging neighbouring land cover and land use types. GIS-based landscape index, coupled with remote sensing analysis, proved its unique value and effectiveness in assessing landscape pattern and dynamics.

1. Introduction

Increasing awareness about the importance of the sustainability of natural resources is stimulating the improvement of current methods to better understand and quantify the landscape evolution, as is the result of complex interactions between physical, biological and social forces in time and space (Turner 1987). Notwithstanding the ease-of-use merit possessed by field methods, such methods are labour intensive and weak to unveil spatial pattern at the landscape scale as well as grasp changes that occurred in a long time frame (Nelson 1983).

Remote sensing data, in conjunction with geographic information systems (GIS) has been recognized as an effective tool in quantitatively measuring landscape

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pattern and its change at a relatively large spatial scale (Nelson 1983, Singh 1989, Metzger and Muller 1996, Frohn 1998, Quattrochi and Luvall 1999, Petit *et al.* 2001, Roy and Tomar 2001). To discover the change of spatial pattern, two types of method have been developed in the past. The first type of method is to conduct change detection in the pixel-by-pixel manner before or after the classification is performed on the original images (Ridd and Liu 1998, Petit *et al.* 2001, Roy and Tomar 2001, Yang and Lo 2002). We hereby refer to it as the raster-based method. Alternatively, the second type of method begins the analysis by converting classification results to vectors; from this, various spatial indices are derived to summarize the spatial pattern at each given time. Then a comparison is made on the spatial indices to detect the spatial pattern changes over different times (Singh 1989, Jensen 1996, Zhao *et al.* 1996, Zheng *et al.* 1997, Macleod and Congalton 1998, Miller *et al.* 1998, Mas 1999, Roy and Tomar 2001, Yang and Lo 2002). Correspondingly, this method is referred to as the vector-based method.

Compared to raster-based change detection methods, the vector-based methods are advantageous in capturing inherent spatial structure of landscape pattern. Within this category, a variety of landscape metrics have been proposed. The first category of commonly used indices is the patch-based indices that characterize the configuration for the individual landscape class or at the whole landscape base (Patton 1975, Forman and Gordron 1986, Gardner *et al.* 1987, Schumaker 1996, Chuvieco 1999, Imbernon and Branthomme 2001). Indices of patch size and patch shape have been widely used to convey meaningful information on biophysically changed phenomena associated with patch fragmentation at a large scale (Viedma and Meliâ 1999, Fuller 2001). These configuration indices vary as a function of the shape of patches and usually correlate with the basic parameter of individual patch, such as the area, perimeter, or perimeter–area ratio, but perform poorly in reflecting the spatial location of patches within the landscape (Imbernon and Branthomme 2001). Hence, another kind of indices was proposed to reflect spatial heterogeneity by quantifying the spatial structures and organization within the landscape. O'Neill *et al.* (1988) first developed dominance and contagion indices based on information theory to capture major features of spatial pattern throughout the eastern United States. According to Gustafson and Parker (1992), the proximity index quantifies the spatial context of patches in relation to their neighbours; specifically, the nearest-neighbour distance index distinguishes isolated distributions of small patches from the complex cluster configuration of larger patches (Turner 1989). The above two groups of indices, the patch-based and heterogeneity-based, reflect two aspects of the same spatial pattern, and complement each other. Notwithstanding the choice of either group of indices relies on the emphasis in a specific research, it is preferred to adopt both groups of indices when speculating on a spatial pattern (Turner and Gardner 1990) because landscape pattern possesses both homogeneous and heterogeneous attributes.

Daqing city, in the Heilongjiang Province of China, is the largest base for the petrochemical industry in China. Over the last decade (1990–2000), Daqing has undergone a high-speed economic development and environmental deterioration as well. The objective of this study is twofold: (1) to analyse and interpret the landscape pattern as well as its change in Daqing during the last 10 years using remote sensing and GIS; and (2) to explore the inter-linkage between landscape change, economic development, and land management. To enable a comprehensive investigation of the complex and heterogeneous landscape in Daqing, we chose a set of landscape indices with the inter-complementary ecological meaning. Finally, these indices are analysed to effectively examine both the current landscape pattern and the retrospective change process for monitoring ongoing changes.

2. Study site and data preparation

2.1 *Study site*

The study was carried out in Daqing city, the energy capital of China, maintaining a variety of landscape types due to its unique geology and climate environment. Daqing lies in the middle of Songlen Plain in Heilongjiang Province in the north-east of China (figure 1), between 122°42′–125°50′ E longitude and 45°20′–47°30′ N latitude. Daqing city has five districts—one city and four counties—and covers an area around 21 000 km^2 with a population of 2.50 million.

The study area shows the typical characteristics of large-scale Mesozoic and Cenozoic land sediment basin covered mainly with meadow, halophyte and swamp. After long geotectonic movements, Daqing ends up with a unique geological structure for the storage of oil. Since the elevation ranges from 126–165 m, the study area is a relatively flat plain with the elevation difference ranges from 10–39 m.

Figure 1. Study area, Daqing city, China.

Mean annual precipitation is 437 mm and the rainy season is in summer and autumn, varying seasonally between hot, wet summer and cool, dry winter.

Daqing, once a rural area, has become the largest oil production base since the oil was explored in 1959. Although Daqing is now diversifying its energy-oriented economy, the petroleum and petrochemical industries are still main backbones of its economy. The continual construction of the oilfield has spoiled the original landscape pattern over the last 50 years. Reduction of swamp, grassland and forest has resulted in the deterioration and desertification, potentially affecting the future landscape pattern, regional environment and climate. Moreover, since the fast economic development, the population in the Daqing region has grown greatly during the last 50 years, increasing from 100 000 in 1945 to 2.5 million in 2000 (Statistic Bureau of Daqing 2001). As a result, the Daqing region, which contains rich landscape types, is subject to rapid changes in landscape pattern, especially in the natural swamp, grassland and forest.

2.2 *Satellite data and other reference sources*

Landsat Thematic Mapper (TM) satellite images were chosen in this study for the change detection of Daqing during the 10-year period between 1990 and 2000. All the images were acquired from late June to September in Daqing area since all the vegetations are growing up during this growing season. Six cloud-free scenes were used to cover the entire study area with two adjacent scenes, path 119 and row 27 and 28, during the following dates: 20 July 1990, 22 September 1996 and 22 June 2000. Digital image processing was performed on a SUN workstation using ERDAS^{TM} software.

Other reference data used in this research are: (1) a soil thematic map at the scale of 1 : 100 000 from the Committee for Agricultural Development Planning of Daqing in the 1980s; (2) a vegetation thematic map at the scale of 1 : 750 000 from the Geography Institution of Changchun, Chinese Academy of Sciences in 1973; (3) a district map at the scale of 1 : 100 000 from Daqing land bureau in 1999; (4) a land use map at the scale of 1 : 100 000 from Daqing land management bureau in 1994; and (5) the social and economic statistical data during 1949–1999 from Daqing statistic bureau.

3. Methods

3.1 *Geometric rectification and radiometric normalization*

Geometric rectification plays a significant role in the process of multi-temporal change detection. In this paper, the two scenes (119/27 and 119/28) acquired in1990 were used as reference images to correct the other four scenes in 1996 and 2000. All images were registered to the UTM map projection, WGS 84, Zone 51, on a SUN workstation using ERDAS^{TM} Software. Fifty ground control points (GCP) were chosen. They were evenly distributed throughout the whole study area and most of them were laid on the distinguishably discerned objects, for example, the intersections of roads, aqueducts, or the fence tree around the agriculture. The registration procedure achieved at an accuracy of less than 0.5 pixel rms. error (RMSE) for both images in 1996 and 2000.

Our study area runs across two scenes of TM imagery. Therefore, a mosaic had to be done in the preprocessing step. Due to the variation of sensor–target–illumination geometry (Mas 1999, Yang and Lo 2002, Wang *et al.* 2004), it is necessary to conduct image-to-image radiometric normalization between the adjacent images so that in the resultant mosaic image, the distribution of brightness values with the two images is as close as possible (Richards 1993). To implement this idea, we performed a histogram matching between the adjacent scenes for the same year and thus, wind up with three mosaic images corresponding to three different years.

3.2 *Landscape classification*

Gained from the long-term field knowledge of geology, geography, vegetation and land use in Daqing, we set up a two-tier hierarchical classification scheme. The first level is composed of three classes: natural landscape, semi-natural landscape, and human landscape. In turn, the second level comprised 10 different classes as listed in table 1. Considering the requirement of traditional maximum likelihood classification (MLC) and the size of our study area, we chose a separate set of training and test samples around 600 pixels for the imageries at each year. The ancillary data mentioned in §2.2, including soil thematic map, vegetation map and land use map, were overlaid on the image to help to select the samples. Landscape maps composed of 10 landscape classes for 1990, 1996 and 2000 were produced with a traditional MLC.

The accuracy of resultant landscape maps was assessed with an independent set of test samples on the study area. An error matrix was firstly generated. The producer accuracy, user accuracy, overall accuracy as well as Kappa coefficient were derived and reported in table 2. We corrected several large errors on the map. For example, the saline was misclassified as city in the vicinity of the lake due to the similar spectral response between the two land cover types.

3.3 *Landscape index analysis*

Although a wide variety of landscape indices have been applied in describing the spatial composition and configuration of landscape pattern, many of them substantially overlap each other (Giles and Trani 1999, Tischendorf 2001). In order to reduce the redundancy, we selected a set of landscape indices that have least mutual correlation while possessing complementary ecological meanings. The indices were calculated with the Fragstats (UMASS 2004) and ARC/INFO software.

Table 1. Hierarchical classification systems and the definitions used in training samples.

First level	Second level	Training samples using colour composite (bands 4, 5, 3)	Code
1. Human landscape	1.1. Agriculture	Primarily for the production of rice and fibre, shows in the image as light or dark red, green with strip texture	1
	1.2. City	Intensively used by the building, and shows in the image as mixed pixels of light blue.	2
	1.3. Village	Usually be around by the agriculture with straightforward edge; mixed texture; and darker than the city	3
2. Semi-natural landscape	2.1. Grassland	Mixed pixels of red, white, and light green.	4
	2.2. Forest	Identified on higher elevations, regular shape, red or dark red	5
3. Natural landscape	3.1. Lake	Smooth, cyan, blue, and sometimes black	6
	3.2. River	Irregular shape, ultramarine	7
	3.3. Saline	White or light, most near to the water	8
	3.4. Floodplain	Along the river, black or dark red	9
	3.5. Wetland	Dark red and distributes along north-east of Daqing	10

Table 2. The accuracy assessment of the 1990, 1996, and 2000 landscape maps from Landsat images by maximum likelihood classification.

	Train sample			Test sample			User accuracy (%)			Producer accuracy (%)		
	1990	1996	2000	1990	1996	2000	1990	1996	2000	1990	1996	2000
Agriculture	624	635	624	616	624	629	64.71	70.97	70.79	80.36	64.25	94.75
City	610	624	622	626	608	612	72.80	87.01	93.33	87.22	79.28	89.05
Village	610	614	607	600	625	613	70.79	74.49	69.61	74.33	71.28	83.69
Grassland	607	605	602	600	609	622	69.09	87.44	87.78	71.17	93.76	76.21
Forest	612	605	606	617	603	633	89.50	83.13	98.64	98.06	91.54	91.47
Lake	611	610	612	614	601	609	97.77	92.72	95.60	99.84	99.67	96.22
River	603	627	608	600	620	633	99.89	99.82	96.37	89.50	87.10	96.21
Saline	637	618	614	609	621	610	91.29	96.31	96.51	82.59	96.78	90.66
Floodplain	624	617	645	611	612	609	69.14	88.71	84.88	52.46	91.18	76.52
Wetland	608	619	613	607	619	601	91.72	98.97	78.02	67.55	93.38	66.72

Overall accuracy (%): 80.77 (1990); 87.77 (1996); 86.24 (2000)
Kappa: 0.79 (1990); 0.86 (1996); 0.85 (2000)

3.3.1 Indices to measure patch attributes

(1) Patch size coefficient variation (PSCOV)

$$\mathrm{PSCOV} = {}^{\mathrm{PSSD}}\!/_{\mathrm{MPS}}$$

$$\text{while } \mathrm{MPS} = \frac{\sum_{i=1}^{m} [a_i]}{m}; \ \mathrm{PSSD} = \sqrt{\frac{\sum_{i=1}^{m} [a_i - \mathrm{MPS}]^2}{m}} \left(\frac{1}{1000}\right) \tag{1}$$

where a_i is the patch size, m is the total number for ith landscape, and MPS is the mean patch size.

PSCOV is one of the typical indices to indicate the distribution of area among the patches by finding out the area difference among patches within one landscape class. Basically, the class with a large PSCOV (or PSSD) is less uniform than that with a small PSCOV (or PSSD) (Chuvieco 1999), i.e. if the landscape class is dominated by several big patches, both PSCOV and PSSD values would be large.

(2) Landscape shape index (LSI)

The first index to characterize landscape shape is the edge density (ED), a simple ratio between the perimeter and area.

$$\mathrm{ED} = \frac{P_i}{A_i} \tag{2}$$

Since the simple ratio is usually affected by the patch size, we used the modified perimeter–area ratio here to imply the shape of landscape (Patton 1975, Schumaker 1996).

$$\mathrm{LSI} = {}^{P_i}\!\Big/_{2\sqrt{\pi A_i}} \tag{3}$$

where P_i and A_i are the perimeter and area of the ith landscape. As the modified index of ED, LSI attains its minimum value when the shape of patches is completely regular, such as a circle, and it increases when the patch turns to be more complex (Schumaker 1996, O'Neill *et al.* 1999, Fuller 2001).

(3) Area-weighted mean patch fractal dimension (AWMPFD)

Fractal dimension, with its value ranging from 1 to 2 for a two-dimensional landscape (Mandelbrot 1967), is another modified shape index to indicate the patch shape in the landscape ecology. It is usually built on the linear regression between the logarithms of perimeter and area (De Cola 1989).

To acquire a normalized fractal dimension, we calculated the area-weighted mean patch fractal dimension using the following equation:

$$\mathrm{AEMPED} = \sum_{i=1}^{m} \left[\frac{2\ln(0.25p_i)}{\ln(a_i)} \left(\frac{a_i}{A}\right)\right] \tag{4}$$

where p_i and a_i are perimeter and area, respectively, of each patch within one landscape class; A is the total area for one landscape class. Theoretically, the AWMPFD of the highly convoluted perimeter will approach closer to 2 than the simple perimeters due to an increasing complexity in the patch shape (Schumaker 1996, Olsen *et al.* 1999, Read and Lam 2002).

3.3.2 Indices to measure spatial heterogeneity

(1) Shannon's diversity index (SHDI):

$$\mathrm{SHDI} = -\sum_{i=1}^{m} [P_i \ln(P_i)] \tag{5}$$

The SHDI measures the landscape diversity using two components: the number of different patch types, m, and the proportional area distribution, P_i, among patch types. Furthermore, the other two indices will be calculated followed by the diversity index to measure the dominance and evenness. They are: patch dominance (PD) and patch evenness (PE):

$$\begin{aligned} \mathrm{PD} &= H_{\max} + \sum_{i=1}^{m} [P_i \ln(P_i)] \\ \mathrm{PE} &= \frac{H}{H_{\max}}; \quad H_{\max} = \ln(m) \end{aligned} \tag{6}$$

where H is the SHDI and m is the number of patch of ith landscape class; P_i is the probability of ith class in the landscape. In this study, we used the ratio between the area of ith class and the total landscape area to denote P_i. Indices of landscape diversity, dominance and evenness have been widely used to indicate the size and distribution of patches in the landscape (O'Neill *et al.* 1988, Viedma and Meliâ 1999).

(2) Contagion index (CONT)

CONT, developed by O'Neill *et al.* (1988), quantifies both composition and configuration of the landscape (Li and Reynolds 1993):

$$\begin{aligned} \mathrm{CONT} &= 1 + \sum_{i=1}^{m}\sum_{j=1}^{n} P_{ij} \ln\left(P_{ij}\right) \Big/ 2\ln(n) \\ P_{ij} &= P_i P_{j/i},\ P_{j/i} = m_{ij} / m_i \end{aligned} \tag{7}$$

where P_{ij} is the probability that a patch of ith landscape is found adjacent to a patch of jth landscape, while m is the patch number within one landscape category and n is the number of landscape categories. P_i is the probability that a randomly chosen polygon belongs to patch type i, and $P_{j/i}$ is the conditional probability. In this study, we set this conditional probability as the ratio of i adjacent to j. A large CONT reflects the clumping of large contiguous patches while a small CONT value reflects a landscape that is dissected into small patches (O'Neill *et al.* 1988, Turner 1990, Li and Reynolds 1993, Griffith *et al.* 2002).

(3) Proximity index (PI)

In landscape ecology, nearest-neighbour distance is defined as the distance from a patch to the nearest neighbouring patch of the same type, based on edge-to-edge distance. Mean nearest-neighbour distance (MMND), nearest-neighbour standard deviation (NNSD) and nearest-neighbour index (NNI) were chosen to calculate in this study as follows:

$$\mathrm{MNND}=\frac{\sum_{i=1}^{m} h_i}{m};\quad \mathrm{NNSD}=\sqrt{\frac{\sum_{i=1}^{m}(h_i-\mathrm{MNND})^2}{m}} \tag{8}$$

$$\mathrm{NNI}=\mathrm{MNND}/\mathrm{ENND};\quad \mathrm{ENND}=\frac{1}{2\sqrt{n/a}}$$

where h_j is the distance from each patch to its nearest neighbour, m is the total number of nearest neighbour to this patch, and n and a are the number and area, respectively, of this class. ENND is the expected value of MNND in random. The NNI ranges between 0 and 1 and the less NNI, the landscape is less random and more clumped. The proximity indices measure both the degree of patch isolation and the degree of fragmentation of the corresponding patch type within the specified neighbourhood of the focal patch (Gustafson and Parker 1992).

(4) Fragment indices (FI)

We chose the total core area (TCA), core area percentage of landscape (CPL) and mean core area per patch (MCA) to denote the landscape fragmentation:

$$\mathrm{TCA}=\sum_{i=1}^{m} a_i^c;\quad \mathrm{CPL}=\frac{\sum_{i=1}^{m} a_i^c}{A};\quad \mathrm{MCA}=\frac{\sum_{i=1}^{m} a_i^c}{m} \tag{9}$$

where a_i^c is the core area, the interior habitat as an undisturbed area in the ecological meaning; A is the total class area, m is the number of patch.

To identify the core area of each patch, we smoothed the sharp edge and calculated the core area within each patch. These edge-to-interior indices provide fragmentation information of the class, i.e. the higher the ratio between core area and total area is, the less fragmented this class would be (Fragstats*ARC 2004).

To summarize, two categories of landscape indices were chosen from the perspectives of the patch attributes and spatial heterogeneity. The patch-based indices consist of PSCOV, LSI and AWMPFD with aims to measure the area distribution and the shape of landscape among the patches. Regarding the spatial heterogeneity-based indices, we chose SHDI to describe the landscape diversity, CI to measure the composition and configuration of landscape, PI to denote the degree of isolation, and FI to measure the landscape fragmentation.

3.4 *Change detection*

Post-classification comparison is often used to detect change in multi-temporal images (Singh 1989; Jensen 1996; Mas 1999; Yang and Lo 2002). In the present study, this procedure was employed on three independently classified maps at 1990, 1996 and 2000. In order to perform multi-temporal analysis, we applied a simple addition using GRID program in ARC/INFO between two adjacent maps, 1990–1996 and 1996–2000 by:

$$\mathrm{Outgrid}=[(\mathrm{grid1})*10]+\mathrm{grid2} \tag{10}$$

where grid1 is the classification code (table 1) on the 'from' image and grid2 is the classification code on the 'to' image. For example, code 14 is the patch transferred from agriculture to grass while code 11 means no change occurred. Using the above equation, we can identify both 'from' landscape and 'to' landscape as well as the 'unchanged' landscape.

4. Results and discussion

In this study, the regional characterization of landscape pattern and landscape change was investigated for the study area over the 10-year period. The landscape map produced from the image in 2000 exhibits a current landscape pattern in Daqing city. All the landscape indices were analysed to describe the landscape pattern in the past, present, and the change between these years. With a close examination of results for each individual landscape, we found out the major converted classes and grasped its trend in this evolution process.

4.1 *Landscape pattern*

Figure 2 is the present landscape pattern map of Daqing in 2000. It reveals a north–south trend throughout the whole study area. Most of the agriculture is distributed in the north and south-east, Lindian and Zhaozhou towns, while the city itself lies in the east along the railway line between Haerbin city and Qiqihaer city. Most of the lakes clump in the east of Daqing, Duerbote town, which is originally a huge pasture with a continuum of grassland.

4.1.1 Patch characteristics of the study area. In Daqing, agriculture is the dominant class and has large continuous patches, occupying 6793.09 km^2 and 32.11% in the whole study area (figure 3, table 3). This can be attributed to the regional characteristics and historical development of this area. The south side of Daqing has fertile soil and sufficient rain for agricultural production. Likewise, as a part of alluvial Songnen plain, the north side of Daqing, Lindian town, is a traditional cultivation basin with ample rain and energy source for farming use. Another dominant landscape is grassland, occupying 4905.67 m^2 and 23.19% in the whole study area (table 3). Mass of grassland is existent mainly in Duerbote grassland, with a large number of lakes and saline inside.

Although the lake landscape does not own the largest area, it has the largest average patch area (1.31 km^2/each). The reason is obvious because lake has a natural connection in space. Agriculture also has a high average area (1.15 km^2/each) although agriculture belongs to a human landscape. Forest, on the contrary, has the smallest average area (0.12 km^2/each). The result indicates that most of the forest in the study area is fragmented or isolated. This is due to the extensive cultivation and timber logging. From table 3, it can be discerned that wetland has a very high PSCOV, so do agriculture and grass. Therefore, these three landscape types have less even-area distribution among the patches. The village has the smallest PSCOV. Since village is a particular man-made landscape type distributed around agricultural land, results show an even-area distribution of village with a regular shape in space.

Patch shape has significant ecological implications to support study of edge effect, landscape change, and ecotone. Usually, the landscape type with an irregular shape will achieve a high value in both edge density and shape index. Table 4 summarizes the edge density and LSI derived in our study area. The high LSI value with the grass landscape suggests an irregular shape and elongated edge of this class throughout the whole study area. Agriculture and village also have high LSI and ED

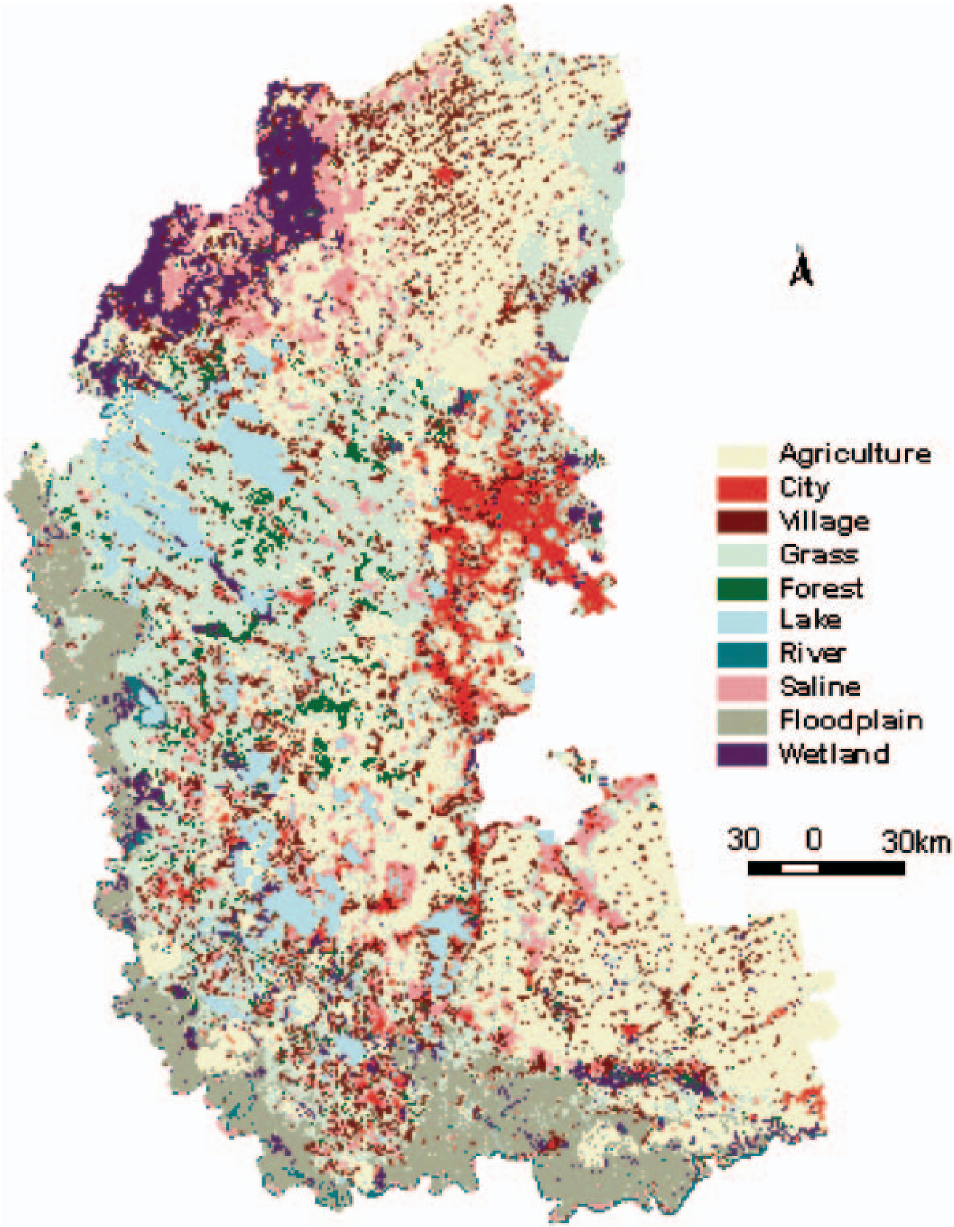

Figure 2. The landscape pattern map of Daqing city in 2000.

caused by the human disturbance. Compared to other landscapes, the lake and river yield the lowest shape index since they are relatively straight edge.

In a further analysis of the patch shape, we compared AWMPFD to judge if the landscape has the fractal characterization in different spatial resolutions, ranging from 30–500 m. Figure 4 shows the high similarity in 30 m, 50 m, 100 m and 200 m. However, the obvious decreasing of fractal dimension with river at 500 m suggests river has a hierarchical structure at this resolution.

4.1.2 Spatial heterogeneity of the study area. The patch-based indices introduced in the previous section characterize the patch size and patch shape, whereas the

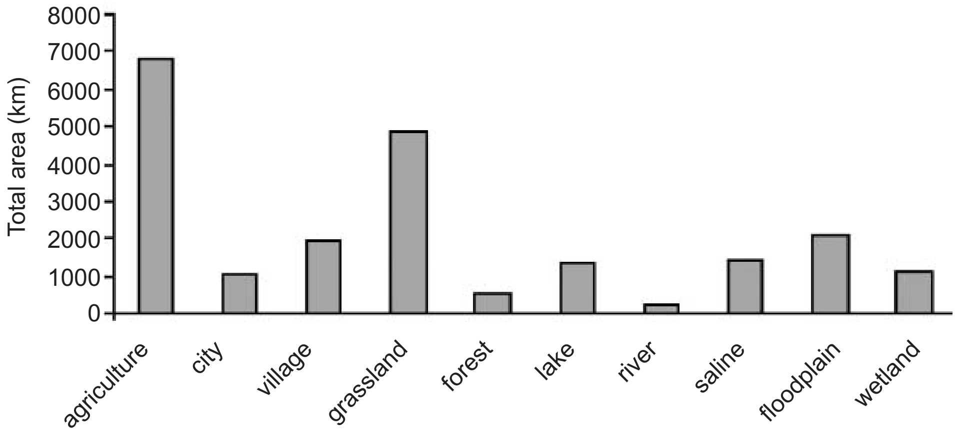

Figure 3. Area of landscape classes.

Table 3. Area index analysis of Daqing Landscape in 2000.

Classes	Area (km^2)	Patch #	% area	Average area (km^2)	PSCOV
Agriculture	6793.09	5888	32.11	1.15	3409.65
City	1025.25	3908	4.85	0.26	2286.56
Village	1899.80	10733	8.98	0.18	373.29
Grassland	4905.67	9905	23.19	0.50	3494.66
Forest	501.01	4228	2.37	0.12	582.83
Lake	1295.56	989	6.12	1.31	986.64
River	210.63	639	1.00	0.33	407.66
Saline	1338.29	3548	6.33	0.38	810.99
Floodplain	2076.34	2875	9.81	0.72	2701.09
Wetland	1111.65	4379	5.25	0.25	3157.78

heterogeneity indices, on the other hand, allow for a better understanding of the spatial characteristics and distribution of the landscape.

(1) SHDI

Table 5 shows the diversity, richness, and evenness of the landscape types in the first level classification. The order of diversity through the study area is: natural landscape 1.46>human landscape 0.81>semi-natural landscape 0.31. PD and PE are two other indices used to measure the distribution of area among patch types (table 5). Since agriculture and grassland, respectively, are two dominant classes in human landscape and semi-natural landscape, both the human landscape and

Table 4. Landscape shape indices of Daqing city in 2000.

Classes	LSI	ED	Landscape type	LSI	ED
Agriculture	46.33	12.11	Lake	8.29	1.64
City	15.29	3.57	River	5.35	0.84
Village	39.17	10.14	Saline	18.94	4.57
Grassland	51.31	13.47	Floodplain	15.36	3.59
Forest	11.84	2.62	Wetland	14.92	3.47

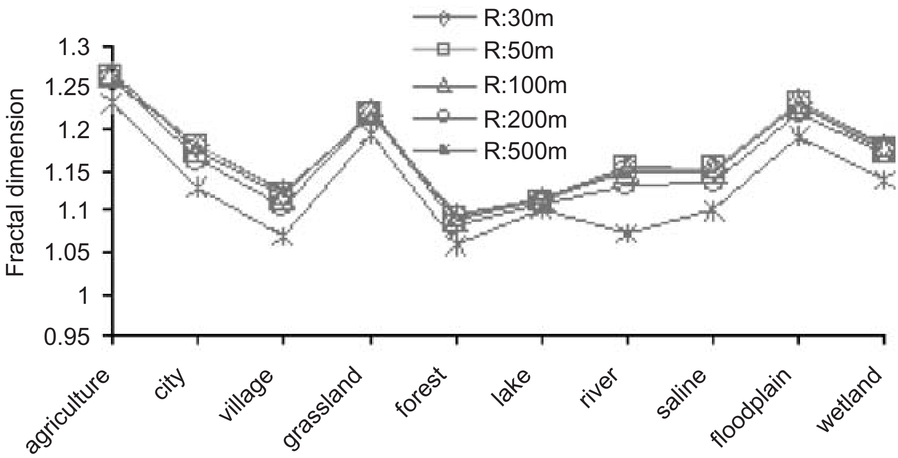

Figure 4. Comparison of fractal dimension of landscape classes at different scales.

Table 5. Shannon's diversity indices of landscape types.

Classes	Shannon's diversity	Patch dominance	Patch evenness
Human landscape	0.81	0.29	0.73
Semi-natural landscape	0.31	0.38	0.45
Natural landscape	1.46	0.15	0.91

semi-natural landscape have larger patch dominance and smaller patch evenness than the natural landscape does. Hence, the Shannon's diversity and patch evenness have obviously inverse relationship with the patch dominance.

(2) CONT

We derived the contagion index for each class in order to measure the clumping trends of the patches in this class. In general, a higher CONT implies a more contiguous and homogeneous spatial pattern. Figure 5 suggests that all the landscapes have similar values (range from 0.84–0.98) in the CONT, and the natural landscapes have a little higher value than the human-disturbed landscapes do in terms of the CONT. The large CONTs in lake and floodplain suggest the patches within these two landscapes are big in size and adjacent throughout the study area. The village has the lowest value of CONT than other classes do. Obviously, the villages spread out within the coverage of agriculture on the landscape map without much spatial connection between each other.

(3) PI

Table 6 presents the mean nearest-neighbour distance (MNND), nearest-neighbour standard deviation (NNSD), and nearest-neighbour index (NNI) computed for the spatial distribution of patches to reflect underlying natural processes or human-caused disturbance patterns within each landscape type. It is easily discerned that agriculture has the smallest value with MNND and NNI (3.12 km and 0.33), while the grassland has the smallest NNSD (2.82 km). Agriculture is clustered across the landscape from north to south, resulting in generally a larger NNSD than grassland. The largest NNI (0.55) value for wetland

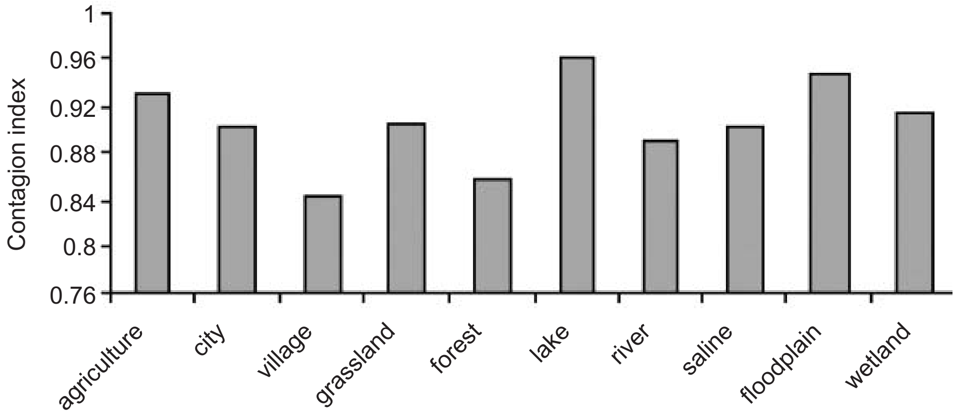

Figure 5. Contagion index for landscape classes.

implies a nearly random distribution with this natural landscape, while the largest MNND (10.06 km) and NNSD (14.52 km) values for river indicate the least clustering existed in river due to its elongated shape in the southern part of Daqing. As a result of these proximity indices, a trend was disclosed: human-disturbed landscapes have smaller proximity value than natural landscapes because of significant decrease of the distance among patches associated with the human activity.

(4) FI

Core-area indices, such as the total core area (TCA), core area percentage of landscape (CPLI), or mean core area (MCA), proved to be useful to distinguish the extent of fragmentation (table 7). River is the longest landscape and has the smallest value in TCA and CPLI in this study area. However, as a continuous landscape, river has higher MCA than forest and village. Such results showed that the TCA, CPLI and MCA have different ecological meanings. In this research, we found CPLI is more informative than TCA because it involves both the interior area and edge area of patch in its calculation.

Figure 6 shows the relationship between the total area, core area, CPLI and ED. In the correlation analysis between each of two indices, the edge density has less relation with the area indices with the R^2 as 0.7428 and 0.5921, while the area indices has higher R^2 as 0.9742 and 1. This suggests that ED, although it is an index to show the fragmentation of the landscape, has a closer tie to the edge effect than the interior ecological environment.

4.2 *Landscape dynamics*

4.2.1 Quantitative description of landscape dynamics. Over the past 10 years, Daqing has experienced tremendous change. The total changed area between 1990–1996 and 1996–2000 are 11 804.88 km^2 and 10 843.31 km^2 and the percentage is 55.84% and 51.27%, respectively. As indicated in figure 7, the most significant change appears to be the spread of agriculture landscape, the destruction of the forests, and the loss of wetlands, i.e. the increasing of the human landscape and the decreasing of the natural landscape.

The trend of the number of each landscape class to change varied with the patch area (figure 8). During the 10 years, the patch number of agriculture and city

Table 6. Proximity indices for landscape classes.

Classes	Agriculture	City	Village	Grassland	Forest	Lake	River	Saline	Floodplain	Wetland
MNND (km)	3.12	4.30	3.78	3.86	5.34	9.82	10.06	4.61	5.21	6.08
NNSD (km)	3.78	6.38	3.17	2.82	7.54	11.96	14.52	6.58	7.03	6.30
NNI	0.33	0.37	0.54	0.53	0.48	0.42	0.35	0.38	0.38	0.55

Table 7. Core area indices for landscape classes.

Classes	Agriculture	City	Village	Grassland	Forest	Lake	River	Saline	Floodplain	Wetland
TCA (km^2)	5129.36	599.74	719.34	3183.36	219.44	1074.60	90.75	754.28	1613.79	700.32
CPLI	24.24	2.84	3.40	15.05	1.04	5.08	0.43	3.57	7.63	3.31
MCA (km^2)	0.87	0.15	0.07	0.32	0.05	1.09	0.14	0.21	0.56	0.16

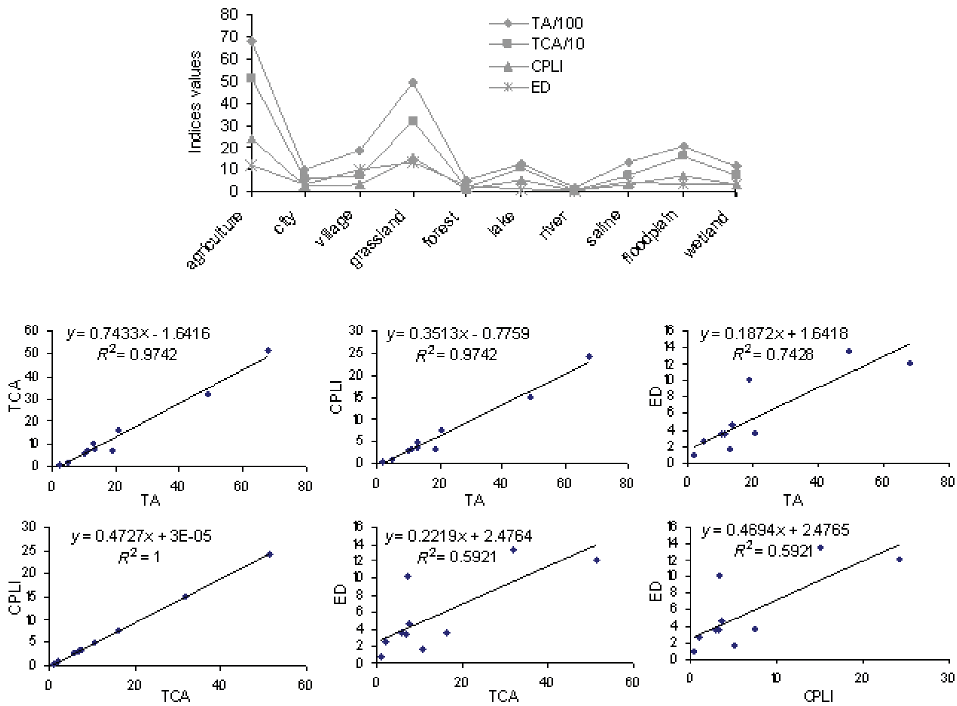

Figure 6. The relationship between total area, core area, core percentage landscape index, and edge density.

increased in the beginning and then decreased. This is primarily due to the 'nibble' of other landscape classes around them by human disturbance. Gradually, these small patches joined into a larger and continuous patch when human disturbances increased. Forest decreased in both the patch area and number of patches during the 10 year period, due to its conversion to grass or cultivated lands. It is worth noting that although the total area of wetland keeps decreasing during 1990–2000, the patch number starts to increase during the second period, 1996–2000. This result

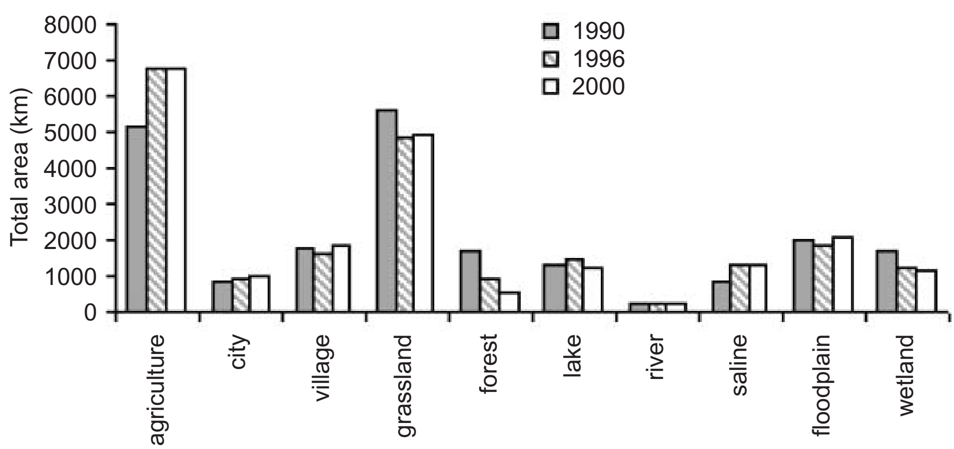

Figure 7. Comparison of landscape area of each class between 1990 and 2000.

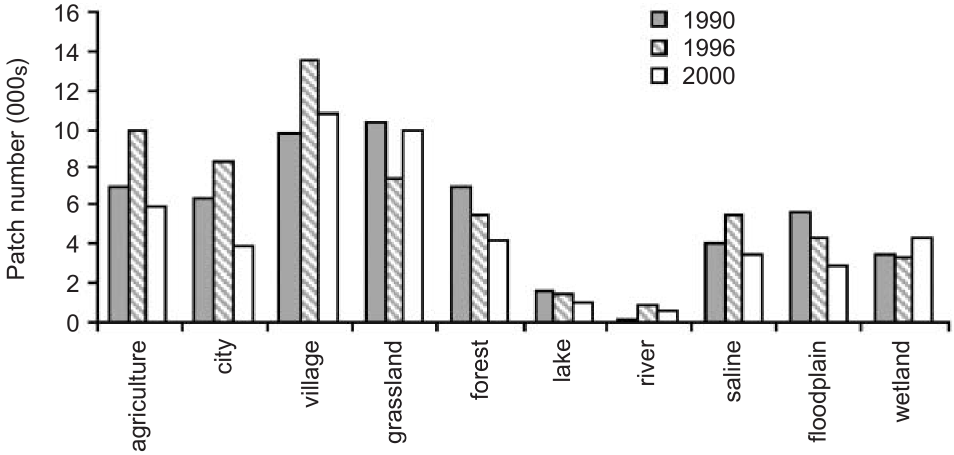

Figure 8. Comparison of landscape patch number of each class between 1990 and 2000.

indicates a gradual fragmentation process of wetland. Shrinkage of small wetlands and fragmentation in the edge of the large ones are mostly found in the north-west of Daqing city.

The proportion analysis of changes in Daqing landscape provides not only the 'from' and 'to' information, but also the quantity of conversion area (table 8). The major changes are summarized as follows:

- Grass was converted to cultivated land during the 10 years, especially between 1990 and 1996. This is in accordance with the significant decrease in the patch number of grass landscape. Although the speed of conversion slows down from 1996 and some cultivated land was regained by the grass, the area of agriculture still keeps on increasing due to the fact that other classes, such as forest and wetland, were converted to agriculture.
- The percentage of forest landscape decreased from 7.86% in 1990 to 4.26% in 1996 and 2.37% in 2000. The fact can be attributed to the commercial logging and expansion of agriculture in the beginning of the 1990s.

Table 8. The first five rank of the main change of Daqing landscape between 1990 and 1996 and 1996 and 2000.

	1990–1996				1996–2000		
Change type	Change patch	Change area (km^2)	% area	Change type	Change patch	Change area (km^2)	% area
Grassland to agriculture	14720	1968.14	9.31	Agriculture to grassland	14406	1452.42	6.87
Agriculture to grassland	5602	754.96	3.57	Grassland to agriculture	8249	1110.14	5.25
Forest to grassland	3119	615.05	2.91	Grassland to floodplain	2414	541.30	2.56
Wetland to grassland	1674	488.03	2.31	Forest to agriculture	2726	420.78	1.99
Forest to agriculture	6264	439.87	2.08	Wetland to grassland	1578	169.39	0.81

- Wetlands kept on decreasing during these 10 years. It is found that most of the wetland was converted to grassland (table 8). A general trend of landscape change was revealed: wetland was degraded into grassland resulting in a more fragmented wetland, whereas grassland was cultivated and taken over by agriculture.

4.2.2 Spatial characterization of landscape dynamics. In this study, we applied similar indices as those of landscape pattern analysis to characterize the change of patch attributes and spatial heterogeneity of each class throughout the study area. Since lake, river and floodplain are greatly affected by precipitation in the particular year, we will not discuss the changes that occurred in these three landscapes. In the following section, we detail analysis of two groups of landscape: (1) increasing landscape, including agriculture, city, and saline; and (2) decreasing landscape, including forest and wetland.

PSCOV and AWMPFD values with the increasing landscapes changed in a similar fashion: decrease in the first period and then increase in the second period (table 9). A possible explanation is that the increasing part is not sprawl out from the original one, but gradually joins into a continuous one from little 'spots' around it, resulting in a more irregular shape first and then becoming regular in the second period. Thus, an opposite trend was reflected in LSI: increase first and then decrease. On the contrary, wetland experienced a completely reversed process. The 'spots' along the irregular edge were replaced by the straight edges, and then fragmented pieces were replaced by other landscapes. Thus, LSI of the wetland first decreased, and then increased during 10 years. However, PSCOV, LSI, and AWMPFD in forest, kept on decreasing during the 10-year period. The different trend in the wetland and forest is explained primarily by their different manner of conversion. Since the forest is more fragmented than the wetland, the small part of the forest is likely to be replaced by other types directly instead of breaking into pieces first.

The results of spatial characterization indices suggest that these indices, as the indicators of relation between the patches, provide complementary information to those shape characterization indices (table 10). The CPLI showed the same trend with the total area, increasing in the growing class and decreasing in the reduced landscape. CONT in agriculture and city showed a slight decline in the first period and followed by a significant increase, while the CONT in saline was steadily

Table 9. Patch attribute indices of Daqing during 10-year period.

	PSCOV			LSI			AWMPFD		
Classes	1990	1996	2000	1990	1996	2000	1990	1996	2000
Agriculture	40.60	31.47	34.10	47.52	63.22	46.33	1.26	1.22	1.26
City	20.54	10.49	22.87	19.54	23.37	15.29	1.15	1.13	1.18
Village	5.46	3.83	3.73	37.54	38.59	39.17	1.14	1.11	1.12
Grassland	50.84	20.15	34.95	60.04	42.63	51.31	1.27	1.19	1.22
Forest	16.31	8.32	5.83	25.64	18.04	11.84	1.16	1.12	1.10
Lake	7.63	7.80	9.87	10.07	9.71	8.29	1.09	1.09	1.11
River	6.18	10.15	4.08	4.61	5.77	5.35	1.21	1.18	1.16
Saline	11.03	6.36	8.11	15.60	22.44	18.94	1.16	1.14	1.15
Floodplain	16.27	22.32	27.01	27.00	19.95	15.36	1.18	1.22	1.23
Wetland	28.58	30.70	31.58	16.34	13.07	14.92	1.23	1.19	1.18

Table 10. Spatial heterogeneity indices of Daqing during 10-year period.

	SHDI			CONT			NNI			CPLI		
Classes	1990	1996	2000	1990	1996	2000	1990	1996	2000	1990	1996	2000
Agriculture	3.47	4.49	3.14	0.92	0.90	0.93	0.42	0.55	0.33	0.17	0.22	0.24
City	6.19	6.96	4.67	0.85	0.83	0.90	0.54	0.70	0.37	0.02	0.02	0.03
Village	7.65	8.21	7.94	0.84	0.82	0.85	0.52	0.64	0.54	0.03	0.02	0.03
Grassland	3.82	4.52	4.76	0.90	0.92	0.91	0.50	0.43	0.53	0.17	0.16	0.15
Forest	5.55	6.04	6.50	0.89	0.87	0.86	0.48	0.60	0.48	0.04	0.02	0.01
Lake	4.47	4.27	3.69	0.96	0.96	0.96	0.45	0.53	0.42	0.05	0.06	0.05
River	2.21	4.43	4.65	0.94	0.90	0.89	0.16	0.35	0.35	0.01	0.01	0.00
Saline	5.57	6.30	5.73	0.88	0.89	0.90	0.49	0.60	0.38	0.02	0.03	0.04
Floodplain	5.07	4.05	2.41	0.90	0.92	0.95	0.45	0.42	0.38	0.06	0.06	0.08
Wetland	3.02	3.07	4.16	0.93	0.93	0.91	0.47	0.45	0.55	0.05	0.04	0.03

increasing during the 10 years. The difference was caused by the limitation in spread direction of saline. Since the saline usually distributes along the lake, it always sprawls in one direction and keeps on increasing in the CONT during these years. All the increasing landscapes had the same trends in SHDI and NNI, which increased first and then decreased. For the typical decreasing landscape, the forest and the wetland, SHDI was always increasing and CONT was always decreasing, which means more and more patches become fragmented and isolated. The different trend in NNI between forest and wetland also implies two different shrinking ways associated with them. The direct replacement of small forest patch by other types drags the NNI up in the beginning. After the small patches finished their conversion, large forest patches are also fragmented into small pieces along the edge, which pulls NNI value back. On the contrary, wetland, continuous in the beginning, was fragmented along its edge first and then replaced by other landscapes. This caused the NNI to decrease first and then to increase.

5. Conclusion

The quantitative analysis of landscape pattern using multi-temporal Landsat TM imagery enabled us to characterize the internal structure of landscape, compare the landscape classes, and monitor the landscape dynamics throughout Daqing city. This study explored the potential of satellite remote sensing, digital image processing, and GIS-related techniques in producing accurate landscape maps and statistical analysis of the landscape pattern.

This study revealed that spatial indices built on the classified vectors were useful to detect landscape pattern and its changes. The modified perimeter–area ratio and fractal dimension were found to be effective in the identification and description of the shapes of landscape types. The SDI reveals the patch diversity at landscape level for natural landscape, semi-natural landscape, and human landscape; CI measures the degree of contiguity and homogeneity by revealing the clumping trends of patches for each class; PI reflects underlying natural processes or human-caused disturbance patterns; while FI measures the degree of fragmentation by the area of interior habitat. All these spatial heterogeneity indices have great potential in providing useful information about the overall spatial pattern of the landscape. With incorporation of more and more biophysical or social–economic factors in the research of this topic, the spatial statistics methods will demonstrate their unique role in the quantitative analysis of landscape ecology.

Landscape dynamics throughout the study area were estimated based on the analysis of multi-temporal maps. This analysis indicated that from 1990 to 2000, Daqing city experienced a vast amount of change due to the oil exploration. The sprawl of city directly leads to the cultivation of the grassland, the loss of forests and wetlands. Based on the derived index, a general trend of landscape change was revealed: wetland was degraded into grassland resulting in a more fragmented wetland, whereas grassland was cultivated and taken over by agriculture.

Current research results can be further improved from the following three aspects. First, to minimize classification errors caused by spectral similarity of land cover types, the contextual knowledge should be taken into account in the classification to solve the belonging of 'confused' pixels. This will lead to a more accurate result in the landscape pattern and dynamics analysis. Second, ecological, social, political, and economic factors should be incorporated in the analysis of change detection. The added awareness of the landscape context from these factors will assist in making objective statements about the changes in time series. Finally, the emphasis of this study is to assess landscape complexity and its dynamic process in the past and current time. A natural future development of our study is to predict future landscape pattern by combining spatial statistics with prediction models, such as the Markov model or cellular Automata model.

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