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Spatial pattern analysis of land cover change trajectories in Tarim Basin, northwest China

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This study attempts to develop a methodology to quantify spatial patterns of land cover change using landscape metrics. First, multitemporal land cover types are derived based on a unified land cover classification scheme and from the classification of multitemporal remotely sensed imagery. Categorical land cover change trajectories are then established and reclassified according to the nature and driving forces of the change. Finally, spatial pattern metrics of the land cover change trajectory classes are computed and their relationships to human activities and environmental factors are analysed. A case study in the middle reach of Tarim River in the arid zone of China from 1973 to 2000 shows that during the 30-year study period, the natural force is dominant in environmental change, although the human impact through altering water resources and surface materials has increased dramatically in recent years. The human-induced change trajectories generally show lower normalized landscape shape index (NLSI), interspersion and juxtaposition index (IJI) and area-weighted mean patch fractal dimension (FARC_AM), indicating greater aggregation, less association with others and simpler and larger patches in shape, respectively. The results suggest that spatial pattern metrics of land cover change trajectories can provide a good quantitative measurement for better understanding of the spatio-temporal pattern of land cover change due to different causes.

1. Introduction

Land cover change is one of the most sensitive indicators that echo the interactions between human activities and the natural environment. In arid environments the land cover change often reflects the most significant impact on the environment due to human activities or natural forces. Remotely sensed data have been used for environment change studies for decades and large collections of remote sensing imagery have made the analysis of long-term changes of environmental elements and the impact of human activities possible.

Land cover change detection focuses mainly on four aspects: (1) detecting if a change has occurred, (2) identifying the nature of the change, (3) measuring the area extent of the change, and (4) assessing the spatial pattern of the change (MacLeod and Congalton 1998). Since the spatial pattern of change is recognized as a good

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indicator of the impact by the other three aspects, its research has become quite active for the study of change detection (Nagendra *et al.* 2004, Narumalani *et al.* 2004).

Methods for studying the spatial pattern of land cover change can be grouped into two categories, namely, temporal series analysis of 'snapshot'-based patch metrics and patch metric analysis on classified temporal categorical trajectories. The former analyses the time series of patch metrics derived from individual 'snapshot' classified images, while the latter focuses on the metrics of categorical trajectories derived from multitemporal images.

Temporal series analysis of 'snapshot'-based patch metrics is a bi-temporal profile method (Coppin *et al.* 2004). Using this method, multitemporal satellite images were first classified into land cover classes for each acquisition date. Landscape metrics are subsequently computed to quantify spatial patterns shown by these land cover classes. The spatial pattern of land cover change on a 'two-epoch' timescale (i.e. the change between two dates) can then be described based on the comparison of these metrics (e.g. Dewidar 2004, Tang *et al.* 2005).With the accumulation of remotely sensed images over the past decades, attempts have been made and reported on applications that extend the bi-temporal profile method to multiple epochs (e.g. Herold *et al.* 2003, McConnell *et al.* 2004).

Patch metric analysis on classified temporal categorical trajectories is a multitemporal profile method based on categorical trajectory analysis. Methods for temporal trajectory analysis were recently developed to trace paths of land cover change for given locations (e.g. Mertens and Lambin 2000, Petit *et al.* 2001, Crews-Meyer 2001, Liu and Zhou 2004). Zhou *et al.* (2004) have reported research where categorical trajectories of land cover change were established and classified according to the driving forces of the change, and pointed out the need for further study of the spatial pattern of such trajectories. Southworth *et al.* (2002) inferred the patterns of landuse change using landscape metrics of change trajectories. Crews-Meyer (2004) assessed the temporal persistence of landuse and land cover through the analysis of 'pixel-history' of the pattern metrics of cover classes.

The majority of spatial pattern analyses are currently based on the 'snapshot' method, which attempted to determine the track of spatial pattern hence to infer the ecological process (Southworth *et al.* 2002, Crews-Meyer 2004). Thus, sometimes it has been difficult to understand the causes of land cover change using this method. For example, in areas that are frequently affected by flood in China's arid zone, the temporary water bodies will make great variations in 'snapshot' spatial pattern indices, such as landscape metrics (McGarigal and Marks 1995), making it difficult for the interpretation of the dynamics and causes of land cover change. Mertens and Lambin (2000) stated that the manifestations of landscape processes can be better reflected by the change trajectory patterns than the 'snapshot' approach.

Although some research progress has been reported about the patch metric analysis on classified temporal categorical trajectories, the method needs to be improved further. When Southworth *et al.* (2002) inferred the patterns of landuse change using landscape metrics of change trajectories, the landuse was classified into two classes, namely, forest and non-forest. Change trajectories (e.g. forest→forest→non-forest) were established based on three epochs, and the landscape metrics of them were then computed. This research focused on the categorical change of a given landuse type (i.e. forest) rather than the comparison of different classes. Crews-Meyer (2004) assessed the temporal persistence of landuse and land cover through the analysis of 'pixel-history' of the pattern metrics of cover classes. Trajectory classes of pattern metrics (e.g. 'decrease in all three periods', 'decrease, stable, increase' and 'decrease, increase, increase' for percentage of area—PCT) were derived. This study principally focused on the trajectories of metrics, rather than the metrics of change trajectories. Further research is therefore needed to develop a methodology that quantifies the spatial pattern of change trajectories so that the spatio-temporal pattern of the change can be better described and its relation to environmental and human factors may be further explored.

This study seeks an efficient and practical method to quantify the spatial pattern of land cover change that can be related to both human activities and natural factors. The basic approach is to derive and interpret spatial pattern metrics of multi-epoch trajectories of land cover change. This method integrates multitemporal and multiscale remotely sensed data from various sources with a monitoring time frame of 30 years, including historical and state-of-the-art high-resolution satellite imagery. The history of land cover change for every location in the study area is traced, and the nature, area extent and spatial pattern of such changes are also analysed.

2. Methodology

The approach of this study is based on the post-classification comparison method, which is commonly employed in remote sensing change detection studies. First, multitemporal images are classified into land cover types for each acquisition date using a unified land cover classification scheme. Then, land cover change trajectories, or categorical 'pixel history', are established based on the classified images. The trajectories are then reclassified according to the nature of land cover changes. Finally, landscape metrics of the reclassified land cover change trajectories are computed and analysed.

2.1 *Study area and data*

The study area is centred at about $41°5'$ N and $85°43'$ E in Donghetan Township, Yuli County, Xinjiang Uygur Autonomous Region of China. It is located at the middle reach of the Tarim River, the longest inland river of China. At the fringe of Taklimakan Desert, the 'green corridor' of Tarim Basin is one of the most important habitation areas in the arid zone of China. The landscape is typical in China's arid zone, with a generally dry and harsh environment, represented by typical desert vegetation and soils. With the increasing land development in recent decades, the fragile environment has experienced quite remarkable changes caused by cultivation and infrastructure construction such as a dam, largely responding to the general development trend and temporal effects of government policies and administrative measures.

Five multitemporal remotely sensed images were acquired for change detection for this study, including Landsat MSS (3 July 1973, 12 October 1976), Landsat TM (25 September 1994), Landsat ETM (17 September 2000) and SPOT HRV (20 July 1984) multispectral images. In addition, a multispectral 4-m resolution IKONOS image was also acquired of September 2000 to assist in field investigations and accuracy assessment of the image classification. The IKONOS image was georeferenced to a 1 : 10 000 map using 22 ground control points (GCPs). The other images were then geometrically corrected and registered on the map coordinates using image-to-image registration with the master IKONOS image. Efforts were made to control registration errors to within half a pixel of the image concerned, so that the errors caused by misregistration would be less critical.

2.2 *Classification*

To minimize the seasonal impacts of remotely sensed data, the post-classification comparison method was employed for image processing, since this method is less sensitive to radiometric variations between the scenes (Mas 1999). Supervised classification using the Maximum Likelihood Classifier was employed to classify individual images independently, using a unified land cover classification scheme to ensure that the classifications of the multiscale, multitemporal images are compatible with each other (Zhou *et al.* 2008). Images were classified into the Level 2 classes, which were subsequently merged into the five unified classes, as listed in table 1. Note that because there was no cropland in the early period of this study, the early-date images (1973–1985) were classified into four land cover types only.

2.3 *Post-classification processing*

The spatial resolution of images affects landscape metric computation greatly (Borak *et al.* 2000, Rocchini 2005). To make the classified land cover images comparable in terms of landscape metrics, the images must have the same spatial resolution. Our approach is to resample the classified images to 50 m, which is close to the lowest spatial resolution (57 m) of all images using the majority rule aggregation—the method that Petit and Lambin (2001) proposed.

After resampling, a majority filter (3×3) was applied to the classified images for the removal of isolated pixels to minimize potential analytical errors.

2.4 *Accuracy assessment*

In this study we have chosen a stratified random sampling scheme for selecting sample points of reference data for classification accuracy assessment. Seven hundred and ninety sample points were selected and input to a GIS. They were then

Table 1. Unified land cover classification scheme for multiscale, multitemporal images. The numbers denote the land-use class code in individual classifications (after Zhou *et al.* 2008).

Level 1 classes	Level 2 classes	Landsat ETM (2000)	Landsat TM (1994)	SPOT (1986)	Landsat MSS (1976)	Landsat MSS (1973)	Unified classes
Cropland	Cropland	1	1	–	–	–	Cropland (1)
Grass and woodland	Dense grass and woodland	2	2	2	2	2	Grass and woodland (2)
	Sparse grass and woodland	3	3	3	3	3	
	Mowing land	4	–	–	–	–	
	Salty grass	5	5	5	5	5	Salty grass (3)
Water body	Ponds	6	6	6	6	6	Water body (4)
	River	7	7	7			
Unused land	Bare ground and sand dunes	8	8	8	8	8	Bare ground (5)

overlaid with the classified images as well as the high-resolution IKONOS multispectral image.

Collecting reference data for accuracy assessment of multitemporal images always presents a serious constraint, because simultaneous 'ground truthing' data over a long period of time are very difficult, if not impossible, to find. In this study, we could only acquire a high-resolution IKONOS multispectral image that was simultaneous with the 2000 Landsat ETM data. Although the IKONOS image has a high enough resolution for 'ground truthing', the 'time gaps' between this 'reference image' and some historical images are large.

In this study, we used the IKONOS image as the source of the reference data to assess the results of the 2000 Landsat ETM classifications. For the other four historical images, we used the IKONOS image as the basis for comparison for proper interpretation. By this means, obvious land cover changes such as grasslands to water and bare ground to cropland could be reliably detected by image interpretation. Field visits and interviews with elderly locals were also conducted for sample points where a clear relationship between the present and historical images could not be established.

2.5 *Establishment and reclassification of land cover change trajectories*

The concept and methodology of land cover change trajectory has been developed (Mertens and Lambin 2000, Petit *et al.* 2001, Crews-Meyer 2001, Zhou *et al.* 2004, 2008). In this study the term trajectory of land cover change refers to successions of land cover types (e.g. G: grass/woodland; C: cropland; S: salty grass; W: water body; B: bare ground) for a given sample unit over more than two observations (epochs). For example, land cover change of grassland→water body→grassland→ grassland→cropland on a pixel over five observations can be specified as a trajectory, meaning that the land was found to be grassland, water body, grassland and cropland over the study period. For ease of discussion, a trajectory of this kind is denoted as G→W→G→G→C.

To establish land cover change trajectories, all classified images were integrated in GIS using raster format with ArcGIS GIS software. Based on the classification scheme shown in table 1, all land cover change trajectories were established (a total of 310 trajectories have been identified) and then reclassified into 10 trajectory classes using a classification scheme proposed by Zhou *et al.* (2008), including four unchanged classes (grass/woodland, salty grass, water body, bare ground), three classes of human induced change (old cultivation, new cultivation, reservoirs/ponds) and three classes of changes by natural causes (grass/woodland, flooded, bare ground).

The *unchanged* class indicated that the same land cover type was found on the sample point over the past 30 years. The *human-induced* change class includes decisive changes due to human activities such as building dam/reservoir and cultivation. Old cultivation indicated that land cover changed to and remained as cropland since 1994. New cultivation indicated that land cover changed to and remained as cropland as cropland since 2000. Reservoirs/ponds indicated that land cover changed to and remained as water bodies since 1986. The *natural* change class includes those indecisive changes due to the natural processes or minor human activities such as light grazing. Grass/woodland indicated that land cover changed periodically between grass/woodland and salty grass. Flooded area indicated that land cover changed periodically between water and other land cover types. Bare ground indicated that land cover changed periodically between bare ground and other land cover types.

2.6 *Computation of landscape metrics*

The computation of landscape metrics of land cover change trajectories was conducted using FRAGSTATS, a program designed to compute a wide variety of landscape metrics for categorical map patterns (McGarigal and Marks 1995, McGarigal *et al.* 2002). In this study, since land cover change trajectories are reclassified into 10 classes, only class-level metrics would apply. Four landscape metrics that are commonly used in ecological studies and supported by FRAGSTATS are used in this study, namely, Percentage of Landscape (PLAND), Normalized Landscape Shape Index (NLSI), Interspersion and Juxtaposition Index (IJI) and Area-weighted Mean Patch Fractal Dimension (FARC_AM). The definition and meaning of these metrics are listed in table 2.

3. Results

Figure 1 shows the land cover change trajectory classification. In figure 1, land cover change trajectories are classified according to whether a categorical change occurred during the study period, and the cause of the change if it happened. The overall accuracies for single-date image classifications range from 81.5% to 86.5%, with Kappa coefficients ranging from 0.63 to 0.77 (table 3). The accuracies of most individual land cover classes are over 75% (table 4). For the purpose of this study, the classification yields a satisfactory, though not ideal, result.

Table 5 shows the results of spatial pattern metrics of land cover change trajectory. The table illustrates the computation results at both Level 1 and Level 2 classes of change trajectories. As the purpose of this study is to assess the human impact on the natural environment, cultivation classes are also merged for computation of the metrics. Table 6 shows the area percentages of major trajectories composed of Level 2 classes of change trajectories.

4. Discussion

4.1 *The percentage of landscape (PLAND)*

PLAND shows the abundance of the individual land cover change trajectory classes. During the 30-year study period, the PLAND of unchanged area was 41.6%, compared with that of human-induced changes (17.0%) and change by natural factors (41.4%). For unchanged area, the PLAND of grass/woodland constitutes 80.3%, and for human-induced change, the PLAND of new cultivation reached 60.8%. For the categories of natural change, flooded area obviously dominates, with a PLAND of 64.3%. The individual trajectory classes of change area also indicated that more changes were related to natural factors, especially flood. Except for 'flooded' natural changes, other land cover changes (e.g. G→G→G→W→C (1.2%), G→W→G→W→C (0.7%), B→W→B→B→B (0.5%)) were also related to flood.

The study area is quite remote, the population is quite small and the residents are mostly semi-nomadic with a limited impact on the environment. Figure 2 shows the inhabitances of the local residents over the study period. It is therefore understandable that most of environmental change is due to natural forces (e.g. flooding) rather than human activities.

Table 2. Landscape metrics for analysing spatial patterns of land cover change trajectories (retrieved from McGarigal *et al.* 2002).

Abbreviation	Name	Equation*	Interpretation
PLAND	Percentage of Landscape	$PLAND = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} \times 100$	A measure of proportional abundance of each class in the area, ranging from 0 to 100. PLAND→0 when class *i* becomes increasingly rare, while PLAND=100 when the entire area consists of a single class.
NLSI	Normalized Landscape Shape Index	$NLSI = \frac{e_i - \min e_i}{\max e_i - \min e_i}$	A measure of class aggregation, ranging from 0 to 1. NLSI=0 when the area consists of a single square or maximally compact patch of the class; NLSI increases as the class becomes increasingly disaggregated.
IJI	Interspersion and Juxtaposition Index	$IJI = \frac{-\sum_{k=1}^{m}\left[\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\ln\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\right]}{\ln(m-1)} \times 100$	A measure of interspersion over the maximum possible interspersion for the given number of classes, ranging from 0 to 100. IJI→0 when the class is adjacent to only one of the other classes. IJI=100 when the class is equally adjacent to all other classes (i.e. maximally interspersed and juxtaposed to other classes).
FARC_AM	Area Weighted Fractal Dimension Index	$FARC\_AM = \sum_{j=1}^{n}\left[\left(\frac{2\ln(0.25 p_{ij})}{\ln(a_{ij})}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right]$	A measure of complexity of the shapes of class boundaries, ranging from 1 to 2. It uses class area as a weighting factor. FRAC_AM→1 for shapes with very simple perimeters such as squares, and FRAC_AM→2 for shapes with highly convoluted, plane-filling perimeters.

*Where i is the class of interest; j is the patch number of class i; P_i=proportion of the landscape occupied by class i; a_{ij}=area (m^2) of patch ij; A=total landscape area (m^2); e_i=total length of edge (or perimeter) of class i in terms of number of cell surfaces (including all landscape boundary and background edge segments involving class i); min e_i=minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces; max e_i=maximum total length of edge (or perimeter) of class i in terms of number of cell surfaces; e_{ik}=total length (m) of edge in landscape between classes i and k; m=number of classes present in the landscape, including the landscape border, if present; p_{ij}=perimeter (m) of patch ij.

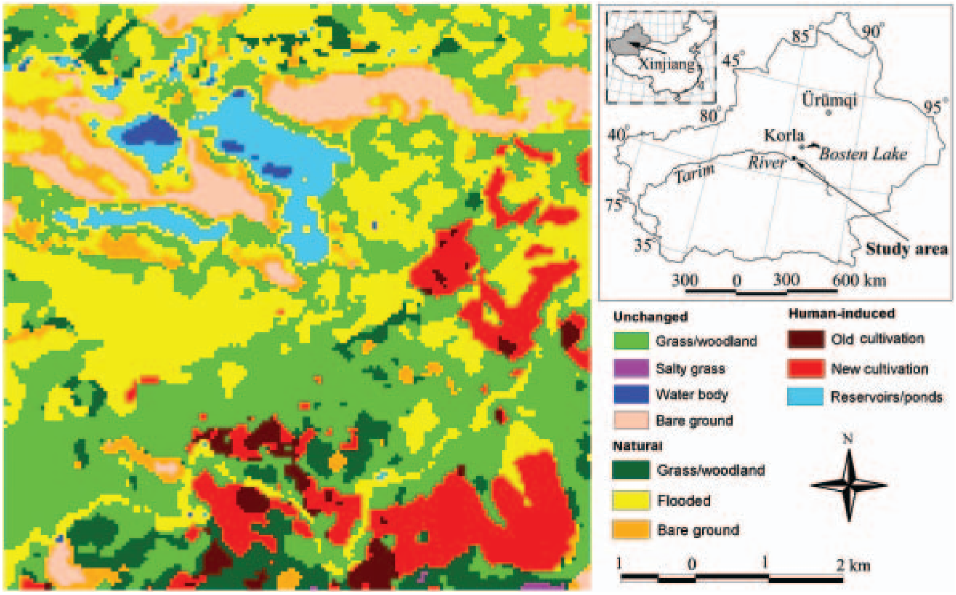

Figure 1. The classification of land cover change trajectories from 1973 to 2000.

These results were inconsistent with the reports that claimed serious land degradation in the middle and lower Tarim River (e.g. Feng *et al.* 2001, Jiang *et al.* 2005, Hou *et al.* 2007). We therefore argue that the scenario of land degradation may vary from place to place along the Tarim River, thus more detailed land cover change detection and analysis is needed, at least at the level of this study, before conclusive statements can be made on the general status of land degradation in the Tarim Basin.

However, it should also be noted that PLAND of new cultivation accounts for 10.6%, which reveals the significant acceleration of land conversion to croplands

Table 3. Overall accuracy assessment of the classification results.

Accuracy measures	1973	1976	1986	1994	2000
Overall accuracy (%)	86.5	85.2	83.7	86.3	81.5
Kappa	0.68	0.63	0.67	0.77	0.68

Table 4. The accuracies for individual land cover classes.

	Accuracy (%)	1973	1976	1986	1994	2000
Cropland	Producer	–	–	–	88.9	62.7
	User	–	–	–	70.6	89.0
Grass and	Producer	91.5	89.8	90.2	91.0	90.5
woodland	User	91.5	91.8	88.2	85.3	80.0
Salty grass	Producer	86.1	92.3	60.7	80.0	61.9
	User	73.8	49.0	79.1	82.8	61.9
Water body	Producer	77.0	64.8	77.2	85.5	86.6
	User	77.0	62.5	63.9	90.2	78.4
Bare ground	Producer	62.7	66.7	68.6	68.6	67.6
	User	66.7	75.6	85.4	90.9	89.6

Table 5. Spatial pattern metrics of land cover change trajectories.

Level 1 classes	Level 2 classes	PLAND (%)	NLSI	IJI	FRAC_AM
Unchanged	Grass/woodland	34.4	0.161	57.9	1.229
	Salty grass	0.1	0.302	0.0	1.083
	Water body	0.6	0.235	31.4	1.048
	Bare ground	6.5	0.131	26.1	1.146
	All unchanged	41.6	0.161	58.8	1.238
Human-induced	Old cultivation	2.1	0.226	50.7	1.074
	New cultivation	10.6	0.137	61.2	1.120
	Reservoirs/ponds	4.3	0.159	30.5	1.132
	All cultivation	12.7	0.109	51.3	1.116
	All human-induced	17.0	0.127	97.9	1.120
Natural	Grass/woodland	6.5	0.250	61.5	1.127
	Flooded	28.7	0.191	62.7	1.168
	Bare ground	6.2	0.387	59.5	1.130
	All natural	41.4	0.173	69.9	1.239

Table 6. The percentages of land cover change human-induced or natural change trajectories.

Level 1 classes	Level 2 classes	Trajectory classes	Percentage
Human-induced	Old cultivation	G→G→G→C→C	1.6
		S→S→G→C→C	0.2
		G→G→S→C→C	0.1
		G→S→G→C→C	0.1
		Others	0.1
	New cultivation	G→G→G→G→C	4.6
		G→G→G→W→C	1.2
		S→S→S→S→C	0.8
		G→W→G→W→C	0.7
		Others	3.3
	Reservoirs/ponds	G→G→W→W→W	3.2
		G→W→W→W→W	0.6
		G→W→W→W→W	0.2
		B→W→W→W→W	0.2
		Others	0.1
Natural	Grass/woodland	G→G→S→G→G	1.2
		G→S→G→G→G	1.1
		S→S→G→G→G	1.0
		S→G→G→G→G	0.7
		Others	2.5
	Flooded	G→G→G→W→G	7.6
		G→G→W→G→G	3.5
		W→G→G→W→G	2.3
		G→W→G→G→G	1.7
		Others	13.7
	Bare ground	B→B→B→G→G	0.7
		B→G→G→G→G	0.6
		B→W→B→B→B	0.5
		G→B→B→B→B	0.4
		Others	4.0

*G: grass/woodland; C: cropland; S: salty grass; W: water body; B: bare ground. Trajectory G→G→G→C→C indicated that land cover was grass/woodland, grass/woodland, grass/woodland, cropland and cropland in 1973, 1976, 1986, 1994 and 2000.

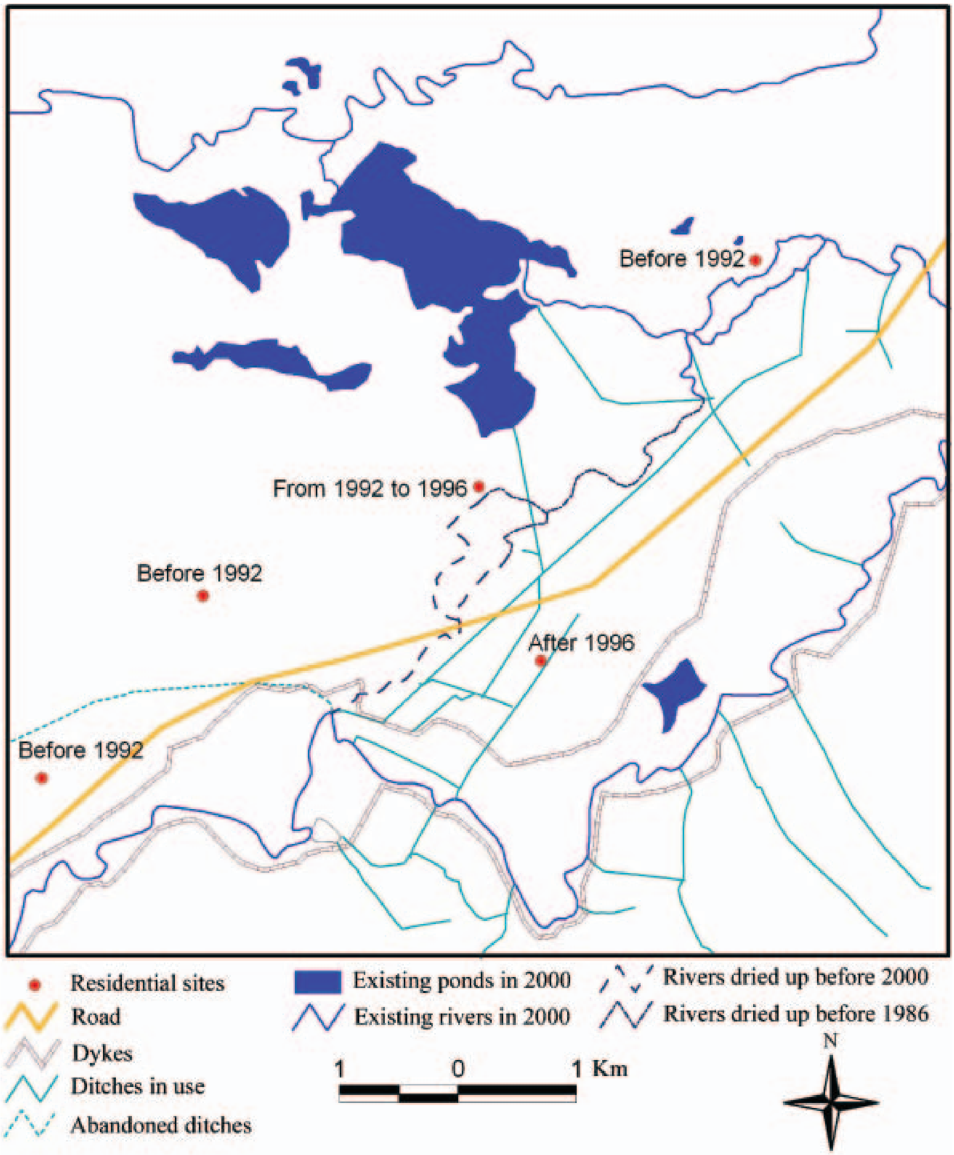

Figure 2. The irrigation infrastructure and residential sites in the study area (compiled based on the visual interpretation of 2000 IKONOS image, field investigation and the interview with local residents in 2002).

from 1994 to 2000, when human impact started to play an important role on environmental change by altering the natural courses of water and surface materials (e.g. constructing ditches in the 1990s, as shown in figure 2).

4.2 *Normalized Landscape Shape Index (NLSI)*

Measured by NLSI, different change trajectory classes have demonstrated some clear differences in spatial aggregation. The human-induced change trajectories generally show a higher-level of aggregation. The NLSI of all human-induced classes is 0.127, which is the minimum among all three Level 1 classes. The NLSI of cultivation classes has shown a significant change (a 39% decrease) in landuse pattern. The 'old cultivation' has a NLSI of 0.226, similar to those of other natural classes. This indicates that cultivation style was still remaining on a small scale, which did not put a significant impact on the natural environment. In contrast, the NLSI of 'new cultivation' is 0.137, which is much less than that of 'old cultivation', suggesting larger-scale farming, which made a large impact on the environment. When merging adjacent patches of both 'old' and 'new' cultivation classes together, the aggregated NLSI is only 0.109, significantly less than all other natural classes. This confirms that recent cultivation exhibited a highly concentrated and aggregated spatial pattern with simple large patches for the efficiency of landuse.

Figure 3 showed the area change of cropland from 1980 to 2000. The area of cropland remained almost unchanged before 1990 but increased with a great pace in the 1990s. The increase was mainly due to the rapid growth of cotton cropping as the area of other types of cropland decreased slightly. This largely reflects the effects of the local policies that encouraged cotton cropping in the 1990s by the government of Xinjiang Uygur Autonomous Region.

Most cotton cropland was reclaimed by the 'private or public enterprises,' not by local farmers and the characteristics of reclamation were commercial profit-oriented agriculture by introducing large machinery, massive irrigation constructions and other modern agriculture input. Because of the limitation of water resources in the arid zone, the cropland must be supported by a well-established irrigation infrastructure. Since the expense of constructing an irrigation infrastructure was costly, the infrastructure will generally be concentrated (see figure 2). Thus, it will be easily understood that the new cultivation displayed a highly concentrated and aggregated spatial pattern.

4.3 *The Interspersion and Juxtaposition Index (IJI)*

IJI describes how a trajectory class spatially associates with other classes. Naturally the unchanged trajectory classes show lower IJI (i.e. spatially adjacent to fewer other trajectory classes) since a given change trajectory class tends to associate with its

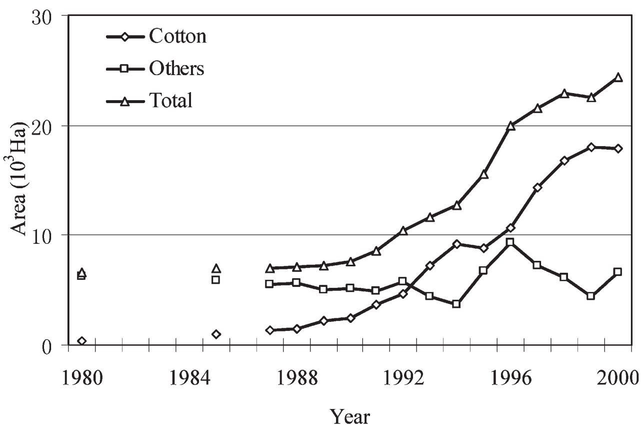

Figure 3. The cropland change in Yuli County from 1980 to 2000 (compiled based on the *Statistic Year Book of Xinjiang Uygur Autonomous Region* (Beijing: China Statistics Press) and *China Rural Statistical Year Book* (Beijing: China Statistics Press)).

corresponding cover type (e.g. unchanged bare ground, or sand dunes tend to be surrounded by periodical changes between cover bare ground and other cover types). Human-induced change generally shows lower IJI compared to natural change trajectory classes. Spatially the cultivation classes show a tendency to be associated with each other, shown by the IJI of all cultivation of 51.3, which is much less than that of natural trajectory classes (IJI=69.9). The reservoirs/ponds trajectory class has shown a strong tendency to associate with unchanged water bodies and flooding zones (i.e. the 'flooded' natural change trajectory) with a low IJI of 30.5. In comparison, the natural change trajectories are more likely interspersed with other change trajectory classes because they often represent the interchange zone between different natural land cover types and areas with human impact.

4.4 *Area Weighted Fractal Dimension Index (FRAC_AM)*

Human-induced change has a lower shape complexity measured by Area Weighted Fractal Dimension Index (FRAC_AM). For all Level 1 classes, human-induced change has the lowest FRAC_AM of 1.120, which was less than 10%, compared with those of unchanged (1.238) and natural (1.239) change trajectories. For cultivation trajectory classes, the new cultivation (FRAC_AM=1.120) has a more complex shape than that of old cultivation (FRAC_AM=1.074, 4% less than that of old cultivation), suggesting that cropland in 2000 was expanded around old cultivation fields. The boundaries of the expanded cropland in 2000 were more complex because of the appearances of holes occupied by the 1994 cropland patches. Actually, the change of shape complexity of old and new cultivation suggests the spatial pattern of cropland expansion: the originally scattered small patches of farmland found in 1994 were expanded to a larger area, and new cultivation is unlikely to occur in the isolated new area because of limited support of irrigation infrastructure.

5. Conclusion

Land cover change in the arid zone is caused by both human activities and natural forces. Sometimes natural factors have a much larger impact than that of human activities. To effectively estimate and describe the dominance and spatial distribution of the forces that caused environmental change, we have proposed a methodology that uses multitemporal remotely sensed imagery to derive land cover change trajectory, and that subsequently computes landscape metrics of the change trajectory as quantitative descriptive parameters.

This study extends previous research reported by Southworth *et al.* (2002) and Crews-Meyer (2004) based on categorical trajectory analysis (Zhou *et al.* 2004, 2008). The landscape metric measurements have been introduced to analyse the spatial pattern of land cover change trajectory classes based on the driving force of environmental change. Taking this approach, the nature of change trajectories (hence the history of the change) can be described by interpreting the metrics of the spatial patches of change trajectories, thus forming a useful foundation for the prediction of the spatial pattern of land cover change with the current driving forces and constraints.

This research has selected four landscape metric measurements to describe the spatial pattern of land cover change trajectory classes in the study area of the arid zone in western China. The findings of the case study can be summarized as:

1. PLAND of change trajectory classes is a good indicator for showing the dominant process of environmental change. In the study area, the dominant process of environmental change was still due to natural forces, but the impact of human activities has increased significantly from 1994 to 2000.
2. Aggregation of patches of land cover change trajectory classes shows the nature of change processes. A higher-level of aggregation often suggests a more aggressive progress from a dominant driving force. In this study, the human induced changes generally show greater aggregation, indicated by lower NLSI, suggesting that human impact is more concentrated than the changes caused by natural forces.
3. Among human-induced changes, the reservoirs/ponds class was closely associated with only a few of the other change trajectory classes (e.g. flooding zones), indicated by its low IJI. The cultivation classes also show low IJI with the tendency of associating with each other.
4. The whole human-induced trajectory class shows a lower FRAC_AM than those of natural changes, indicating less complexity in shape. This suggests that large, relatively regularly shaped patches are the general spatial pattern when lands were converted from natural cover types to cultivated lands or reservoirs.

Numerous challenges, however, are also raised from this study. First, similar to all other remote sensing studies, the uncertainty in classification and change detection based on multitemporal and multiresolution remotely sensed images will always produce a significant impact on the analytical results. To what extent the impact may affect the final analytical results is certainly subject to further study. Secondly, the interactions and associations among different land cover change trajectories need to be further explored by introducing other landscape metrics or other spatial pattern measures. The development of more comprehensive and representative parameters to describe spatio-temporal patterns and processes shown by remotely sensed data is also recommended.

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