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Expressing the spatio-temporal pattern of farmland change in arid lands using landscape metrics

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ABSTRACT

Identifying, recording and monitoring land cover change on the Earth's surface is a complex procedure. Spatio-temporal modelling is an effective approach to simplifying and simulating the process. Existing spatio-temporal modelling methods are typically based on either, an overlay of multi-temporal land cover maps, or temporal trend analysis of spatial pattern indices. Consequently, an understanding of the spatial dynamics of any changes is either fragmental in the former case, or invisible in the latter case, due to the lack of adequate geographical location information.

In the arid zone of western China, a widely accepted belief is that rapid farmland expansion and the subsequent abandonment of the farms, or their mis-management, would lead to soil salinisation and desertification. In order to better understand the spatio-temporal pattern of farmland change, this paper proposes an integrated approach that combines the two methods of pixel-based trajectory analysis and class-level spatial pattern metrics. Multi-temporal remote sensing images were collected beginning in 1994, a year that captured the initial effects of the period of rapid farmland expansion. Historical change trajectories were established for each pixel and categorized according to change types (*i.e.* expanding or shrinking). The spatial dynamics of farmland change can then be illustrated by mapping the change trajectory classes. Spatial patterns of farmland change were quantified by employing distribution-related landscape metrics, such as indices of interspersion (IJI), connectivity (COHESION) and isolation (ENN), to analyse farmland development models of the two river basins in the study area. Shape indices, including overall shape (nLSI) and edge shape (FRAC), were applied to appraise the structural stability of the farmlands over time. Results indicate that, over the past two decades, the area subject to farmland expansion was significantly larger than that experiencing farmland abandonment. The relatively rapid expansion of farmland exhibited a concentrated pattern, and generally followed a layer-based development model. The study showed that the proposed research method effectively visualized and quantified the spatio-temporal dynamics of farmland change.

1. Introduction

Land use and cover change (LUCC) is increasingly recognized as a sensitive indicator of earth systems (Zhou et al. 2008a). In the arid zone of western China, rapid and frequent LUCC has been observed around the oases where the majority of the regional population is concentrated. The observed changes largely reflect the impact of human activities on the fragile natural environment (Turner et al., 1994). Changes became most noticeable from the early 1990s when local governments launched and supported an agricultural development plan (Hu and Li, 2010). It is a commonly held belief that the rapid expansion of farmland (irrigated land, primarily cotton fields) and its subsequent abandonment or neglect would lead to increasing soil salinity and ultimately to desertification (Zhang et al., 2003; Ma et al., 2011). Thus, the ability to monitor and model farmland change around these oases is essential both for determining the environmental carrying capacity and for sustaining regional economic development.

Over recent decades, remotely sensed data has been widely used for detecting and monitoring land cover change, primarily because of the large areal coverage that can be achieved and the rapid

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response to surface changes (Singh, 1989; Lu et al., 2004). Typically, land cover change detection methods focus on determining whether a change has occurred, the destination of the change, and how the change has evolved over time (MacLeod and Congalton, 1998; Sui et al., 2008). The core objective of these studies is to fully understand the process of LUCC.

In order to describe and simulate a change process, most change detection studies employ spatio-temporal modelling methods. These procedures comprise two main components – the temporal and the spatial characteristics. With regard to the temporal aspects, temporal trajectory analysis has been shown to be a useful tool, when compared to bi-temporal change detection, for long-term change detection studies (Coppin et al., 2004; Kennedy et al., 2007; Zhou et al., 2008a, 2008b; Griffiths et al., 2010), because LUCC is a complex and sequential process. With regard to the spatial aspects, spatial pattern indices have been devised to describe spatial features (Lambin et al., 2003; Narumalani et al., 2004; Lin et al., 2010; Fan and Myint, 2014). A variety of indices have been developed and employed by different researchers, primarily because quantitative methods have the ability to clearly resolve complex natural phenomena by assigning values. Moreover, comparisons between these values can provide further elucidation (Turner et al., 2001). There are two general methods for spatio-temporal modelling. The first method is based on temporal trajectory analysis of time-series land-cover maps (*e.g.* Amiri et al., 2009; Long et al., 2009; Li et al., 2013b). Change dynamics are retrieved from a comparison of individual observations. In addition, a likely condition of land cover at a specified time in the future can be projected based on the antecedent states, *e.g.*, the Cellular Automata Model of Li and Yeh (2000) and of Herold et al. (2003), the Markov Chain Model of Petit et al. (2001), the CLUE-S Model of Verburg et al. (2002), and the Logistic Regression Model of Huang et al. (2009). The second method is based on temporal trend analysis of spatial pattern indices. Change dynamics are retrieved by measuring the variation of quantitative indices over time. Among the various indices available, landscape metrics introduced from landscape ecology are widely applied to evaluate the incidence of changes in space (*e.g.* Seto and Fragkias, 2005; Sakamoto et al., 2006; Kong et al., 2009; Huang et al., 2014).

Numerous research studies have reported the application of temporal trajectory analysis to spatial units such as pixels or small patches. For example, Crews-Meyer (2002, 2004) employed landscape metrics to assess the stability of agricultural land by adopting farmland patches as the basic analytical unit. Southworth et al. (2002) applied landscape metrics to pixel-based change trajectories to assess the degree of fragmentation of forest land cover over three epochs. Zhou et al. (2008b) and Zhou and Sun (2010) developed these earlier studies by grouping pixel-based change trajectories into several categories in order to analyse the driving forces behind the observed changes. These studies attempted to link spatial patterns and the processes of land cover change by combining the procedures of pixel-based trajectory analysis and landscape metrics.

With regard to the existing spatio-temporal modelling methods, temporal dynamics are well understood. In contrast, spatial dynamics are fraught with difficulties. They are either, only partially revealed by the analysis of time-stamping spatial objects, or not revealed by the trajectory trend analysis of spatial pattern indices, due primarily to the lack of geographical location information. It is extremely difficult to directly perceive the process of change from the viewpoint of spatio-temporal visualization. Although pixel-based or patch-based approaches are capable of retaining the locational information of a change, the descriptive judgement of any change trend is necessarily empirical. Further, interpretation of landscape metrics and their ecological significance remains a challenge for land cover change studies (Li and Wu, 2007).

In order to develop a comprehensive understanding of the temporal and spatial aspects of farmland change in the arid zone of western China, and for a more complete understanding of the farmland expansion processes, some fundamental research questions need to be addressed, namely: (1) What are the spatio-temporal characteristics of farmland change in the region? (2) Can a particular change model of farmland development/expansion be identified? (3) How can the change model be expressed using quantitative methods?

With the research objective of simulating the spatio-temporal process of farmland change, this study aims to develop an effective methodology for modelling the observed spatio-temporal patterns, in particular to represent the spatial dynamics of the changes. In addition, the study also attempts to evaluate the structural stability of the farmlands, and to develop a farmland expansion model using quantitative landscape metrics.

2. Methodology

The generic approach adopted in this study is based on the well-established post-classification comparison method (Lillesand et al., 2015), in which multi-temporal remote sensing images are individually classified into land cover classes. By merging the identified land cover classes into two general classes, namely, farmland and others, pixel-based change trajectories can then be established to track historical changes. Given that the process of farmland change can be separated into slices by time stamp, the spatial dynamics of the changes can be visualized by displaying the change segments, which are themselves discriminated by the change trajectories. For quantitative description and identification of the farmland development model, changes of the spatial patterns is illustrated by landscape metrics.

2.1. Study area and data

This study was conducted in Yuli County in the Xinjiang Uygur Autonomous Region of western China (Fig. 1). Yuli County, which covers an area of around 60,000 square kilometres, is located in the lower reaches of the Tarim River, the longest inland river in China. The Tarim River along with the Konqi River, which has its source in Bosten Lake to the north, supply the majority of the water to this arid region. These two rivers nurture a typical oasis environment on the fringes of the Taklimakan Desert – the second largest desert in the world. Together, the two rivers create a “green corridor” that supports a large population. Consequently, the study area is one of the most important areas of habitation in the arid zone of Xinjiang. Since the mid-1990's, the region has witnessed the rapid development of irrigated agriculture. Consequently, water abstraction in the upper reaches of the two rivers has increased markedly, resulting in a significant reduction in the water supply to the lower reaches. The deteriorating ecological conditions have led to a worsening living environment, with potentially disastrous consequences for the fragile ecosystem.

Five images from four platforms were used to analyse long-term farmland change in the area. These included multispectral images from Landsat series satellites (Landsat-5 and Landsat-7), the China–Brazil Environment and Resource Satellite (CBERS-02), and the Environment and Disaster Monitoring/Forecast Micro-satellite (HJ-1/A). The characteristics of the images are shown in Table 1. Acquisition dates were selected to cover periods when there was a large contrast between green vegetation and other land cover types in order to assist feature identification during multispectral image classification (Lillesand et al., 2015). Each image was initially processed using systematic atmospheric and geometrical corrections.

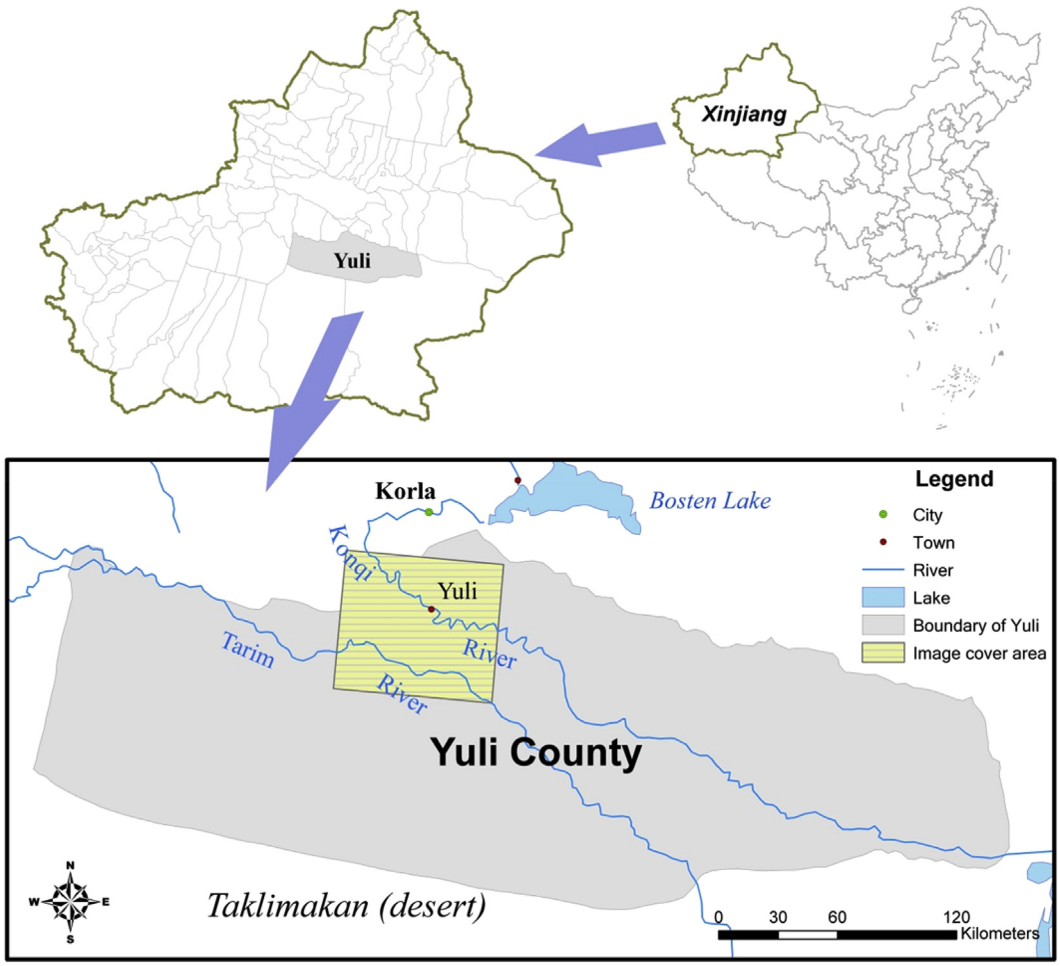


Fig. 1. Location of the study area.

Image-to-image registrations were then conducted. In this study, the 2005 image was registered and geo-referenced to a 1:50,000-scale topographical map. The other images were then registered to the 2005 image, with geometric errors of less than half of a pixel. Finally, the images were all resampled to a unified spatial resolution of 30 m.

2.2. Identification of land cover types

Given that the multi-temporal images used in the study were from different platforms, the selected post-classification comparison method is considered to be an effective method of reducing the impacts of radiometric variations that arise from different sensors. The Maximum Likelihood Classifier (MLC) method was employed to segregate the images into six land cover classes. These were subsequently merged into two general cover types, namely "farmland" and "others". The overall accuracy and the *kappa* coefficient were then computed to evaluate the classification results. Because it was difficult to obtain historical reference data, more than 700 samples for each acquisition date were randomly selected from the original images and visually interpreted. This procedure provided the reference data required for accuracy assessment. To assess the accuracy of merged cover types, an additional 200 samples were randomly selected using the same procedure. All the images were independently classified and assessed.

Table 1
Characteristics of satellite images used in the study.

Satellite	Sensor	Spatial resolution (m)	Acquisition date
Landsat-5	TM	30	25/9/1994
Landsat-7	ETM	28.5	17/9/2000
CBERS-02	CCD	19.5	15/9/2005
HJ-1/A	CCD	30	06/9/2010
HJ-1/A	CCD	30	07/8/2013

2.3. Establishment of change trajectory classes

Classified images were integrated into a Geographic Information System (GIS) prior to establishing the farmland change trajectories. The trajectory is defined as the sequence of changes of land cover types. For example, a change trajectory on an individual pixel can be specified as "others – farmland – others – farmland – others" to specify a path of farmland change. In this study, each classified image was converted into a binary image by assigning '1' to "farmland" pixels and '0' to "others". The binary images were then merged with proper bit-offsets according to their acquisition dates to create a "trajectory image" in which every possible change trajectory could be identified by a unique value for each pixel.

The number of all possible trajectories is determined by the number of classes (c) and the observation dates (n), designated as c^n. In this study, $c = 2$ and $n = 5$, thus the total number of possible change trajectories is $2^5 = 32$. This value is impractically large for the visualization and analysis of simple farmland expansion/abandonment. Therefore, the farmland change trajectories were generalized into the four categories of “expansion”, “permanent abandonment”, “ephemeral farmland” and “temporary abandonment” using the following criteria:

(1) The pixel shall be identified as “farmland expansion”: if the cover type had changed from “others” to “farmland” on a particular observation date and had remained as “farmland” for at least one subsequent observation.
(2) The pixel shall be identified as “permanent abandonment”: if the cover type had changed from “farmland” to “others” on a particular observation date and had remained as “others” for at least one subsequent observation.
(3) The pixel shall be identified as “ephemeral farmland”: if the cover type at the last observation was “farmland” and had changed from “others” at the previous observation.
(4) The pixel shall be identified as “temporary abandonment”: if the cover type at the last observation was “others” and had changed from “farmland” at the previous observation.

In addition, two broad classes of farmland change path were focused upon, namely stable farmland and permanently abandoned farmland. Stable farmland is retrieved from the accumulation of farmland expansion in the foregoing years until a particular observation time-point. This means that once a parcel of land had become farmland, it has not subsequently been transferred to other land cover types. Permanently abandoned farmland is identified by the same rule of accumulation.

2.4. Quantification of spatial patterns of farmland change

Landscape metrics, a quantitative tool for measuring spatial patterns of land cover change, was introduced by ecologists in the late 1980s (Krummel et al., 1987; O'Neill et al., 1988). Unlike traditional geo-statistical indices such as *Moran's I*, which simply describes a general spatial distribution pattern (*i.e.* clustered, dispersed or random), landscape metrics measure spatial structures. Ecological applications of landscape metrics focus upon landscapes, land cover types or individual patches. Depending upon the specific objectives of the research project, landscape-level, class-level or patch-level landscape metrics are applied (Turner et al., 2001). Class-level metrics are considered to be appropriate in this study because the research target is the incremental change parts in the different years that were generated from the categorical change trajectories. Also, because very few indices contain unique information, and others, among the more than a hundred landscape metrics will be redundant (Ritters et al., 1995), five representative indices were selected. Given that the description of the spatial dynamics of change was the research objective, those chosen related to spatial configuration. The selected indices are *Interspersion and Juxtaposition Index* (IJI), *Patch Cohesion Index* (COHESION) and *Area-weighted Mean Euclidean Nearest-Neighbour Distance* (ENN_AM), which are used to describe a general farmland development model, and *Normalized Landscape Shape Index* (nLSI) and *Area-weighted Mean Fractal Dimension Index* (FRAC_AM), which are used to present the spatial configuration details of the model. Calculation of the selected landscape metrics was carried out using FRAGSTATS 4.1, a program developed for landscape pattern analysis (McGarigal et al., 2012).

2.4.1. Identification of the farmland development model

Spatial dynamics of a change can be illustrated by the spatial distribution of different farmland change trajectory classes. Therefore, three landscape metrics related to spatial distribution were adopted, namely IJI, COHESION, and ENN_AM.

The IJI is a relative index that represents “the observed level of interspersion as a percentage of the maximum possible given the total number of patch types” (McGarigal et al., 2012). High values of IJI indicate a better-developed interspersion of a particular class among the other classes; Consequently, the class with the highest value is referred to as having an interspersed distribution pattern, *i.e.* a “salt and pepper” mixture. In contrast, a lower value indicates that the class in question is poorly interspersed, with less items in the class adjacent to other classes; Thus, most of the classes with lower values usually imply a layer distribution.

However, it should be noted that using IJI alone may not be sufficient to distinguish a farmland development model. As shown in Fig. 2, it is difficult to discriminate between cases (b) and (c) because they both show lower IJI values for all classes compared to case (a). Therefore, supplementary measures are necessary. In this study COHESION and ENN_AM were selected to measure the connectivity and the distance between patches of the same class to distinguish the tier/circular (case (b)) and multi-directional (case (c)) spatial patterns of farmland expansion as illustrated in Fig. 2.

2.4.2. The stability of farmland in spatial configurations

Within a fragile ecosystem, the stability of land cover is commonly considered to be a definitive criterion for judging if a change is, or is not, sustainable. To measure the stability of farmland in terms of its shape, two shape-related metrics were employed. These were nLSI and FRAC_AM, which describe the overall shape and the edge shape of the farmland, respectively.

A fundamental assumption is that fragmentation will cause the overall shape of a farmland patch to become more complex. Aggregated shape describes a closer connection among patches, which means that the status of farmland is more stable. Fig. 3 shows four possible situations with different overall shapes. Fig. 4 illustrates three cases with different degrees of complexity.

3. Results

3.1. Accuracy assessment of farmland identification

The initial classification exercise yielded overall accuracies ranging from 87.5% to 93.8%, and *kappa* coefficients ranging from 0.85 to 0.93. After merging the final two general classes, satisfactory classification accuracies were exhibited, with overall accuracies ranging from 93.8% to 98.1%, and *kappa* coefficients ranging from 0.88 to 0.96. For the final two classes, the resulting accuracy of the “farmland” class is better than that of the “others”, possibly because native vegetation was mis-classified into the farmland class.

3.2. Mapping spatial dynamics of farmland change

Fig. 5 illustrates the spatial dynamics of farmland change in Yuli County from 1994 to 2013, with the change trajectories of interest highlighted. Fig. 6 displays changes in the spatial configurations of stable and permanently abandoned farmlands. For farmland expansion, grassland and non-utilized land accumulatively account for almost 90% of the changed area. For farmland abandonment, the major change types are grassland and urban land use, whose areas occupy 69% and 17%, respectively.

3.3. Quantification of spatial dynamics

Table 2 shows measurements of the spatial distribution of farmland change trajectories. The distribution-related indices,

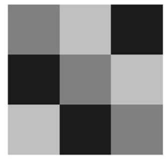
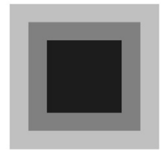
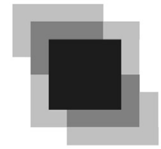
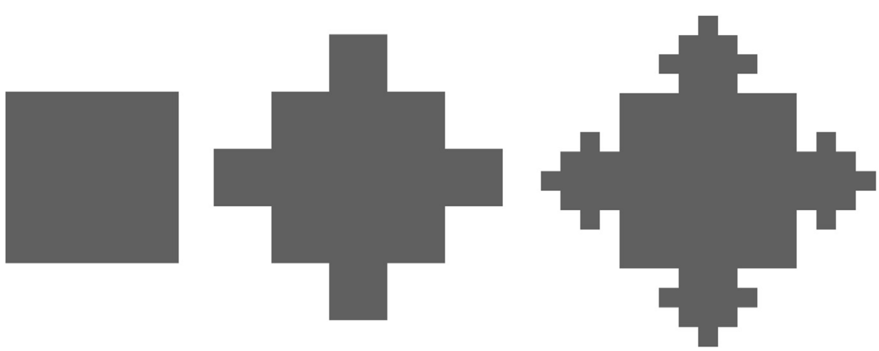
Pattern	 (a)	 (b)	 (c)
IJI	Equally high (close to 100)	Equally low (lower for core)	Increased (lower for core)
COHESION	No clear tendency	Equally high (close to 100)	Decreased (higher for core)
ENN_AM	High	Low	High

Fig. 2. Spatial distribution patterns and the corresponding indices. The grey-level represents farmland increments at different periods.

(a) (b) (c) (d)

Fig. 3. Examples of different overall shapes. The nLSI values are: 0 for case (a); 0.17 for case (b); 0.33 for case (c); 1 for case (d).



(a) (b) (c)

Fig. 4. Examples of different edge shapes. The FRAC_AM values are: 1 for case (a); 1.137 for case (b); 1.253 for case (c).

including IJI, COHESION and ENN_AM, were applied to segments of a change process at different times (*i.e.* the categorized change trajectories illustrated in Fig. 5). Farmland development models were separately analysed for the Konqi River basin and the Tarim River basin in Yuli County.

Table 3 shows the quantified results of the spatial configurations of farmlands at different times. Shape indices, including nLSI and FRAC_AM, were applied to the broad farmland change paths (*i.e.* the stable and permanently abandoned farmland categories illustrated in Fig. 6).

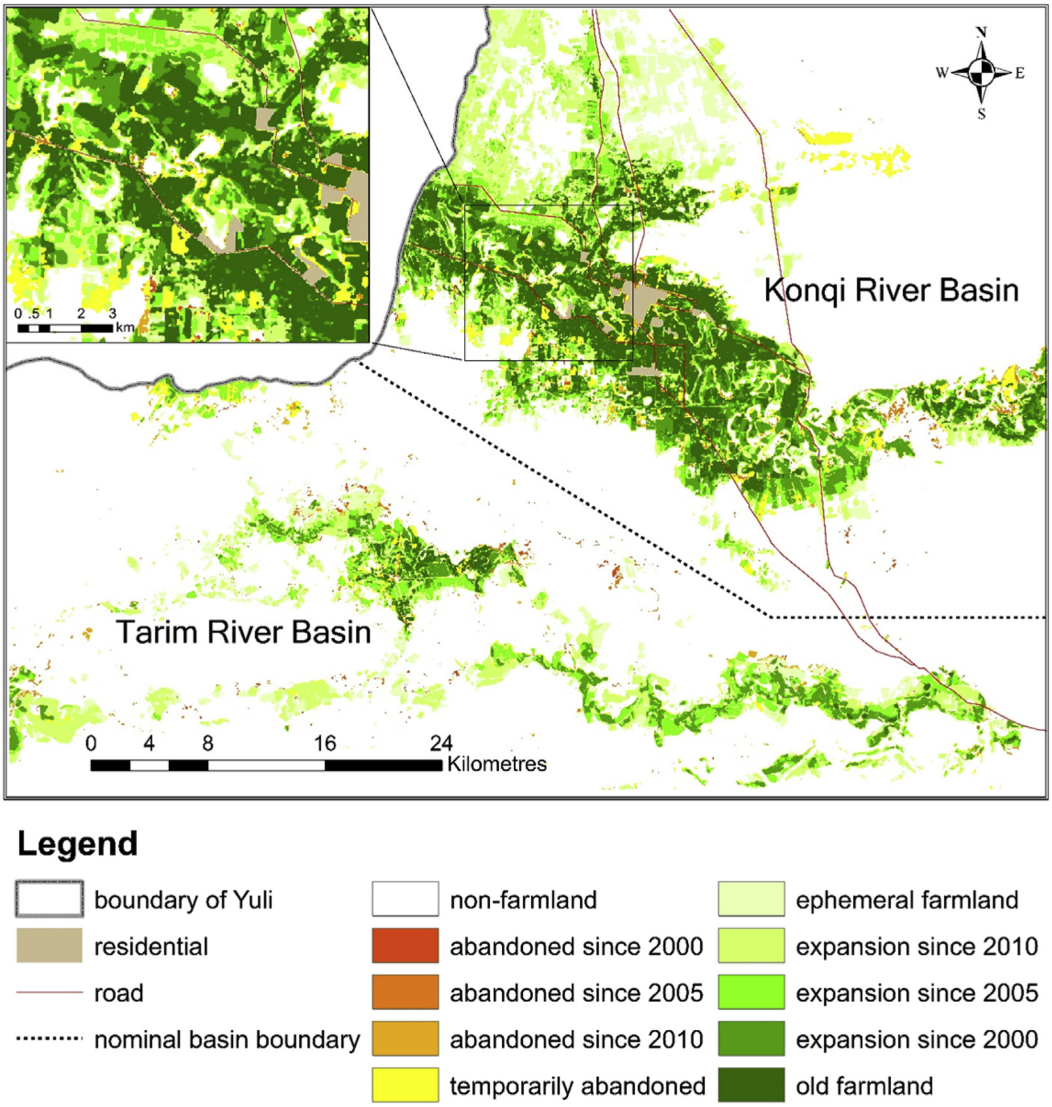


Fig. 5. Farmland change trajectories in Yuli County from 1994 to 2013.

4. Analysis and discussion

4.1. Spatio-temporal pattern of farmland change

In general, farmland expansion was the dominant process of land cover change in Yuli County over the past two decades. From the statistics shown in Table 3, it is clear that the area of stable farmland increased by more than 300%. It is especially noticeable that the annual growth rate was over 11 percent in the earlier years, slowing to around 8 percent in later years. In spatial terms, the old farmland was mainly distributed along the river valleys, while newly cultivated farmlands tended to be located at the fringes of the older farmlands, as shown in Fig. 5.

Quantitative analytical results verify the above findings. Farmland expansion in the two river basins exhibits a similar change pattern. For both basins, IJI shows a generally increasing trend for farmland expansion trajectory categories before 2013 (Fig. 7a and b). The results suggest that newly cultivated farmlands were more likely to be distributed, albeit with a more dispersed distribution, at the fringes of older farmlands that are much closer to the rivers. This concentration near rivers is primarily due to the dependency of the farmlands on available water resources and irrigation systems in this arid zone. Although farmland change is generally considered to be a human-induced land cover change because, for example, the spatial configuration of farmland relies on the development and construction of local irrigation systems, changes are also affected and limited by natural phenomena. This is illustrated by the severe drought of 2013 when the water supplied to the mid-lower reaches of the rivers was greatly reduced (Shang and Yin, 2014). At that time, newly cultivated farmlands tended to be located in the upper reaches but retreated back towards the river banks, exhibiting less adjacency to the old farmlands. This may explain the lower IJI values of the incremental change parts in 2013.

Correspondingly, connectivity and aggregation indices support the inferences drawn from the spatial dynamics of farmland change, and the impact of irrigation systems on the farmland development model. With regard to farmland expansion trajectory categories, COHESION values tend to show a decreasing trend before 2010 (Fig. 7c and d), while ENN_AM values present an increasing trend and maintain higher values (Fig. 7e and f). This indicates that the degree of connectivity and aggregation of the newly cultivated farmland is decreasing at the same time that the

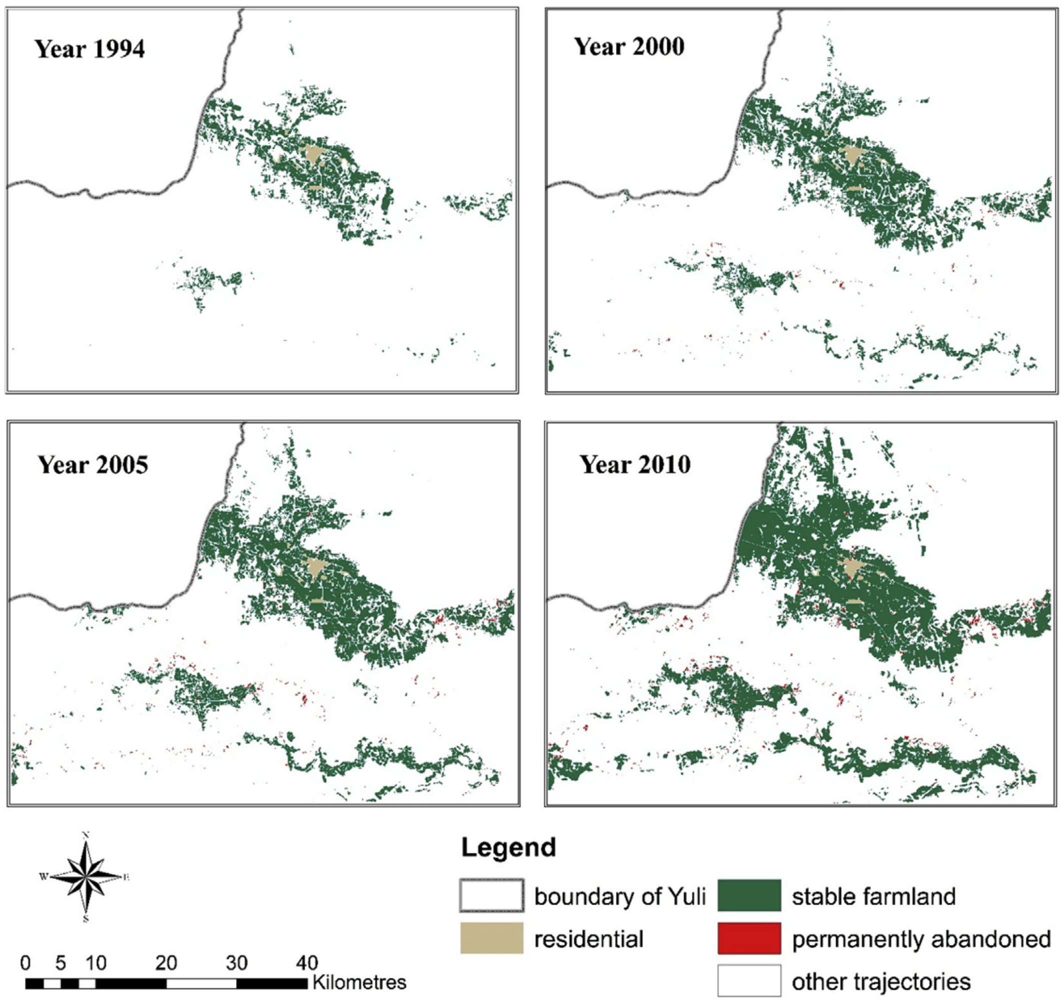


Fig. 6. Stable and permanently abandoned farmlands in four different years.

Table 2
Trajectory classes and their metrics.

Trajectory category (1994–2013)	Description	Konqi river basin			Tarim river basin		
		IJI	CO[a]	ENN	IJI	CO[a]	ENN
x-x-x-x-x	Old farmland	60.96	97.62	74.99	62.90	95.02	116.19
o-x-x-x-x	Expansion since 2000	64.54	92.75	99.35	66.77	95.10	125.20
?-o-x-x-x	Expansion since 2005	63.08	86.63	100.19	63.43	92.56	108.11
?-?-o-x-x	Expansion since 2010	79.59	96.29	93.90	75.24	94.23	117.04
?-?-?-o-x	Ephemeral farmland	51.15	95.68	102.74	54.12	91.60	127.09
x-o-o-o-o	Abandoned since 2000	57.58	67.07	333.21	33.97	72.34	266.02
?-x-o-o-o	Abandoned since 2005	68.29	79.26	226.13	54.57	72.73	272.11
?-?-x-o-o	Abandoned since 2010	70.41	69.37	187.93	61.25	73.13	220.51
?-?-?-x-o	Temporarily abandoned	77.05	87.09	115.61	71.19	82.23	127.53

where: x = "farmland", o = "others", ? includes "x" and "o";
[a] CO denotes COHESION.

Table 3
Shape indices and area statistics of stable and permanently abandoned farmlands at different times.

		1994	2000	2005	2010
Stable farmland	Area (ha)	14,090	27,194	37,068	57,698
	nLSI	0.110	0.087	0.076	0.047
	FRAC_AM	1.185	1.204	1.224	1.211
Permanently abandoned	Area (ha)	–	414	1126	2095
	nLSI	–	0.438	0.404	0.396
	FRAC_AM	–	1.073	1.093	1.096

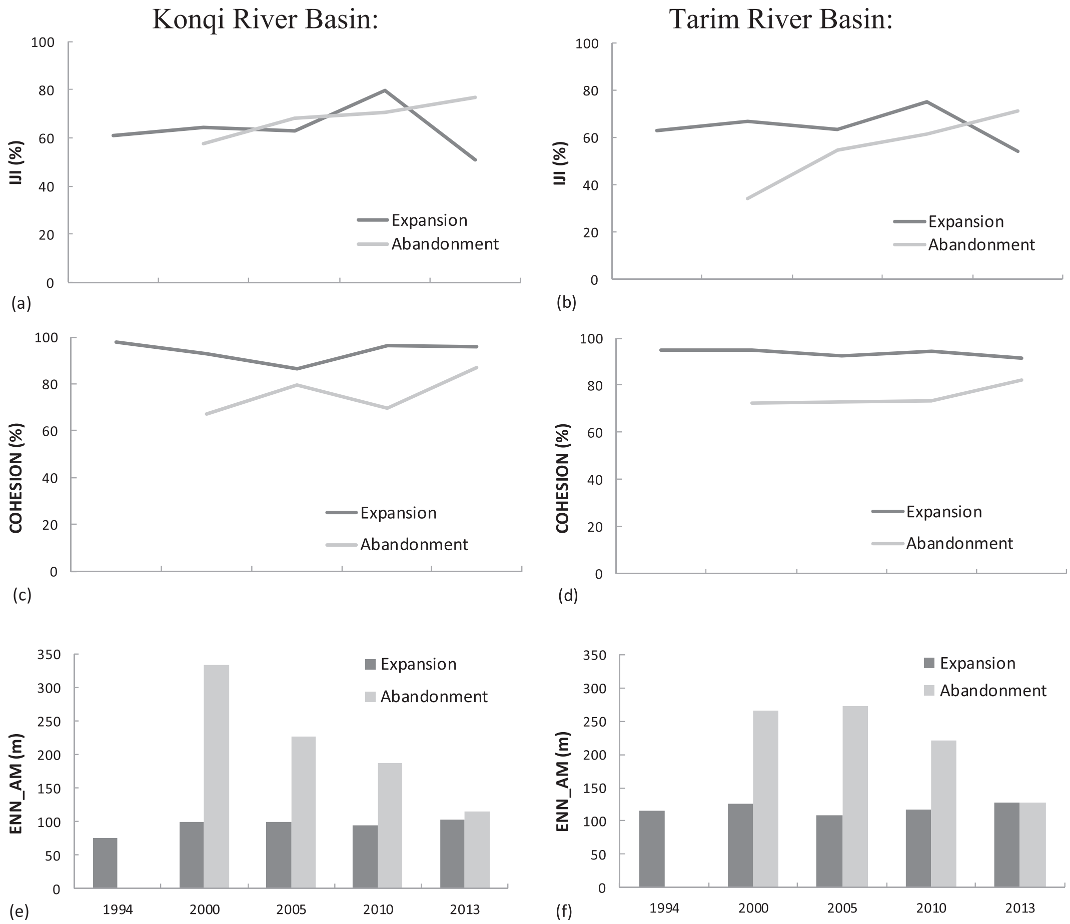


Fig. 7. Trends of spatial distribution metrics of incremental change parts.

area of farmland is being enlarged.

Compared to newly cultivated farmlands, abandoned farmlands occupied a very small area at every observation time. Thus, the spatial pattern of farmland abandonment is another interesting phenomenon. The low IJI values in the earlier years of the study period suggest that only isolated and scattered farmland abandonments occurred among non-farmland-related change trajectories without a significant area change. The rapid increase of IJI

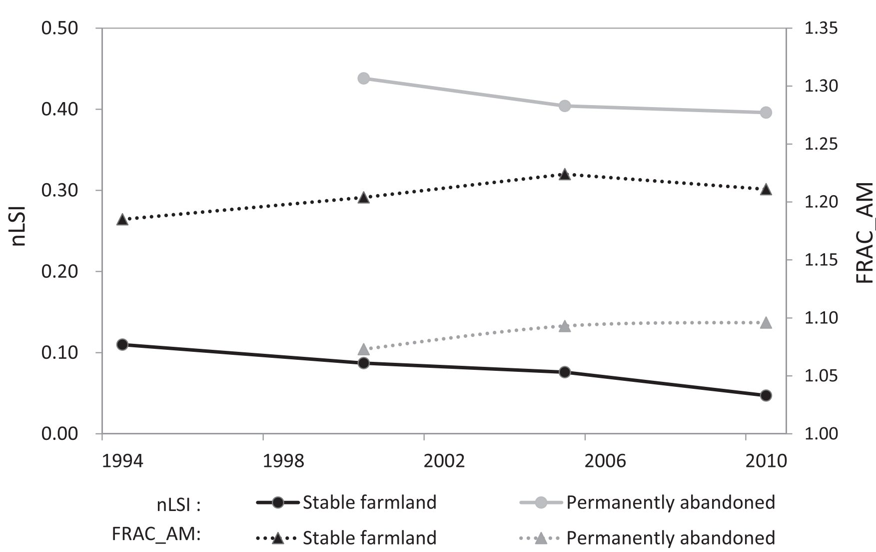


Fig. 8. Changes of shape indices of stable and permanently abandoned farmlands.

values in subsequent years indicates that farmland abandonment is more common, and is scattered among farmland-related change trajectories in the following years. Also, abandoned farmlands maintain lower values of COHESION and much higher values of ENN_AM, a finding that implies that farmland patches are abandoned in isolated pockets, and also have smaller areas.

Examination of farmland structural stability during the process of farmland expansion revealed a decreasing nLSI (Fig. 8), which indicates that smaller patches of stable farmland tended to be merged into larger patches, farmland becoming more aggregated. Further, the increasing FRAC_AM shows that stable farmland exhibits a more complex edge shape during a period when farmland expansion was accelerating. With regard to farmland abandonment (refer to Fig. 8), the higher nLSI implies that farmland abandonment occurred with a dispersed distribution. At the same time, the increasing FRAC_AM expresses a more complex edge shape as the permanently abandoned farmlands accumulated. This finding suggests that farmland abandonment was a somewhat random process, because well-organized development plans that rely on irrigation systems always ensure that the shape of farmland is aggregated with a regular edge.

4.2. Comparison with previous spatio-temporal pattern analysis

For quantifying the spatio-temporal pattern of a change, traditional methods of employing geo-statistics can elucidate the general features of a spatial distribution pattern (Fan and Myint, 2014; Du et al., 2015). Aside from geo-statistical indices, landscape metrics with the ability to describe spatial configurations at various scales have been widely used for decades (Jenerette and Wu, 2001; Li et al., 2013a). Commonly, spatial pattern indices, including landscape metrics, have been applied to land cover types. Any change could be perceived by examining variations of the metrics over time. This type of spatio-temporal pattern analysis can be regarded as “temporal trajectory analysis of spatial pattern indices”. Although landscape metrics have provided a reliable tool for quantifying the spatial structure of a landscape and for tracing the turning point of a change, several shortcomings are also evident. The method does not adequately display the spatial dynamics of the change. Finally, difficulties also exist in change prediction and with determining the linkage between the pattern and the process of land cover change (Li and Wu, 2007).

In contrast to most studies that apply spatial pattern indices to land cover types, the landscape metrics adopted in this study were instead applied to change trajectory categories, such as the pattern of expanded farmland since 2000 (Fig. 5), or the accumulated stable farmland in 2010 (Fig. 6). Spatial, rather than temporal, dynamics of farmland change was modelled, as well as change models developed using cartographical and quantitative means. By focussing on change trajectory categories, this study attempts to combine the ecological significance of landscape metrics with the interpretation of spatial patterns. In real world applications, the spatio-temporal modelling method provides a general information of farmland development model and its spatial distribution details as well. It is better for understanding how farmland developed over time. This would benefit managers or local government. An efficient plan of land use development and water consumption could be carried out, relying on the knowledge of the general change model and quantified indices of change spatial pattterns.

4.3. Known issues of uncertainties

Potential uncertainties were inherent at two major stages of this study, namely, during the establishment of change trajectories and during the spatial pattern analysis. Establishment of change trajectories is the fundamental stage. Long-term temporal trajectory analysis usually requires the utilisation of multi-temporal and multi-sensor images, which may incur problems such as unmatched image parameters. In order to minimize the impacts of radiometric calibration among images with different acquisition conditions and sensors, the images were classified independently. The accuracy of the classification, therefore, may be propagated to the later-stages of image processing, thus having a significant impact on the image comparison results (Coppin et al., 2004). The accuracy of trajectory analysis might be even more problematic when numerous multi-temporal data layers were used in the analysis (Congalton and Green, 2009). Furthermore, because changes within the period of two observations cannot be detected, selecting the most appropriate time scale is critical for trajectory-based change detection (Lunetta et al., 2004; Sui et al., 2008). Given the difficulties of acquiring successive images, a one-year interval is considered to be suitable for detecting annual changes in this study.

The interpretation of landscape metrics could create misunderstandings about land cover change patterns. Given that most landscape metrics were designed to describe the spatial pattern of individual species or cover types, their application to the change patches should be subjected to further interpretation in order to obtain a better understanding of the findings. This study indicates that it is essential to use a set of metrics, rather than a single one, to provide a more comprehensive view of the various characteristics of the target features, thus avoiding potentially controversial outcomes. Moreover, attention should be paid to spatial scale effect when applying landscape metrics to measure spatial patterns. The results of spatial analysis at one scale are frequently different from the analysis at another scale (Li and Wu, 2007). For modelling water-oriented farmland change, the study is limited to the river basin scale, which means farmland expansion models in the two river basins are separated and regarded as individual cases.

5. Conclusions

This study investigates a methodology for integrating pixel-based trajectory analysis and landscape metrics to quantify and analyse the spatio-temporal pattern of farmland change in the arid zone of western China. Results indicate that the rapid development of farmland exhibits a concentrated pattern within two river basins, and generally follows a layer-based expansion model in multiple directions. At the river basin scale, the proposed method is effective in expressing the spatio-dynamic process of farmland change and in highlighting the farmland development model.

The study also provides several important conclusions about the research methodology that was adopted. A set of carefully selected metrics is the key to understanding the spatial pattern of farmland change in all its different aspects. Also, the choice of temporal interval is critical, because it determines the kind of change that may be detected. Given the arguments that the results of spatial analysis might not be uniform at various spatial scales, future work will be focused on applying the methodology to sub-catchments of the river basins.

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