

MODELLING SPATIO-TEMPORAL PATTERN OF LANDUSE CHANGE USING MULTITEMPORAL REMOTELY SENSED IMAGERY

Qiming Zhou^{1,2}, Baolin Li³ and Bo Sun¹

¹ Department of Geography, Hong Kong Baptist University, Kowloon Tong, Hong Kong SAR, China
E-mail, pp. qiming@hkbu.edu.hk

² State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University
129 Luoyu Road, Wuhan, Hubei 430079, China

³ State Key Laboratory of Environment and Resources Information System,
Institute of Geographical Sciences and Resources Research,
Chinese Academy of Sciences Beijing, 100101, China

KEY WORDS: Multitemporal Image Processing, Change Detection, Change Trajectory Analysis, Land Cover, Aridzone

ABSTRACT:

Remotely sensed data is the most important data source for environmental change study over the past 40 years. Since large collections of remote sensing imagery have been acquired in a time frame of successive years, it is now possible to study long-term spatio-temporal pattern of environmental change and impacts of human activities. This study seeks an efficient and practical methodology for landuse monitoring and spatio-temporal pattern analysis by integrating multitemporal remotely sensed data in a monitoring time frame of 13 years at the middle reach of Tarim River in the aridzone of China. Multi-source and multi-scale remotely sensed images are used, including multispectral images acquired by Landsat 5 and 7, China-Brazil Earth Resources Satellite (CBERS) and Beijing-1 (BJ-1). The temporal trajectories of landuse change have been established for analysing its spatial pattern for a better understanding of the human impact on the fragile ecosystem of China's arid environment. This study analyzed spatial pattern of landuse change trajectories based on the post-classification comparison method. All images were classified into 5 to 6 classes, which were then combined into two main classes, namely, farmland and the others. Area statistics and temporal trajectories of changed farmland were then derived using the classification results. The result shows that in the study period of 13 years, the farmland has increased over two times with an annual growth rate of over 10%. It is also shown that farmland abandon was significant in some areas due to some environmental issues such as shortage of water resource and salinity. Using the method, one can re-establish the history of landuse change and related such change with other environmental and socio-economic data, so as to gain better understanding on the response of natural environment to the human impact that may be introduced as the consequence of economic development and government policies.

1. INTRODUCTION

Landuse and land cover change (LUCC), associated with climate changes have become a focus of the study on the interactions between human activities and natural environment. Land cover change can be regarded as one of the most sensitive indicators that echo these interactions (Zhou *et al.*, 2008). Especially in an arid environment where the ecosystem is always considered to be fragile, land cover change often reflects the most significant impact on the environment due to human activities or natural forces. Remote sensing can be a good tool for getting wide impression on land cover change. In decades, remotely sensed data have been used for environmental change study and great efforts have been made to analyze changes of environmental elements and impacts of human activities.

Change detection on land cover focuses mainly on four aspects, pp. (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 spatial pattern of the change is regarded as a good indicator of the impact by the other three aspects, its research has become quite active in change detection study (Nagendra *et al.*, 2004).

Many remote sensing change detection methods have been developed to monitor land cover change and to build spatio-temporal patterns of change, in order to derive better

understanding of causes and consequences of the change, and to model the tendency of the change. In general, remote sensing change detection methods can be divided into two broad classes, termed as bi-temporal change detection and temporal trajectory analysis (Coppin *et al.*, 2004). The former is based on the comparison between two dates, and the latter analyzes the tendency of change in a multiple epoch or a continuous time scale.

Techniques have been developed to support these two categories of change detection methods. For example, the commonly used methods of image differencing and image ratioing detect land cover change by comparing images acquired on two different dates using the difference or ratio of digital number values of the images (Lillesand *et al.*, 2004; Coppin *et al.*, 2004). For trajectory analysis, the time series analysis of NDVI (Normalized Difference Vegetation Index) is widely used for modelling land cover change (e.g. Petit *et al.*, 2001; Hayes and Cohen, 2007). The trajectory analysis is typically based on the imagery with high temporal, but often low spatial, resolution such as MODIS.

With the accumulation of remotely sensed images over the past decades, it is now possible to analyze the spatial pattern of land cover change over a long period using images with a higher spatial resolution and multitemporal coverage. A time series analysis of multitemporal images will be helpful to understand the sequence patterns of land cover change during the long

period and to forecast the trend of changes in future (Tottrup and Rasmussen, 2004; Liu and Zhou, 2005). However, to understand causes of land cover change, study often focuses on the metrics (e.g. Crews-Meyer, 2004, 2006) of land cover types that form a part of input parameters together with other environmental or human factors. Further research is therefore needed to develop a methodology that quantifies the spatial pattern of change trajectories so that spatio-temporal pattern of the change can be better described and its relation to environmental and human factors may be further explored (Zhou *et al.*, 2008).

For aridzone management, ability to detect successive land cover changes is considered essential since the fragile ecosystem in the arid environment may be frequently changed in response to the changing conditions. With the accumulation of mid- or high-resolution imagery, an integrated method of bi-temporal change detection and temporal trajectory analysis seems to be a practical solution to provide details on the spatio-temporal pattern of land cover change.

This research aims to investigate the environmental impacts due to rapid expansion of cultivated land in the marginal area of aridzone in western China. With the implementation of China's national 'Western China Development' Strategy, the rapid economic growth has been significant in the past decade. This growth, however, has fundamentally based on the large consumption of natural resources such as land and water, which in turn created great impact on the arid environment where the ecosystem is fragile and vulnerable due to the harsh natural conditions.

In order to find the balance of economic growth and environmental conservation to achieve sustainable regional development, this research is needed to investigate on what happened in the past and the trend of change in the near future.

2. METHODOLOGY

The method of this study is based on post-classification comparison approach, which is commonly employed in remote sensing change detection studies. 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 further reclassified according to the nature of land cover changes.

2.1 Study Area and Data Used

The study area is centered at Yuli County, Xinjiang Uygur Autonomous Region of China. (Figure 1) It locates at the middle reach of 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 aridzone of China. The landscape is typical in China's aridzone, with a generally dry and harsh environment, represented by typical desert vegetation and soils.

Since early 1990's, the national and local governments' policy has stimulated considerable investment on irrigated agriculture in the fringe area of the Taklimakan Desert. The irrigated farmland has been trebled, mainly by converting lands originally covered by natural rangeland vegetation into irrigated cotton fields. However, this has also raised serious questions on

whether this rapid growth can sustain given the intensified competition on water resources. When the supply of water become unsustainable, then the newly cultivated farmland will most likely be abandoned, leaving the sandy bare soil exposed to the strong seasonal wind without the protection of original rangeland vegetation.

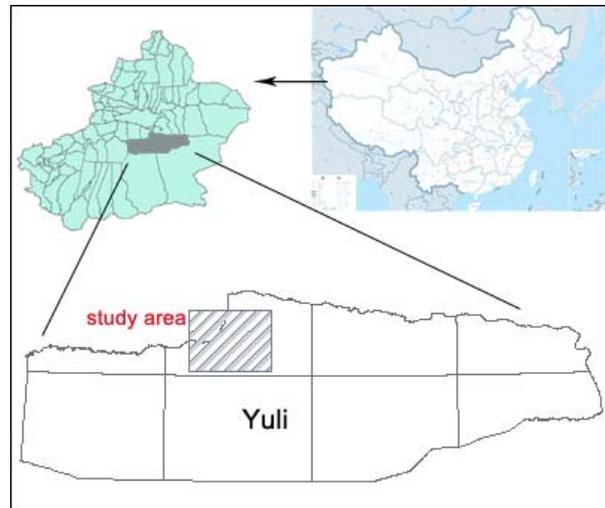


Figure 1. The study area (as shown in the shaded area that is covered by the images used for this study).

Five multispectral remotely sensed images from Landsat TM/ETM, CBERS and BJ-1 CCD data have been acquired for this study. The images cover most farmlands of Yuli County surrounded by desert and Gobi (stony desert). The overwhelming majority of the farmlands in Yuli is cotton fields, where the growing season is from April to October. Accordingly, the images used for this study were acquired in August or September to cover the period where the contrast between farmlands and other land cover types is high in the spectral region covered by the multispectral images (Table 1).

Satellite	Sensor	Resolution (m)	Date
BJ-1	CCD	32	31/8/2007
BJ-1	CCD	32	10/8/2006
CBERS 2	CCD	19.5	15/9/2005
Landsat 7	ETM	28.5	17/9/2000
Landsat 5	TM	30	25/9/1994

Table 1. Image data used in this study.

2.2 Image Processing

Image registration

The 2005 CBERS image was registered and geo-referenced based on the topographic map at a scale of 1:50,000. The other images were then geometrically corrected and registered using image-to-image registration using the 2005 image as a master. Efforts have been made to control the registration errors within half a pixel of the correspondent image so that the errors of change detection caused by mis-registration are less critical. The adopted coordinate system is Transverse Mercator with central meridian of 87°.

Classification

A supervised classification method using the Maximum Likelihood classifier is employed to classify these five images independently. Each image was classified into 5 to 6 classes independently to delineate land cover types. The land cover classes were then recoded and merged into only two classes, namely, farmland and the others. A post-classification process was applied to the unified classification results to remove isolated pixels using a majority filter with a 3×3 window.

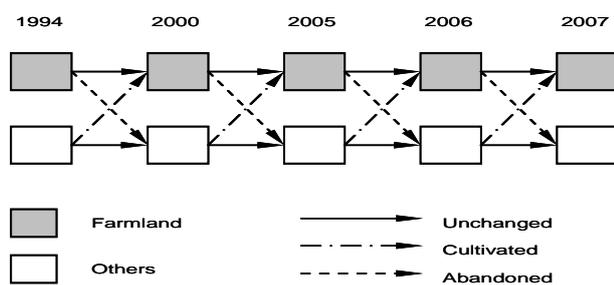
In order to make the image data comparable at the same spatial resolution so as to establish change trajectories at the pixel level, all the images need to be resampled to a 30m resolution after classification.

Accuracy Assessment

The standard method of error matrices is used to assess classification accuracy for each image date. Both overall accuracy and kappa index are computed as the accuracy assessment indices. The accuracies of these classified images are assessed independently. For each classified image, more than 200 sample points including farmland and the others are randomly located on the original image with the reference to the field investigation data as the reference data set.

2.3 Pattern Analysis of Landuse Trajectories

The focus of this study is the change of farmland in the study area. According to the field investigation and some other literatures, the majority of the farmland in this region is cotton fields, which is also the decisive factor on the demand of water resource – the fundamental constraint on the sustainable development of the region, so that the change between different crops is not concerned. Thus, the landuse trajectory in this research is simply defined as the situation of changes between farmland and the other land cover types. A trajectory can be specified as o-o-c-c-c, meaning that the land was not cropped in 1994 and 2000, transformed to farmland in 2005, and remained as cultivated in 2006 and 2007. For the five-epoch, two-class scenario, the total number of possible trajectories is 32 (2⁵). Figure 2 shows all possible landuse change trajectories and the meaning of changes based on this classification scheme.



To establish and analyse landuse change trajectories, all classified images are integrated in geographical information system (GIS) using ArcGIS software with a raster format

Figure 2. All possible landuse change trajectories based on the classification scheme used in this study.

3. RESULTS

3.1 Classification and Area Statistics

The spatial registration accuracy for the images is adequate for this study with RMSE less than 0.2 pixels. On the basis of the

assessment on only two combined classes, the classifications have shown high accuracy between farmland and the others. The overall accuracy of image classification ranges from 88.9% to 95.2%, with kappa coefficient ranging from 0.76 to 0.90 (Table 2).

Image	Overall Accuracy (%)	Kappa
2007 (BJ-1)	92.5	0.837
2006 (BJ-1)	90.7	0.799
2005 (CBERS 2)	88.9	0.762
2000 (ETM)	95.2	0.896
1994 (TM)	93.8	0.877

Table 2. Classification accuracy assessment

Table 3 shows the area statistics of farmland, which are compared with some reference data found in government statistic books. It should be noted that the reference data do not include some isolated administrative units in this study area, so that some differences in the statistics between image and reference are expected.

Statistics based on image classification		
Year	Area (k ha)	% of total area
2007	43.5	11.7
2006	36.1	9.5
2005	34.4	9.0
2000	23.5	6.1
1994	12.2	3.2
Reference data (the whole country)		
Year	Area (k ha)	Cotton (%)
2007	35.5	99.3
2006	32.0	98.7
2005	28.0	97.2
2001	20.0	88.0

Table 3. Area statistics of farmland and the comparison between image and reference data

Source of reference data, pp. Bureau of Statistics of Yuli Country (<http://tjj.xjzb.gov.cn/html/xstj/652823/2007918163639.htm>; <http://tjj.xjzb.gov.cn/html/xstj/652823/20061025182742.htm>).

The results show that during the 13-year period from 1994 to 2007, the area of permanent farmland has increased from 12,190 to 43,470 ha, occupying from 3.2% to 11.7% of the total study area. More significantly, the increasing rate has been alarming. During the earlier period of 21 years from 1973 to 1994, the area of farmland has increased by about 12,000 ha (before 1973, there was almost no farmland in this area) (Zhou *et al.*, 2008). In comparison, during the 13 year study period, the area of farmland has increased by over 31,280 ha, with average annual growth rate of 10.3%. Especially, the average growth rate reaches to 12.3% in the last three years.

3.2 Landuse Change Trajectories

Figure 3 shows the spatial pattern of the area expansion of farmland in the study area. Generally speaking, the expansion of

farmland is mostly associated with the existing old farmland. The recent acceleration of cultivation is clearly shown by the large area of new cultivation in the fringe agricultural area, and along the river-bed where seasonal flood prevents land being cultivated previously.

Table 4 lists some major trajectories of landuse change. Besides dominant trajectories of farmland expansion, the trajectories of abandoned farmland are also shown. Besides these, there are some marginal trajectories (i.e. the land cover changed forward and backward between farmland and others) that account for about 3.3% of the total area.

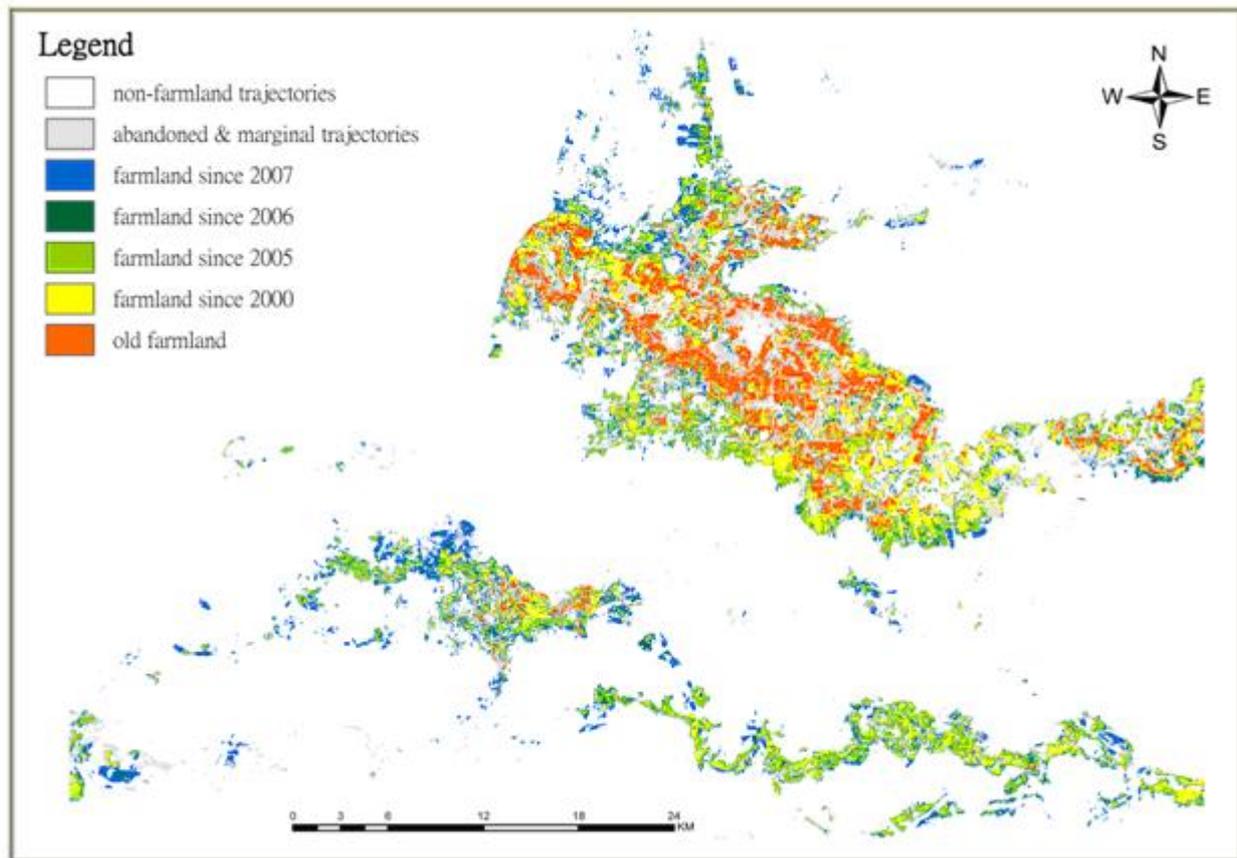


Figure 3. Farmland trajectories in the study area from 1994 to 2007.

Trajectory (07-06-05- 00-94)	Description	Area (k ha)	%
XXXXX	old farmland	6.76	2.02
XXXXO	farmland since 2000	7.17	2.14
XXXOO	farmland since 2005	8.55	2.55
XXOOO	farmland since 2006	3.27	0.98
XOOOO	farmland since 2007	7.88	2.35
OXXXX	abandoned since 2007	1.11	0.33
OXXXX	abandoned since 2006	0.15	0.05
OOXXX	abandoned since 2005	0.25	0.07
OOOOX	abandoned since 2000	0.35	0.10
OXOXO	marginal trajectories	10.91	3.26
...			
OXXXX	non-farmland trajectories	288.70	86.15
Total		335.10	100.0

(where cover type "X" = farmland; "O" = others).

Table 4. Trajectories and their areas of farmland change

4. DISSCUSSION

With the constraint of image data acquisition, it is impossible to acquire multitemporal images of same kind over the 13 year study period. Post-classification comparison method has therefore been employed to cope with the multi-sensor multitemporal images. The principal advantage of the post-classification comparison method is that the images acquired on different dates by different sensors are independently classified, so that the problems of radiometric calibration among images of different dates by different sensors are minimized. However, It has been argued that the post-classification comparison method may overestimate land cover change due to uncertainties in data (Vanoort, 2005), including those by errors in image registration and classification, and misunderstanding of trajectories. The final accuracy of the post-classification comparison and trajectory analysis is largely dependent upon the accuracy of the initial classifications (Coppin, 2004).

In this study, land cover types have been delineated through image classification. When assessing the accuracy of classification, reference data sets have been acquired through visual interpretation of images with the assistance of field data. Ideally error assessment when using post-classification comparison method should follow the traditional error assessment method using simultaneous ground reference data

(Liu and Zhou, 2004). Nevertheless it is argued that sampling on typical visual interpretation keys for general classes such as farmland and others would be sufficient for obtaining high-quality reference data sets for classification accuracy assessment.

According to the statistics provided by bureau of statistics of Yuli Country (Table 3), the dominant crop of the region is cotton and its domination has been increasing, accounting for 88.0% of farmland in 2001 to 99.3% in 2007. This clearly reflects the impact of government policy in the pass years that regards cotton production as one of the major "growth points" in the regional economic development.

Large-scale commercial cotton cropping has obviously increased demand on natural resources, particularly the water resource. When the shortage of water supply happens, newly cultivated farmland is more likely to be abandoned. In the year of 2007, the highest expansion rate of new cultivation was observed, while the area of abandoned farmland also reached to the largest. It is therefore alarming that the rapid expansion of agricultural land may not be sustainable and the abandoned farmland is at great risk to desertification.

It is also noticed that 23.5% of the total farmland trajectories are classified as "marginal". The trajectories of this kind may reflect three scenarios:

1. The marginal farmland that has been cultivated and abandoned in succession, where the agriculture infrastructure (e.g. irrigation system) typically is not well established,
2. The temporary small farmland areas in the fringe of the desert, and
3. The image processing uncertainties due to registration and classification errors.

Given the fact that the total water resource in the study area has not significantly changed in the last decades, the area of farmland has perhaps reached its limit in this region. Unless much more significant measures are in place to increase efficiency of water use (e.g. the introduction of more advanced irrigation techniques), the stress caused by the unbalanced demand and supply of water resource is expected to be worsened if the current trend of farmland expansion continues.

5. CONCLUSIONS

This study has demonstrated a trajectory-based approach to monitor and analyze landuse change in aridzone. In the environment, the supply of arable land has been considered to be unlimited but use of such land is severely limited by the supply of water. Our approach does not only consider the spatial pattern of expanding farmland, but also take care of situation of the process of land cover change (or temporal patterns of farmland expansion). Through using multitemporal images, the causes and consequences of farmland expansion can be better monitored and analysed, so as to provide better clues for the solution of sustainable development in such fragile ecosystem.

The results show that farmland has rapidly increased in Yuli during the 13 year study period. In contrast, signs have been shown that the lack of water supply has resulted in farmland abandon that could cause severe land degradation due to salinity and wind erosion. Although challenges remain with numerous research questions unanswered, the study nevertheless encourages further effort to develop more advanced

methodology for establishing more robust and reliable spatial pattern indicators, so that spatio-temporal pattern of landuse change can be better understood. The aim of further studies is also on the regional balance of water resources, corresponding to the dynamic change of landuse and crop cover.

ACKNOWLEDGES

The research is supported by National Key Basic Research and Development Program (2006CB701304), Research Grants Council Competitive Earmarked Research Grant (HKBU 2029/07P), and Hong Kong Baptist University Faculty Research Grant (FRG/06-07/II-76).

REFERENCES

- Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B. and Lambin, 2004. Digital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing*, 25(9), pp. 1565–1596.
- Crews-Meyer, K.A., 2004. Agricultural landscape change and stability in northeast Thailand: historical patch-level analysis. *Agriculture Ecosystems & Environment*, 101, pp. 155-169.
- Crews-Meyer, K.A., 2006. Temporal extensions of landscape ecology theory and practice: examples from the Peruvian Amazon. *Professional Geographer*, 58(4), pp. 421-435.
- Hayes, D.J. and Cohen, W.B., 2007. Spatial, spectral and temporal patterns of tropical forest cover change as observed with multiple scales of optical satellite data. *Remote Sensing & Environment*, 106, pp. 1-16.
- Liu, H. and Zhou, Q., 2004. Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison. *International Journal of Remote Sensing*, 25(5), pp. 1037-1050.
- Liu, H. and Zhou, Q., 2005. Developing urban growth predictions from spatial indicators based on multitemporal images. *Computers, Environment & Urban Systems*, 29, pp. 580-594.
- Lillesand, T.M., Kiefer, R.W. and Chipman, J.W., 2004. *Remote Sensing and Image Interpretation* (Fifth Edition). Wiley, New Jersey.
- MacLeod, R.D. and Congalton, R.G., 1998. A quantitative comparison of change-detection algorithms for monitoring eelgrass from remotely sensed data. *Photogrammetric Engineering & Remote Sensing*, 64(3), pp. 207-216.
- Nagendra, H., Munroe, D.K., Southworth, J., 2004. From pattern to process: landscape fragmentation and the analysis of land cover/land cover change. *Agriculture, Ecosystems & Environment*, 101, pp. 111–115.
- Petit, C., Scudder, T. and Lambin, E., 2001. Quantifying processes of land-cover change by remote sensing resettlement and rapid land-cover changes in south-eastern Zambia. *International Journal of Remote Sensing*, 22(17), pp. 3435-3456.
- Tottrup, C. and Rasmussen, M.S., 2004. Mapping long-term changes in savannah crop productivity in Senegal through

trend analysis of time series of remote sensing data.
Agriculture, Ecosystems & Environment, 103, pp. 5445-560.

Vanoort, P.A.J., 2005. Improving land cover change estimates by accounting for classification errors. *International Journal of Remote Sensing*, 26(14), pp. 3009-3024.

Zhou, Q., Li, B. and Kurban, A., 2008. Trajectory analysis of land cover change in arid environment of China, *International Journal of Remote Sensing*, 29(4), pp. 1093-1107.