

VEGETATION TRAJECTORY ANALYSIS OF THE RIPARIAN ECOSYSTEM IN THE LOWER REACH OF TARIM RIVER IN NORTHWEST CHINA

Alishir Kurban^{1,3*}, Han-ming Duan², Xi Chen¹, Maryamgul Abdurahman^{1,3}, Abdimjiti Ablekim¹, Mahmut Barat⁴

1 Xinjiang Institute of Ecology and Geography, Chinese Academy of Science, Urumqi 830011, Xinjiang, China;

2 College of Land and Resources, China West Normal University, Nan Chong, 637002, Sichuan, China;

3 Graduate University of the Chinese Academy of Sciences, Beijing 100049, China

4 Administration Bureau of Tarim River Basin, Korla 841000, China

Abstract: Tarim River, flowing through Xinjiang Uygur Autonomous Region, is the longest inland river in China. The riparian ecosystem in the well-known ‘green corridor’ of the lower reach of Tarim River ebbed constantly from 1950s as the consequences from expansion of farmland and construction of the Dashkol reservoir which blocked the stream in 1972. In 2000, the ‘green corridor’ riparian ecosystem was temporally re-linked to its original water source by the initiation of the “emergency ecological water transfusion project” after frequent disruption in the past 28 years. This paper analyzed the processes and trends of the vegetation change during the period of intermittent water transfusion, based on multi-temporal remotely sensed data. According to the acquisition time and image quality, the representative image, acquired by China-Brazil Earth Resources Satellite (CBERS), for each year was chosen. The images were classified into land cover types as vegetation and non-vegetation using a pre-determined SAVI threshold. Vegetation cover change trajectory at each pixel was then established using the multi-temporal, classified images. Based on the nature of change shown by the trajectories, all possible 64 trajectories were then characterized into five classes, namely, stable non-vegetation, stable vegetation, change into vegetation, change into non-vegetation and unstable changes. Based on the analysis of the spatial distribution of different change tendencies and the change process discovered by the change trajectory, as well as the findings from ground investigation, the vegetation composition and the causes of its change during the study period can be inferred. The result indicates that 7.9% of the study region shows the tendency of change to vegetation, resulted from the growth of herbage and refresh of weakened shrub. Only 2.7% has changed to non-vegetation. The unstable change, however, occupied 10.4%, suggesting the frangibility of native vegetation. The analysis of change process, supplemented by ground investigation and GIS analysis, shows that the change to vegetation mainly took place in lower lands since 2003, when the quantity of water transfusion was peaked. The study

demonstrates that temporal trajectory analysis is a promising method for the monitoring on the processes and trends of vegetation change in arid zone, where vegetation response to the natural condition change is sensitive. Moreover, the use of free CBERS imagery reduces the cost of data acquisition and analysis, so that the sampling frequency in space and time by remotely sensed data can be greatly improved.

Key Words: process of vegetation change; temporal trajectory analysis; the lower reaches of Tarim River; CBERS/CCD

Introduction

The monitoring of vegetation restoration is an important aspect of vegetation change detection specifically in the restoring and reconstructing a damaged ecosystem. Remote sensing is a mainstream technology for vegetation monitoring in some spatial scale. Because remote sensing almost observation the vegetations located differed space site at the same time; and more important, the observation of remote sensing could perform periodically; the another advantage is cheaper for data acquirement.

Change detection of vegetation based on remotely sensed data usually aim to obtain the three aspects information: location of change, the direction (from-to) and the process (how change). The process information is even more important for vegetation restoration monitoring. Because it is useful to analyze the driving of ecological factor to vegetation, along with the ecological factor own change.

Different Change detection approaches have its emphases on different change information. At present, most detection methods belong to the bi-temporal change detection approach, measuring land cover changes based on a 'two-epoch' timescale, i.e. the comparison between two dates. In general the aim of bi-temporal change detection is to obtain details of 'change/no change' or 'from-to' information in between the detection dates^[1]. To obtain the progress information of change over the period, temporal trajectory analysis have been developed and applied, by constructing the 'curves' or 'profiles' of multi-temporal data^[2]. Due to the limitation of data accessibility and computing capacity, the temporal trajectory analysis is mostly based on low spatial resolution and high temporal resolution images such as AVHRR and MODIS^[2].

It is possible to balance the temporal and spatial resolution for change process monitoring, along whit the costs reducing of data acquisition and analysis and the improvement of computing capacity. So far, some research based on high spatial resolution data such MSS, TM/ETM+, SPOT ^{[1][3][4]} have been finished.

This study build up the temporal trajectory of image pixels based multi-temporal remote sensing datum; and the main aim is to monitor the process and tendencies of vegetation restoration. In the temporal trajectory, every pixel could transform between vegetation style and non-vegetation style among five years, in which year water condition in study area changed evidently.

Methodology

Study area

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This study focus on the vegetation restoration in the lower reach of Tarim River, which range is at about 87°30'~88°40'E,39°20'~40°40'N; locates at the Lower Reaches of the Tarim River, from the Dashkol Reservoir to Lake Taitema, between the Taklamakan and the Kuruk deserts(fig.1). This region is extremely arid with annual precipitation less than 50mm, but potential evaporation more than 2000mm per annum^[5]

Tarim River, flowing through Xinjiang Uygur Autonomous Region, is the longest inland river in China. The riparian ecosystem in the well-known ‘green corridor’ of the lower reach of Tarim River ebbed constantly from 1950s as the consequences from expansion of farmland and construction of the Dashkol reservoir which blocked the stream in 1972. In 2000, the ‘green corridor’ riparian ecosystem was temporally re-linked to its original water source by the initiation of the “emergency ecological water transfusion project” after frequent disruption in the past 28 years.

In the past half a century, the vegetation decayed distinctly due to the drying of river. From 2000, vegetation restored gradually along with the replenishment of water. For restoration the vegetation, the central government of China committed a total of 10.7×10^9 Yuan (RMB) for implementation of an emergency project conveying water to the Tarim River. Water was discharged from Dashkol Reservoir one time per year from 2000(It was two times in 2000). After ecological water transfusion, the level of groundwater rises obvious along the dried-up watercourse in the Lower Reaches of the Tarim River^[6]; accordingly, the riparian vegetation shows improvement to a certain degree.

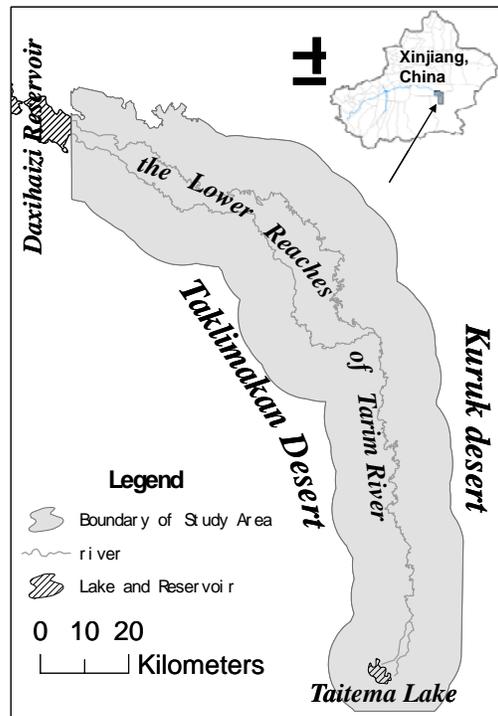


Image Preprocessing

The China Brazil Earth Resources Satellite (CBERS) CCD images was collected for this area from 2000 to 2005. The CCD Camera taken by CBERS has five spectral bands; the wavelength range of each band is displayed as follows, 0.45-0.52 μm , 0.52-0.59 μm , 0.63-0.69 μm , 0.77-0.89 μm , and 0.51-0.73 μm ; the spatial resolution is 19.5 meters. The path/row numbers of CCD images covering our study area are 30/55, 30/56, 31/55. All images acquired are level 2 product, which have been radiometrically and geometrically corrected using systematic model. Excellent images once a year were selected from candidate images according to accepting data and image quality.

All images selected to analyze were performed spatial matching based image-to-image registration approach (table.1). The GCPs in every CCD image was not less than 30; Quadratic polynomial was used to geometric correction and the Root Mean Square errors should not be more than one pixel. The images were resampled through the nearest neighbor method.

Table.1 The path and row numbers of CBERS/CCD images and their acquired dates

Year Path/Row	2000	2001	2002	2003	2004	2005
30/55	08.17	07.21	10.06	07.19	08.30	10.20
30/56	08.17	07.21	10.06	07.22	08.30	09.24
31/55	08.14	08.13	08.12	07.22	08.27	09.21

Vegetation signal extraction

For constructing the temporal trajectory of vegetation restoration, CBERS/CCD images were classified into vegetation and non-vegetation at first. In the classification system, “vegetation” contains all kinds of vegetations; water, bare land, build-up land and other non-vegetation area all were regarded as “non-vegetation”.

Classification was performed using Soil Adjusted Vegetation Index (SAVI)^[7] threshold. SAVI was developed specially to extract vegetation signal in the sparse vegetation region, and this feature of SAVI even accord with the status of our study area. The SAVI could be expressed as formula (1),

$$\text{SAVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}}(1 + L) \quad \text{Formula(1)}$$

Where, NIR and R mean the near-infrared band and visible red band respectively. In the case of CBER/CCD, the near infrared layer is band 4 and the visible red layer is band 3; and 0.5 was adopted for the L value.’

Through an SAVI threshold, which should be the biggest SAVI of non-vegetation pixel or the least one of vegetation pixel, every image was classified into vegetation and non-vegetation, and transformed to a binary-map(fig.2). Because the images were not normalized on radiometric character, it should not to use the same threshold to classify all images. Every image were extracted its own threshold respectively. The threshold was ascertained by direct human interpretation base on the colors and spatial pattern of CBERS/CCD itself and the interpretation result of SPOT covering the same area; prior knowledge of study area was used indirectly to determine the SAVI threshold.

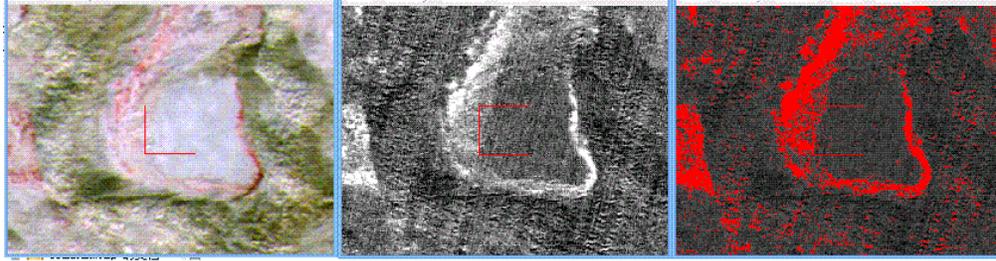


Fig.2 CBERS/CCD image (left) was classified into vegetation (red area in right image) and non-vegetation (black area)

Classification accuracy assessment

All CBERS/CCDs were shot in the past, so the classification could not be validated using ground synchronous sample. At the same time, there is no higher spatial resolution for reference. The CBERS/CCD images themselves are the only source for accuracy assessment. The results of direct human interpretation were used to evaluate accuracy^[4].

Sample size was determined using the standard formula^[8]: $N = Z^2 \times P \times (1 - P) / E^2$, where $Z = Z$ value (e.g., 1.96 for 95% confidence level), $P =$ expected accuracy, and $E =$ allowable error. For 80% accuracy, 95% confidence level, and 5% margin of error, so 246 is the least sample size. In fact, a sample of 271 pixels was selected from each year. We used the same points to interpret in different year based on the color and spatial character for evaluating the accuracy of classification in corresponding year. The results of accuracy assessment were displayed as table.2. The overall accuracy of every year overruns 80%. Such accuracy is acceptable considering that there are just two classes in the classification system.

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Table .2 Accuracy assessments of classification based on direct image interpretation

year	random points' gross	Wrong point	Accurate point	overall accuracy
2000	271	28	243	89.67%
2001	271	29	242	89.30%
2002	271	31	240	88.56%
2003	271	39	232	85.61%
2004	271	24	247	91.14%
2005	271	31	240	88.56%

Construction and classification of temporal trajectory

The temporal trajectory of land cover displays the process of land cover change between different classes along with the passing away of time. It could be expressed as ranks composed of different land cover classes that the pixel belonged to in the given time. In this study, for example, the temporal trajectory of land cover in some pixels could be expressed as 'n→n→n→n→v→v' (n=non-vegetation, v=vegetation). (Fig 3).

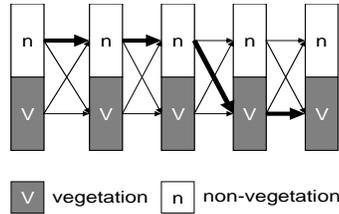


Fig.3 All possible trajectories of land cover change. In the fig, the trajectory highlighted means that the land cover belonged to non-vegetation in the first four years, but converted to vegetation in last two years.

The total quantity of potential temporal trajectories could be calculated by follow formula: $N_t = n \times n \times \dots \times n = n^m$, Where N_t means the total quantity of potential temporal trajectories; n means the quantity of classes in the classification system; m means the times adopted to monitor the change. In this study, $n=2$ and $m=6$, so $N_T=64$.

Trajectory of every pixel was constructed through image calculation among the vegetation/non-vegetation binary-maps of 6 years. The result is a temporal trajectory map, in which every pixel has a code corresponding to its trajectory.

These 64 trajectories were further characterized into 5 categories (Fig.2) according to the trends of changes.

(1) Stable non-vegetation. This category means the land cove always belong to non-vegetation and no vegetation restoration occur among study period. The trajectory could be expressed as ‘ $n \rightarrow n \rightarrow n \rightarrow n \rightarrow n$ ’.

(2) Stable vegetation. The class of land cover always belong to vegetation. The trajectory is ‘ $v \rightarrow v \rightarrow v \rightarrow v \rightarrow v$ ’.

(3) Change into vegetation. It means land cover changes from non-vegetation at initial stage into vegetation laterly. This trend means vegetation restoration occur. The typical trajectory is ‘ $n \rightarrow n \rightarrow v \rightarrow v \rightarrow v$ ’. Sometimes, land cover maybe change into non-vegetation in the middle one or two years, but recovers to vegetation next year. These cases were seen as ‘change to vegetation’ too, such as ‘ $v \rightarrow n \rightarrow v \rightarrow v \rightarrow v$ ’.

(4) Change into non-vegetation. This trend indicates degradation of vegetation. The typical trajectory is ‘ $v \rightarrow v \rightarrow v \rightarrow v \rightarrow n$ ’.

(5) Unstable change. All other trajectories, which were not classified into above four categories, were seen as ‘unstable change’. These trajectories have no a clear trend. The classic trajectory is ‘ $v \rightarrow n \rightarrow v \rightarrow n \rightarrow v$ ’.

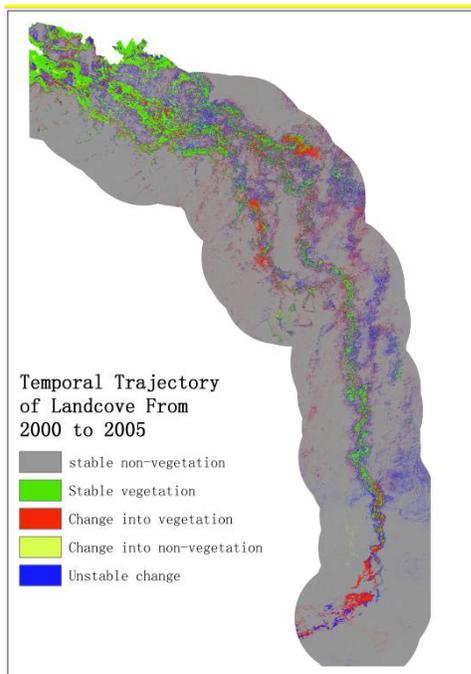


Fig.4 Temporal Trajectory of land cover from 2000 to 2005 in the lower reaches of Tarim River

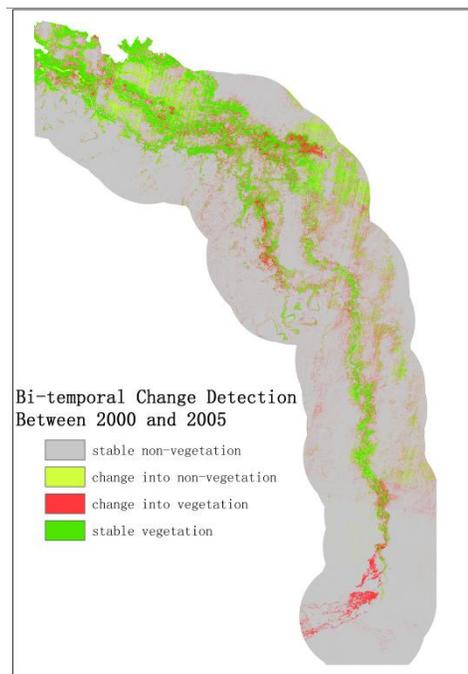


Fig.5 Change direction of land cover from 2000 to 2005 detected by bi-temporal change detection approach

Results and discussion

The change of vegetation acreage

The acreage of vegetation and non-vegetation every year was counted from the vegetation/non-vegetation binary-maps (table.3). It was found that the vegetation acreage increased with the increase of the water transfusion times; this situation indicated the existence of vegetation restoration. However, the minimum occur in the second year rather than the first year between water transfusions. It means that degeneration of vegetation occur in the early years despite the surface water was supplied. Therefore, the change trend and process was nonlinear.

Table.3 Statistics of vegetation and non-vegetation area between 2000~2005

Year(km ²)	2000	2001	2002	2003	2004	2005
					1058.9	1002.3
Vegetation area	852.06	636.36	883.44	725.93	4	4
Non-vegetation area	4189.6	4405.3	4158.2	4315.7	3982.7	4039.3
	0	1	2	4	2	2

Nonlinear change among study period indicated that some change could not be opened out through classical bi-temporal change detection approach; it is particular to change process. We should explore a new approach to reveal more detail of vegetation change.

The quantities of different trends of land cover change

The quality attribute of different change trends were compiled based the temporal trajectory map (table.3). We could find that ‘stable non-vegetation’ occupy an overwhelming advantage, which is coincident with the sparseness of vegetation in this arid area. The proportion of ‘change into vegetation’ is 7.94%, which is considerable comparing with ‘stable vegetation’. It means that vegetation restoration is marked during water transfusions. The proportion of ‘change into non-vegetation’ is only 2.66%, which shows that the degeneration of vegetation was not severe. The surpassing of ‘change into vegetation’ on ‘change into non-vegetation’ would result of vegetation restoration, which inference is coincident with last section’s discovery. In addition, 10.43% pixels belonged to ‘unstable change’.

The difference between temporal trajectory analyze and classical approach

The difference between temporal trajectory analyzes and classical approach are more concerned. So the quality attribute of different change direction between 2000 with 2005, picked up by bi-temporal change detection approach were displayed for comparison (table 4).

Table.4 The quantities of different change trends extracted respectively by temporal trajectory analysis and bi-temporal change detection

Temporal trajectory analysis from 2000 to 2005		Bi-temporal change detection between 2000 and 2005	
Trends of change	proportion	directions of change	proportion
stable non-vegetation	71.17%	stable non-vegetation	75.07%
stable vegetation	7.80%	stable vegetation	11.85%
change into vegetation	7.94%	change into vegetation	8.03%
change into non-vegetation	2.66%	change into non-vegetation	5.05%
unstable change	10.43%		
total	100.00%	total	100.00%

There are marked differences between these two change detection approaches displayed from table 4. This is particularly true in ‘stable vegetation’ and ‘change into vegetation’. The proportions of such two trends extracted from temporal trajectory analysis are less than the result from bi-temporal change detection. This phenomenon results from that bi-temporal change detection ignores the middle processes. For example, some pixels, whose change trajectory is ‘v→n→v→n→v→n’, would be judged as ‘unstable change’ in temporal trajectory analysis; but ‘change into non-vegetation’ would be adopted to describe the change direction in bi-temporal change detection. However, the middle processes are important to understand the environment change, especially in vegetation restoration. We should pay particular attention to the unstable changes; because the frequent fluctuations of land cover types in these pixels denoted the environment and ecosystem are fragile.

Explanation for differed change trends

Land cover changes, containing vegetation changes, are driven always by some ecological factors. At the same time, land cover change could indicate the environment change. In this section we would explore the connotation of different change trajectory, mainly according to the plants components contained in corresponding space. The plants components datum were from ground surveys in 2007.

(1) Stable vegetation and Stable non-vegetation. The spatial distributions of 'stable vegetations' were consistent with the trees and shrubs, in which the dominant species were *Populus euphratica* and *Tamarix*. These vegetations are close to the river where the water condition is better than other regions. So vegetation always keeps at a good condition. During water transfusions, the coverage of vegetation in these pixels had no marked change. Therefore, the land cover types of these regions were stable and belong to 'vegetation'.

The spatial distributions of 'stable non-vegetations' were consistent with the semi-mobile dunes and traveling dunes. Some bare lands belonged to 'stable non-vegetations' too. There were no any plants during water transfusions, so the trajectories were 'stable non-vegetation'.

(2) Change into vegetation. These trends mainly located in some depression regions near to river. The plants are main reed, and other shrubs and grasses. These regions could be supplied more easily, in which the river flooding easily formed some temporary lakes. After drying-up of these lakes, grasses grew anew and extended wide quickly. The most classical region was Chiwinkol, which was a lake 30 years ago, located in the north of Arghan (Arghan is the junction point of Old Tarim River and Chiwinkol River, which are offshoots of Tarim River after Dashkol Reservoir). In Chiwinkol, 85.85% of all pixels show the trends of 'Change into vegetation'.

(3) Change into non-vegetation. The vegetation was main shrubs, and scattered far from river. These pixels did not get water supply effectively, these vegetation still degenerate among water transfusion project. Some pixels distributed in the riverbed and appeared as lines, which resulted from the vegetation death by submerging during water transfusions.

(4) Unstable change. The pixels showed this trend is very scattered and located mainly at the fringe of 'stable vegetation'. Their trajectories were various and any trajectories' proportions were not bigger than 7%. These cases result from that the plants of these regions consisted mostly of weak shrubs and therophyte (annual grasses), which vegetation relies highly on surface water. Therefore, they fluctuated frequently with the change of water condition. In addition, the errors of images registration would lead frequently changing, which showed false 'unstable change'.

Conclusions and suggestions

We could get these conclusions as follows:

(1) Through constructing change trajectory, the approach of Temporal trajectory analysis could pick up the detail of change among study period. This approach could overcome the defect of bi-temporal change detection for detection middle process. But the middle process have some special significance when changes are nonlinear.

(2) Temporal trajectory analysis is helpful to understand the relationship between

vegetation change and environmental factor. In vegetation restoration monitoring, this approach could be used to explain that in where and why restoration occur.

(3) We should realize the errors' particularity in temporal trajectory analysis. There two sources of errors. One is the errors of images registrations, because this approach deal with multi-temporal images. Other one is from images classifications. We should reduce errors in image processing to the best of our abilities.

References

- [1]Zhou Q, Li B, Kurban A.,2008, Trajectory analysis of land cover change in arid environment of China. *International Journal of Remote Sensing*, 29(4),1093-1107
- [2]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, pp. 1565–1596.
- [3]Rick L. Lawrence, William J. Ripple.,1999, Calculating Change Curves for Multitemporal Satellite Imagery, Mount St.Helens 1980-1995. *Remote Sensing of Environment*, 67, 309–319
- [4]Robert E. Kennedy, Warren B. Cohen, Todd A. Schroeder., 2007, Trajectory-based change detection for automated characterization of forest disturbance dynamics. *Remote Sensing of Environment*, 110, 370-386
- [5]Y-N Chen., H. Zilliacus, W.-H. Li, H.-F. Zhang, Y.-P. Chen. 2006, Ground-water level affects plant species diversity along the lower reaches of the Tarim river,Western China. *Journal of Arid Environments*, 66 ,231–246
- [6]Y-N Chen., H. Zilliacus, W.-H. Li, H.-F. Zhang, Y.-P. Chen. 2006, Ground-water level affects plant species diversity along the lower reaches of the Tarim river,Western China. *Journal of Arid Environments*, 66 ,231–246
- [7]Huete A R. 1988, A soil adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25,295-309.
- [8]Fei Yuan, Kali E. Sawaya, Brian C. Loeffelholz, Marvin E. Bauer. 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. *Remote Sensing of Environment*, 98,317-328.