Postprint: Landscape Pattern Analysis of Oasis in Arid Regions Based on Multi-temporal Imagery from 1990 to 2019

Authors: Song Qi, Shi Zhou, Feng Chunhui

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Abstract

Using 226 scenes of Landsat imagery data from the Alar Reclamation Area between 1990 and 2019, different classification methods were compared to select the most accurate method, and the characteristics of landscape pattern changes over a continuous 30-year period were analyzed from the perspectives of patch type level, landscape level, abrupt changes, and spatial distribution. The results indicate that multi-temporal object-oriented classification achieved the best performance, with an overall accuracy of 96.57% and a Kappa coefficient of 0.95. At the patch type level, cultivated land became increasingly fragmented during the 30-year period, the dominance of unused land decreased, the landscape shapes of orchards and forest-grassland became more complex, while the landscapes of water bodies and construction land tended toward equilibrium. At the landscape level, landscape shape became more complex and fragmented, landscape connectivity decreased, and landscape richness and heterogeneity increased. The Alar Reclamation Area experienced an abrupt change in landscape pattern in 2005. In terms of spatial distribution, a trend of diffusion from the central Tarim River region to the surrounding areas was observed.

Full Text

Analysis of Landscape Pattern in Arid Oasis Based on Multi-Temporal Imagery from 1990 to 2019

SONG Qi[1], SHI Zhou[2], FENG Chunhui[3], MA Ziqiang[4], JI Wenjun[5], PENG Jie[3], GAO Qi[6], JIANG Xuewei[1]

[1]College of Horticulture and Forestry, Tarim University, Alar 843300, Xinjiang, China
[2]College of Environmental and Resource Science, Zhejiang University, Hangzhou 310058, Zhejiang, China

[3]College of Agriculture, Tarim University, Alar 843300, Xinjiang, China
[4]Institute of Remote Sensing and Geographical Information Systems, School of Earth and Space Sciences, Peking University, Beijing 100871, China
[5]College of Land Science and Technology, China Agricultural University, Beijing 100193, China
[6]Changji Geological Environment Monitoring Station, Changji 831100, Xinjiang, China

Abstract

This study utilized 226 scenes of Landsat imagery data from the Aral Reclamation Area between 1990 and 2019 to compare different classification methods and select the approach with highest accuracy. The continuous landscape pattern changes in the Aral Reclamation Area over more than 30 years were analyzed from four perspectives: patch type level, landscape level, abrupt changes, and spatial distribution. The results demonstrate that multi-temporal object-oriented classification yielded the optimal outcome, achieving an overall accuracy of 96.57% and a Kappa coefficient of 0.95. At the patch type level, cultivated land became increasingly fragmented over the 30-year period, the dominance of unused land decreased, the landscape shapes of orchard land and forest-grassland became more complex, while water bodies and construction land tended toward greater equilibrium. At the landscape level, landscape shapes became more complex and fragmented, landscape connectivity decreased, and landscape richness and heterogeneity increased. The landscape pattern of the Aral Reclamation Area underwent a sudden change in 2005. Spatially, the changes exhibited a diffusion trend from the central Tarim River region toward the periphery.

Keywords: Landsat; multi-temporal object-oriented; continuous time series; landscape pattern; mutation point detection; Aral Reclamation Area

1 Introduction

Global environmental issues such as global warming, glacial melting, and biodiversity loss have become increasingly prominent. Coupled with frequent human activities, these factors have disrupted normal ecological balance and gradually deteriorated regional ecological environments. To understand the impacts of global warming on ecological environments, it is necessary to analyze regional landscape patterns and explore how human activities affect landscape ecosystems. The extraction and analysis of landscape pattern information can not only characterize spatial complexity but also determine the distribution of resources and environment within ecosystems. Studying landscape patterns can reveal potential ecological significance and landscape patterns within the seemingly disordered mosaic of landscape patches.

Regional landscape classification is fundamental to analyzing landscape pattern changes. Traditional ground survey methods are time-consuming, laborintensive, and have limited applicability. With the application of remote sensing technology, remote sensing imagery data has become the preferred data source for landscape pattern change analysis due to its low cost, convenient acquisition, wide coverage, and long time series availability. However, most current landscape pattern studies use typical temporal cross-section data and pixel-based classification methods (such as support vector machine) that are prone to produce salt-and-pepper effects and require cumbersome post-processing, often resulting in low classification accuracy and ultimately affecting regional landscape pattern analysis. Moreover, landscape pattern changes often do not occur at key years, making typical temporal cross-section data likely to miss critical node information and fail to accurately capture landscape pattern changes, with insufficient grasp of continuous information.

The Aral Reclamation Area, located at the confluence of the Aksu, Hotan, and Yarkant Rivers, serves an irreplaceable function as a landscape ecological barrier. The area is significantly influenced by human activities, with vegetation dominated by artificial vegetation rather than natural vegetation, resulting in a simple landscape structure, fragile ecological environment, and substantial landscape pattern changes. Therefore, this study selected the typical artificial oasis of Aral Reclamation Area in northwest China as a case study to analyze long-term regional landscape pattern change information, which can provide valuable reference for related research in arid regions of northwest China.

2 Materials and Methods

2.1 Study Area

The Aral Reclamation Area is situated at the confluence of the Aksu, Hotan, and Yarkant Rivers, geographically located between 40°22 -40°57 N and 80°30 - 81°58 E, covering a total area of 4105.92 km^2. The terrain slopes from northwest to southeast with an average elevation of 1012 m. The ecosystem belongs to the desert-oasis type, with sandy loam as the main soil type. Water resources are primarily distributed in the Tarim River and three major plain reservoirs (Shengli, Duolang, and Shangyou). Located in the hinterland of the Eurasian continent and on the northern edge of the Taklamakan Desert, the area has a warm temperate extreme continental arid desert climate with variable weather, frequent sandstorms, dust, and frost disasters, low annual precipitation, and high evaporation. The Aral Reclamation Area is dominated by cotton and jujube cultivation and is China's largest long-staple cotton production base, with small areas planted with fragrant pears, apples, grapes, corn, wheat, sorghum, and other crops.

2.2 Data Sources

All available Landsat remote sensing images of the Aral Reclamation Area from 1990 to 2019 were obtained, totaling 226 scenes. To improve the interpretation accuracy of subsequent remote sensing image classification, 219 scenes with cloud cover below 10% were selected from all images. Landsat images with a spatial resolution of 30 m from Path/Row 145/33 in southern Xinjiang were used as the basic data for this study, with cloud coverage and image numbers shown in [Figure 2: see original paper].

2.3 Methods

2.3.1 NDVI Maximum Value Composition All 226 remote sensing images obtained from 1990 to 2019 underwent preprocessing operations including radiometric calibration, atmospheric correction, image registration, and cropping. The Normalized Difference Vegetation Index (NDVI) was then extracted from each image using the formula:

$$NDVI = \frac{NIR - R}{NIR + R}$$

where NIR represents near-infrared band reflectance and R represents red band reflectance.

The technical flowchart is shown in [Figure 3: see original paper]. The maximum NDVI composite images for each year were obtained through annual maximum value composition of the time series data ([Figure 4: see original paper]). The multi-temporal remote sensing image composites not only eliminated cloud cover effects but also showed higher vegetation coverage, which is beneficial for subsequent landscape classification. The interannual variation of NDVI in the Aral Reclamation Area from 1990 to 2019 is shown in [Figure 5: see original paper], clearly indicating an increasing trend in vegetation coverage over the past 30 years.

2.3.2 Classification Method Referring to existing classification methods in Xinjiang cases, the object-oriented classification method was selected for landscape classification. This method comprehensively considers the spectral, shape, and grayscale characteristics of various landscape types. eCognition software was used for multi-scale segmentation of multi-temporal remote sensing images. After multiple tests, the optimal segmentation scale was found using the Estimation of Scale Parameter (ESP) evaluation tool. The Random Forest classification algorithm was then applied for information extraction. In this region, the NDVI values differ for cultivated land, forest-grassland, orchard land, and non-vegetation areas, enabling classification based on these differences. Additionally, water bodies, construction land, and unused land show significant differences in geometric and texture features, which served as classification references. Reasonable image classification rules were constructed, and classification was performed using the optimal multi-temporal object-oriented method.

2.3.3 Landscape Pattern Change Analysis Method Referring to existing cases, quantitative analysis of landscape pattern change characteristics in the

Aral Reclamation Area was conducted from both patch type level and landscape level perspectives. Commonly used landscape indices were selected to analyze landscape fragmentation, dominance, complexity, aggregation, connectivity, and diversity. Since the study covers a long time series, abrupt changes may occur in landscape patterns. The cumulative anomaly method was used to detect landscape pattern mutations in the study area, calculated as:

$$LR_i = \sum_{i=1}^{n}(R_i - \bar{R})$$

where LR_i is the cumulative anomaly value for year i, R_i is the landscape index value for year i, and $\bar{R}$ is the multi-year average of the landscape index sequence.

To verify the reliability of the detected mutation points, the authenticity of mutation points obtained by the cumulative anomaly method was validated. Finally, landscape indices were visualized using different moving window sizes. After comparing various window sizes, the optimal window was selected to reflect spatial variation characteristics of landscape patterns. Ultimately, landscape pattern changes in the Aral Reclamation Area were comprehensively analyzed from perspectives of landscape fragmentation, dominance, complexity, aggregation, connectivity, diversity, mutation points, and spatial distribution.

3 Results and Analysis

3.1 Classification Results and Accuracy Assessment of Different Methods

Taking 2019 as an example, after referencing high-resolution remote sensing imagery and conducting field surveys of the study area, 500 classification samples were selected for pixel-based classification methods, including 120 for cultivated land, 80 for forest-grassland, 70 for water bodies, 60 for construction land, 90 for orchard land, and 80 for unused land. The classification results of the three methods were compared ([Figure 6: see original paper]). The multi-temporal object-oriented classification method produced the best results, while multi-temporal pixel-based and single-temporal object-oriented classification results were more fragmented, prone to "misclassification" and "omission" errors.

A total of 500 validation samples were randomly selected from the Aral Reclamation Area, and the confusion matrix method was used to evaluate classification accuracy. The multi-temporal object-oriented classification method achieved the highest overall accuracy and Kappa coefficient at 96.57% and 0.95, respectively. Detailed accuracy assessment is shown in . The user accuracy and producer accuracy for each type exceeded 98.79%, indicating that this classification method is feasible for this study area. However, water bodies and unused land were easily confused because small wetlands near water bodies in the Aral Reclamation Area were often misclassified as unused land. Nevertheless, the misclassified wetland area was small and did not affect the overall classification result.

Compared with multi-temporal pixel-based classification, the overall accuracy of the optimal multi-temporal object-oriented classification method increased by 12.22%, and the Kappa coefficient increased by 0.14, with producer accuracy for each landscape type showing varying degrees of improvement. Compared with single-temporal object-oriented classification, the overall accuracy improved by 3.57%, and the Kappa coefficient increased by 0.04. This demonstrates that multi-temporal object-oriented classification can effectively distinguish different landscape types and avoid the salt-and-pepper phenomenon as well as omission and misclassification errors caused by vegetation phenological differences.

3.2 Landscape Pattern Analysis at Patch Type Level

Landscape index changes at the type level in the Aral Reclamation Area from 1990 to 2019 are shown in [Figure 7: see original paper].

Patch Density (PD): Cultivated land, forest-grassland, and orchard land showed relatively high patch densities. The patch density of cultivated land exhibited an increasing trend, indicating that cultivated land landscapes became more fragmented. Orchard land patch density values mutated in 2005, suddenly increasing, likely due to policy guidance and rising jujube prices that caused some cultivated land to convert to orchard land. Water body, construction land, and unused land patch density values showed minimal change without obvious trends.

Largest Patch Index (LPI): Unused land had the largest LPI values, but showed an overall decreasing trend. Orchard land LPI values showed an overall increasing trend. The maximum LPI value for unused land occurred in 1990, while the minimum occurred in 2019. This likely resulted from initial land reclamation expansion followed by reduced conversion rates of unused land, with cultivated land expansion primarily converting from forest-grassland.

Area-Weighted Mean Fractal Dimension (FRAC_{AM}): Forest-grassland and orchard land had significantly higher fractal dimensions than other types, indicating the most complex landscape patch shapes. From 1990 to 2019, fractal dimensions of cultivated land, construction land, and unused land increased, while water bodies showed a decreasing trend.

Cohesion Index (COHESION): Orchard land showed an increasing trend from 1990 to 2019, indicating enhanced aggregation of orchard land during this period.

3.3 Landscape Pattern Analysis at Landscape Level

Landscape index changes at the landscape level in the study area from 1990 to 2019 are shown in [Figure 8: see original paper].

Number of Patches (NP) showed a fluctuating upward trend, indicating increased landscape fragmentation. **Landscape Shape Index (LSI)** showed similar trends to NP, suggesting increasing landscape complexity. **Largest Patch Index (LPI)** showed a significant decreasing trend, indicating more small patches and fewer large patches in recent years, with overall spatial distribution becoming more fragmented. **Shannon' s Diversity Index (SHDI)** showed an overall increasing trend, indicating enhanced heterogeneity in the study area. **Contagion Index (CONTAG)** showed a decreasing trend, indicating reduced landscape connectivity.

The cumulative anomaly method was used to detect mutation points in the landscape pattern ([Figure 9: see original paper]). Taking 2005 as the boundary, the cumulative anomaly showed a decreasing trend before 2005 and an increasing trend after 2005, indicating that landscape fragmentation, complexity, and diversity in the Aral Reclamation Area showed a pattern of first decreasing then increasing. Conversely, the CONTAG curve showed the opposite trend, indicating that landscape connectivity first increased then decreased. The year 2005 was identified as the mutation year for the Aral Reclamation Area' s landscape pattern.

To verify the reliability of this mutation point, the continuous time series data from 1990 to 2019 was divided into two sub-series at 2005, and the Kolmogorov-Smirnov test was used to examine differences between the two sub-series. The results () showed significant differences ($p < 0.01$) between the sub-series for all indices, confirming the reliability of the detected mutation. Beginning in the second half of 2003, large areas of wasteland were reclaimed as farmland, and crop planting began in 2004 with a sharp increase in crop area, leading to increased vegetation coverage. This caused significant increases in landscape fragmentation, complexity, and diversity, and a decrease in connectivity, resulting in a clear mutation in the Aral Reclamation Area' s landscape pattern.

3.4 Landscape Pattern Analysis Based on Moving Windows

In visualizing landscape indices, moving window size selection is crucial as different window sizes produce significantly different landscape pattern maps. After continuous debugging and comparison of square moving windows with side lengths of 300 m, 600 m, 900 m, 1200 m, 1500 m, and 1800 m, a 1200 m window was ultimately selected for visualization analysis ([Figure 10: see original paper]).

Patch Density Analysis: Excessive human activity causes patch fragmentation. Patch density reflects the degree of landscape fragmentation and can effectively indicate human activity intensity and land use degree. Due to the Tarim River in the central study area, agricultural development is better near water sources, and the landscape structure is more stable, while human activities are also more intense. The central Tarim River region shows higher patch density, likely related to increasing human activities, industrial land, and farmland area in recent years. Industrial wastewater and agricultural drainage in the Aral Reclamation Area are mostly discharged to remote areas, causing sporadic plant communities to grow in these regions and increasing plant diversity. These vegetation patches are not contiguous but show discrete spatial distribution patterns, ultimately increasing patch numbers in remote areas.

Shannon's Diversity Index Analysis: Spatial visualization analysis of Shannon' s diversity index ([Figure 10: see original paper]) shows higher values in the central Tarim River region, with an overall trend of decreasing from the Tarim River center outward. This is related to more frequent human activities and more stable land use structures in the central region, while peripheral areas are mostly unused land with simple landscape structures and ample development space.

4 Discussion

Most studies use only 2-3 scenes of remote sensing imagery, which can only reflect general landscape pattern evolution trends and cannot capture detailed evolution characteristics over long time scales, easily missing critical "inflection point" information in continuous long time series. This study downloaded all Landsat imagery data for the study area from 1990 to 2019 without difference, totaling 226 scenes. NDVI maximum value composition was performed on images from different months within the same year to obtain annual maximum value composite multi-temporal imagery. This landscape pattern analysis based on continuous long time series multi-temporal remote sensing imagery not only effectively compensates for the shortcomings of previous analyses based on 2-3 scenes of imagery and fully reflects detailed change characteristics of the study area' s landscape pattern over the past 30 years, but also avoids misclassification errors caused by different crop growth seasons. Therefore, temporal selection of imagery data is crucial in landscape pattern change analysis, directly affecting the accuracy and reliability of research results.

Drivers of Landscape Pattern Changes: (1) After 2005, drip irrigation technology gradually became popular, making previously uncultivable high-lying land cultivable and enabling cultivation in low-lying, saline-alkali areas, leading to continuous increases in oasis cultivated land area, continuous decreases in unused land area, and gradual increases in landscape richness and heterogeneity. (2) Adjustment of planting structure. The shift from cotton fields to forestry and fruit industries impacted oasis landscapes, increasing patch density, largest patch index, fractal dimension, and cohesion index of orchard land, causing uneven spatial distribution of oasis landscapes and enhanced landscape aggregation. (3) Impact of agricultural technological progress. Technological progress (drip irrigation popularization) greatly improved groundwater utilization efficiency in this arid region with little rain, high temperatures, and water shortage, thereby affecting soil and vegetation, increasing landscape richness and heterogeneity, and influencing oasis landscape patterns.

Objectivity of Landscape Index Analysis: The analysis has certain objectivity depending on the study area' s actual conditions and research focus. For example, when analyzing landscape patch numbers and related patch density, this study focused on cultivated land, forest-grassland, and orchard land, which occupy large area proportions, and explained the mutual conversion among them, while briefly introducing water bodies and construction land with smaller areas. Therefore, landscape index analysis has some subjectivity, and results may vary significantly among different researchers.

5 Conclusions

This study analyzed landscape pattern changes in the Aral Reclamation Area from 1990 to 2019, with main conclusions as follows:

1) Comparison of three classification methods—multi-temporal object-oriented, multi-temporal pixel-based, and single-temporal object-oriented—demonstrated that multi-temporal object-oriented classification achieved the highest accuracy, with overall accuracy of 96.57% and Kappa coefficient of 0.95. This represented improvements of 12.22% and 0.14, respectively, compared with multi-temporal pixel-based classification, and improvements of 3.57% and 0.04 compared with single-temporal object-oriented classification, effectively avoiding salt-and-pepper effects and omission/misclassification errors caused by vegetation phenological differences.
2) At the patch type level, from 1990 to 2019, cultivated land landscapes in the Aral Reclamation Area tended to fragment, dominance of unused land decreased, landscape shapes of orchard land and forest-grassland became more complex, and landscapes of water bodies and construction land tended toward equilibrium. At the landscape level, landscape shapes became more complex and fragmented, landscape connectivity decreased, and landscape richness and heterogeneity increased. The reclamation area' s landscape pattern underwent a sudden change in 2005, with significant increases in landscape fragmentation, complexity, and diversity, and decreased connectivity.
3) In terms of spatial distribution, landscape index distribution was relatively uniform in the Tarim River coastal zone with frequent human activities and complete landscape structure. The landscape pattern showed a trend of spreading from the Tarim River coastal zone to remote areas, with more obvious expansion trends toward the northeast and southwest directions.

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Note: Figure translations are in progress. See original paper for figures.