Land Cover Changes and Driving Forces in the Oases of the Southern Margin of the Tarim Basin: Postprint

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Abstract

Taking the Cele Oasis on the southern margin of the Tarim Basin as the study area, and based on four periods of land use and remote sensing images as well as meteorological, hydrological, and socio-economic data, we analyzed the characteristics of land use/cover change in the Cele Oasis from 1990 to 2018. The results show that: (1) Various land use types in the Cele Oasis underwent significant transformation, with farmland area expanding outward in all directions, the distribution area of forest land shifting substantially, and conversion among grasslands of different coverage levels occurring frequently. (2) A total area of 138.41 km^2 in the oasis underwent change, accounting for 53.85% of the total area; the single dynamic degree of each type in descending order was: high-coverage grassland > farmland > low-coverage grassland > construction land > medium-coverage grassland > unused land > forest land, and the bidirectional dynamic degree in descending order was: high-coverage grassland > farmland > low-coverage grassland > construction land > forest land > medium-coverage grassland > unused land. (3) The forest and grass vegetation index of the oasis was below 0, indicating that forest land and grassland have been in a continuous state of degradation; the main driving forces of land use change in the oasis were population, precipitation, and runoff.

Full Text

Abstract

This study examines land cover change and its driving forces in the Cele Oasis, located on the southern margin of the Tarim Basin. Using four phases of land use data and remote sensing imagery from 1990 to 2018, along with meteorological, hydrological, and socio-economic datasets, we analyzed the spatiotemporal characteristics of land use/cover change in the Cele Oasis. The results reveal significant transformations across all land use types: farmland expanded outward in all directions, forest distribution shifted substantially, and grasslands with different coverage levels underwent frequent interconversion. Overall, 138.41 km^2 (53.85%) of the total area experienced land use transitions. The single dynamic degree of various land use types, in descending order, was: high-coverage grassland > farmland > low-coverage grassland > construction land > medium-coverage grassland > unused land > forest land. The bidirectional dynamic degree, in descending order, was: high-coverage grassland > farmland > low-coverage grassland > construction land > forest land > medium-coverage grassland > unused land. These patterns indicate that forest land and grassland have been in a continuous state of degradation. The forest-grass vegetation index remained below zero throughout the study period, confirming the persistent degradation of forest and grassland ecosystems. The primary driving forces behind these land use changes were population growth, precipitation patterns, and river runoff.

Keywords: desert oasis; Cele Oasis; land use; spatiotemporal change; NDVI; driving forces

Introduction

Land cover change serves as a core indicator for analyzing the interplay of economic, social, and natural environmental factors, playing a crucial role in global environmental change processes. Land use represents the outcome of multiple factors operating within specific human-environment relationships. As the foundation of terrestrial ecosystems, land not only supports human survival but also constitutes the primary medium through which humans interact with the environment. With societal progress and rapid productivity development, human land use practices have continuously transformed and intensified, leading to dramatic changes in land use patterns. Scholars worldwide have conducted extensive research on land use change across various temporal and spatial scales, utilizing remote sensing and geographic information systems integrated with diverse theoretical frameworks and mathematical models to investigate spatiotemporal processes, simulation predictions, dynamic mechanisms, and landscape patterns. Recent advances have improved the spatial resolution of land use simulation technologies, providing more accurate descriptions for global change studies. Liu et al. proposed novel approaches for analyzing land use change through remote sensing imagery and human-computer interactive interpretation methods.

Oasis land use change research represents a particularly important domain at the regional scale. Chinese oases are predominantly distributed in northwestern regions including Xinjiang, Gansu, Ningxia, and Inner Mongolia, with the majority located in Xinjiang. These oases support 95% of Xinjiang's population and economic output. However, oasis ecosystems are extremely fragile, where even minor human disturbances can increase the risk of habitat fragmentation and subsequently impact regional ecological and hydrological processes. Under human influence, land cover patterns in arid zone oases are undergoing rapid transformation, significantly affecting the delicate ecological balance. Numerous studies have examined oasis land use change from perspectives of habitat quality, landscape structure, land use intensity, and risk assessment, employing correlation analysis and principal component analysis to identify driving factors and inform sustainable land management strategies.

1. Materials and Methods

1.1 Study Area

The Cele Oasis is situated on the southern margin of the Tarim Basin (Figure 1) within Cele County, Hotan Prefecture, Xinjiang. The study area boundary was delineated based on the actual distribution range of the oasis, with geographic coordinates of 35°18 ~39°18 N, 80°03 ~82°10 E. The terrain slopes from high in the south to low in the north, with elevations ranging from 1296.5 to 1370.5 m, forming an alluvial piedmont plain in the central region. The Cele River flows through the oasis with an average annual runoff of 1.28$×10^{8}$ m^3. The regional climate is classified as warm temperate arid desert, with a mean annual temperature of 11.9°C, extreme maximum temperature of 42.0°C, and extreme minimum temperature of -23.9°C. Annual precipitation averages 35.1 mm, while evaporation reaches approximately 2595.3 mm—far exceeding precipitation. The frost-free period lasts about 230 days, with annual sunshine duration of 2686 hours.

1.2 Data Sources

Land use data for the Cele Oasis from 1990 to 2018 were obtained from the Chinese Academy of Sciences' Resource and Environmental Science Data Center (http://www.resdc.cn/), with a spatial resolution of 30 m × 30 m. The classification system includes six primary land use types: farmland, forest land, water bodies, construction land, grassland, and unused land. Grassland was further subdivided into three secondary categories: high-coverage grassland, medium-coverage grassland, and low-coverage grassland. These datasets have undergone quality control and accuracy verification, achieving comprehensive classification accuracies of 94.3% for primary types and 91.2% for secondary types, and have been widely applied in land cover monitoring studies across China.

Remote sensing imagery was acquired from the United States Geological Survey (USGS) Earth Explorer (http://earthexplorer.usgs.gov/). Cloud-free Landsat images with low cloud cover were selected for each year, with a pixel resolution of 30 m × 30 m. The imagery includes Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI data, with path/row designation of 146/34. Four scenes corresponding to the land use data years were selected during the growing season to reflect actual vegetation conditions. Preprocessing was conducted using ENVI software, including radiometric calibration, atmospheric correction, and image cropping. NDVI was calculated using the appropriate bands for each sensor: for Landsat 5 TM, red band (0.63-0.69 m) and near-infrared band (0.76-0.90 m); for Landsat 8 OLI, red band (0.63-0.67 m) and near-infrared band (0.85-0.88 m). Anomalous values were removed to obtain final NDVI spatial distribution datasets.

Accuracy assessment was performed by generating 500 random points across the study area using ArcGIS, ensuring coverage of all land use types. These points were used to validate the land use data from the Resource and Environmental Science Data Center, with uncertain cases resolved using historical high-resolution Google Earth imagery. The validation results showed classification accuracies of 91.2% for 1990, 92.7% for 2000, 94.3% for 2010, and 93.8% for 2018.

Meteorological data (annual temperature, precipitation, and evaporation) were obtained from the Cele Meteorological Station, while runoff data were provided by the Cele Hydrological Station. These datasets have been analyzed in previous studies and were used here to examine long-term trends affecting land use patterns.

1.3 Research Methods

We first analyzed the spatiotemporal distribution characteristics of land use types in the Cele Oasis using four phases of land use data. The land use transfer matrix was then calculated to quantify changes in land use type areas. The forest-grass vegetation index was applied to assess gains and losses of forest and grassland during conversion processes. Dynamic degree analysis evaluated the magnitude of change for each land use type. Finally, Kendall trend analysis, principal component analysis, and multiple linear regression models were employed to identify driving factors of land use change over recent decades.

1.3.1 Land Use Transfer Matrix A Markov transfer matrix model was used to describe quantitative conversions between land use types:

$$P_{mn} = \begin{pmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mn} \end{pmatrix}$$

where n represents the number of land use types, and P_{mn} is the transition probability from land use type m to type n. The transition probabilities must satisfy $\sum_{n=1}^{N} P_{mn} = 1$ and $P_{mn} \leq 1$.

1.3.2 Forest-Grass Vegetation Change Index This index reflects the degree of vegetation cover change and was used to analyze forest and grassland dynamics:

$$I = \frac{G_t - G_0}{G_0} \times 100\%$$

where I is the forest-grass vegetation change index, G_0 and G_t are the proportions of forest-grass land area at the initial and final time periods, respectively. A positive I value indicates increasing forest-grass vegetation, with larger values representing faster growth rates; negative values indicate decreasing vegetation.

1.3.3 Land Use Dynamic Degree The single dynamic degree expresses the rate of area change for a specific land use type over time:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%$$

where K is the dynamic degree, U_a and U_b are the initial and final areas of a land use type, and T is the study period length. Positive K values indicate increasing trends, negative values indicate decreasing trends, and the absolute magnitude reflects the rate of change.

The bidirectional dynamic degree represents the combined rate of expansion and contraction, reflecting the intensity of mutual conversion between land use types:

$$K_i = \frac{U_i + \Delta U_{i-j}}{U_a} \times \frac{1}{T} \times 100\%$$

where U_i is the area converted from type i to other types, ΔU_{i-j} is the area converted from other types to type i, and U_a is the initial area of type i.

1.3.4 Normalized Difference Vegetation Index (NDVI) NDVI is calculated using spectrally sensitive bands:

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

where R is the red visible band and NIR is the near-infrared band. The resulting values range from -1 to 1, with higher values indicating healthier vegetation.

1.3.5 Kendall Trend Analysis The Kendall test was used to analyze trend characteristics of driving factors. This non-parametric test requires only independent data and is robust against outliers. The standard normal statistical variable z is calculated as:

$$z = \frac{S - E(S)}{\sqrt{Var(S)}}$$

where S is the test statistic. At a given confidence level α, if $|z| > z_{\alpha/2}$, the null hypothesis is rejected, indicating a significant increasing or decreasing trend. Positive z values indicate upward trends, while negative values indicate downward trends.

1.3.6 Multiple Linear Regression Multiple linear regression models the relationship between multiple independent variables and a dependent variable. In this study, land use types were set as dependent variables Y, and driving factors as independent variables X:

$$Y = a_0 + a_{1X}1 + a_{2X}2 + \cdots + a_{kX}k$$

where a_0 is the intercept and $a_1, a_2, \cdots, a_k$ are regression coefficients.

2. Results

2.1 Land Use Distribution and Change

2.1.1 Spatial Distribution Patterns The four-phase land use distribution maps reveal that farmland was concentrated within the oasis interior during 1990, gradually expanding outward to become the dominant land use type. Grasslands with varying coverage levels were distributed around the farmland periphery. Forest land showed dramatic spatial redistribution: in 1990 it was concentrated in the northeastern part of the oasis, shifted to the northwest by 2000, and became scattered within farmland areas by 2010 and 2018, with overall area substantially reduced. Unused land was located at the oasis margins, showing continuous area reduction with minimal new additions. Construction land was distributed within the oasis interior, expanding noticeably after 2000 as central towns grew, with additional expansion in the southeastern oasis after 2010, though the magnitude remained relatively small.

Between 1990 and 2018, all land use types in the Cele Oasis underwent significant spatial and areal changes (Figure 3). Farmland area increased substantially, particularly through expansion into peripheral areas, most notably in the northeastern direction. Forest distribution shifted dramatically, with large-scale reduction in area and scattered new additions. Different grassland coverage types gradually retreated toward the oasis margins while frequently converting among themselves.

2.1.2 Land Use Transitions Using ArcGIS spatial analysis tools, we quantified specific conversions between land use types (Table 1). The results show that farmland, construction land, and water bodies increased in area, while forest land, unused land, high-coverage grassland, medium-coverage grassland, and low-coverage grassland decreased. Specifically, forest land converted primarily to farmland (52.37 km^2) and desert (70.80 km^2). High-coverage grassland converted to farmland (27.85 km^2), medium-coverage grassland, and low-coverage grassland. Low-coverage grassland converted to farmland (83.34 km^2), while unused land converted to farmland (45.44 km^2). Farmland expansion totaled 138.41 km^2, a 27.85% increase, making it the largest land use type in the oasis. Construction land increase originated mainly from unused land conversion (45.44%).

The oasis experienced net forest-grass vegetation loss of 52.37 km^2, with degradation area reaching 83.34 km^2. The forest-grass vegetation index was -2.23% for 1990-2000, -8.07% for 2000-2010, and -1.75% for 2010-2018, indicating accelerated vegetation loss during 2000-2010 but slower loss during the most recent period.

2.2 Dynamic Degree Analysis

To further analyze conversion rates, we calculated single and bidirectional dynamic degrees (Table 2). Between 1990 and 2018, farmland, high-coverage vegetation, low-coverage vegetation, and construction land showed positive single dynamic degrees, indicating area expansion. Forest land, medium-coverage vegetation, and unused land showed negative single dynamic degrees, indicating area reduction.

The bidirectional dynamic degrees for all land use types exceeded their single dynamic degrees, revealing frequent internal conversions and low stability. Larger bidirectional dynamic degrees indicate greater susceptibility to external influences. High-coverage grassland showed the highest dynamic degree, reflecting its volatile conversion patterns.

2.3 NDVI Change Characteristics

As the most commonly used vegetation response indicator, NDVI accurately reflects vegetation growth conditions across different coverage levels. Using ArcGIS raster calculator, we computed mean NDVI values for the four periods (Figure 4). The spatial distribution consistently showed higher values in the center decreasing toward the periphery. NDVI values fluctuated between -0.46 and 0.60, with degraded areas (27.56% of the oasis) concentrated in marginal desert zones, while improved areas (72.44%) were mainly within farmland regions.

The degradation in marginal areas relates to two factors: (1) expansion of construction land and irrigation channels within farmland, and (2) significant forest reduction after 2000. The improvement within farmland areas reflects changes in crop planting structure—from grain crops before 2000 to economic crops after 2000, which typically exhibit higher NDVI values.

2.4 Driving Factor Analysis

2.4.1 Characteristics of Driving Factors The Cele Oasis, as a typical arid region ecosystem with simple structure, is highly sensitive to both natural and anthropogenic changes. We examined six key factors: annual precipitation, mean annual temperature, evaporation, Cele River runoff, population, and grain yield.

Kendall trend analysis revealed (Figure 5): - **Precipitation**: Significant decreasing trend during 1990-2000, then increasing but not significantly after 2000 - **Temperature**: Decreasing then increasing trend, with significant warming after 2000 (UF statistic exceeding 0.05 significance level) - **Evaporation**: Decreasing then significantly increasing after 2000 - **Population**: Continuous significant increase after 2000 - **Grain yield**: Significant increase after 2010 - **Runoff**: Non-significant increasing trend

These trends indicate a shift toward warmer, drier conditions with reduced precipitation and increased evaporation, directly affecting natural vegetation and indirectly influencing vegetation patterns through soil moisture regulation. Population growth drives farmland expansion, while increased agricultural water demand (82.1% of Cele River water is used for irrigation) reduces downstream water availability for natural vegetation.

2.4.2 Regression Analysis To address multicollinearity among factors, principal component analysis extracted two components explaining 85.3% of variance (Table 3). The first component (economic-social factors) loaded heavily on population and grain yield; the second component (natural factors) loaded on evaporation and temperature.

Multiple regression analysis (Table 4) showed: - **Farmland**: Positively correlated with both components ($R^2 = 88.74\%$), particularly with economic-social factors - **Construction land**: Strong positive correlation with economic-social factors ($R^2 = 96.50\%$) - **Unused land**: Negatively correlated with both components ($R^2 = 81.44\%$), decreasing with population pressure and natural vegetation growth - Other land use types showed lower correlation with driving factors

3. Discussion

This study of a typical vulnerable oasis on the southern Tarim Basin margin reveals substantial changes in land use type distribution and area, with 53.85% of the total area experiencing conversion. Farmland expanded dramatically, particularly northeastward, while forest land migrated from the periphery to scattered interior locations with continuous area reduction. Grasslands retreated to oasis margins.

Three categories of driving forces were identified:

Anthropogenic factors: (1) Population growth increased demand for timber, fuelwood, and grazing land, leading to deforestation and grassland degradation; (2) Upstream reservoir construction reduced water flow to desert areas, affecting natural vegetation; (3) Canal systems diverted river water for crop irrigation, indirectly causing large-scale natural vegetation decline.

Natural factors: Precipitation and runoff played significant roles. As oasis area and water demand increased, less water reached downstream areas, preventing vegetation recovery and reducing groundwater recharge, which lowered water tables and caused vegetation dieback.

Policy factors: Western Development Strategy, Tarim River ecological restoration projects, and provincial aid programs (particularly Tianjin's assistance to Cele County) promoted economic development and population growth, driving continuous land reclamation and artificial oasis expansion.

While natural factors primarily affect low-coverage vegetation through long-term cumulative effects, anthropogenic factors exert immediate and dominant influence on land cover change.

4. Conclusions

1) **Spatial patterns**: Land use types in the Cele Oasis showed significant spatial redistribution. Farmland expanded substantially, particularly toward the northeast. Forest land shifted from the northeast to scattered interior distribution. Grasslands retreated to oasis margins, while unused land area continuously decreased. The forest-grass vegetation index remained below zero throughout the study period, confirming persistent degradation.

2) **Temporal dynamics**: From 1990 to 2018, 53.85% of the area experienced land use conversion. Farmland, residential construction land, and water bodies increased, while forest land, unused land, and all grassland categories decreased. Dynamic degree analysis revealed that farmland, high-coverage vegetation, low-coverage vegetation, and construction land had positive single dynamic degrees, while forest land, medium-coverage vegetation, and unused land had negative values. All land use types showed bidirectional dynamic degrees exceeding single dynamic degrees, indicating frequent internal conversions and low stability.

3) **NDVI patterns**: NDVI values were higher in the center and decreased toward the periphery. Degraded areas (27.56%) concentrated in marginal desert zones, while improved areas (72.44%) were within farmland regions, reflecting changes in crop structure from grain to economic crops.

4) **Driving forces**: Construction land, farmland, and unused land were most significantly affected by driving factors. Farmland and construction land changes correlated positively with anthropogenic factors, while unused land changes correlated negatively with both anthropogenic and natural factors. The oasis ecosystem's simple structure makes it highly vulnerable to natural and human-induced changes, with human factors serving as the direct and dominant drivers of land cover change.

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