Postprint: Remote Sensing Monitoring of Vegetation Cover in Central Asia Based on Multi-temporal Landsat Imagery

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Abstract

Given the strong ecological fragility and high sensitivity characteristics of Central Asia, it is necessary to conduct broad-scale, long-term vegetation cover monitoring to align with the sustainable development goals of the "Green Silk Road". In view of this, this study jointly utilized Landsat 5 and Landsat 8 satellite datasets and leveraged the Google Earth Engine (GEE) geospatial data cloud computing platform to estimate fractional vegetation cover for 12 periods in Central Asia from 1993 to 2018. The results indicate: (1) The overall vegetation cover level in Central Asia is relatively low, yet exhibits significant spatial heterogeneity. (2) During 1993–2018, vegetation cover trends remained relatively stable in most regions of Central Asia, while areas such as the Kazakhstan Hills and Fergana Basin showed increasing trends in vegetation cover, and regions including the Ural River Basin and Syr Darya River Basin exhibited negative vegetation cover trends. (3) In terms of temporal characteristics of fractional vegetation cover, the overall vegetation cover in Central Asia cumulatively increased by 3% from 1993 to 2018, with vegetation cover in Kyrgyzstan and Tajikistan increasing by 3.96% and 5.86%, respectively. (4) Bare soil areas showed a retreating trend, with a total area reduction of 25.9$×10^{4}$ km^2, while the extents of low, medium, and high vegetation cover areas exhibited oscillatory increases. This study combines remote sensing big data and geospatial cloud computing to conduct regional-scale dynamic monitoring of vegetation cover in Central Asia, which can provide technical support and quantitative data for ecological assessment and succession analysis in the region.

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Full Text

Vegetation Coverage Monitoring in Central Asian Countries Using Multi-temporal Landsat Images

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Abstract

Central Asia exhibits strong ecological fragility and high sensitivity, necessitating broad-scale, long-term vegetation coverage monitoring to align with the sustainable development goals of the "Green Silk Road." In this study, we estimated vegetation coverage in Central Asia across 12 periods from 1993 to 2018 using the Google Earth Engine geospatial data cloud computing platform with Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) satellite datasets. Data preprocessing included cloud masking, temporal median filtering, and image mosaicking to generate annual, cloud-free composites. The Normalized Difference Vegetation Index (NDVI) was calculated from the near-infrared and red bands, and the dimidiate pixel model was applied to estimate fractional vegetation coverage (FVC). Linear regression analysis was then conducted to assess temporal trends. The results revealed that: (1) The overall vegetation coverage level in Central Asia was relatively low but exhibited significant spatial heterogeneity; (2) Most regions showed stable vegetation trends between 1993 and 2018, with increasing coverage in the Kazakhstan Hills and Fergana Basin, while the Ural River Basin and Syr Darya River Basin displayed decreasing trends; (3) The total vegetation coverage cumulatively increased by 3.96%, with Kyrgyzstan and Tajikistan showing increases of 5.86% and 3.96%, respectively; (4) Bare soil areas retreated by a total of 25.9$×10^{4}$ km^2, while low, medium, and high vegetation coverage areas showed oscillatory expansion. This study demonstrates that combining remote sensing big data with geospatial cloud computing enables effective regional-scale dynamic monitoring of vegetation coverage, providing technical support and quantitative data for ecological assessment and succession analysis in Central Asia.

Keywords: vegetation coverage monitoring; Central Asian regions; Landsat images; NDVI; Google Earth Engine; multi-temporal

1 Study Area and Data

1.1 Study Area Overview

Central Asia comprises five countries: Kazakhstan, Kyrgyzstan, Tajikistan, Uzbekistan, and Turkmenistan, covering approximately 4.05$\times10^{6}$ km^2. Geographically situated between 35°11 -55°24 N and 46°16 -87°38 E, the region lies between China, Russia, Iran, Pakistan, and Afghanistan. The terrain slopes from high elevations in the southeast (Pamir Plateau, Karakoram Mountains, Tianshan Mountains, Altai Mountains) to lowlands in the northwest (Turan Lowland). Mountain ranges block warm, moist air from the Indian Ocean, while abundant sunshine creates conditions where evaporation far exceeds precipitation, making this one of the world' s most typical arid zones. Rivers flow northwestward as inland waterways without ocean outlets. Under temperate continental climate conditions, the dominant land cover types are grassland and desert. The region holds significant strategic importance as a crucial node on the Silk Road Economic Belt, with rich energy resources that complement China' s economic structure. With the advancement of the "Belt and Road" national strategy, Central Asia' s geographical advantages have become increasingly prominent, forming a "community of shared destiny" with China. This necessitates a development model that balances economic growth with ecological protection, requiring higher scientific standards for coordinating regional economic structures and ecological environments.

1.2 Data Description

This study utilized Landsat TM and OLI data from NASA' s Landsat program. The analysis employed the Landsat Surface Reflectance (LSR) product, which includes atmospheric radiation correction. To ensure complete spatial coverage of Central Asia, images from the World Wide Reference System (WRS) path/row system were selected (Table 1). Due to the large latitudinal and longitudinal span and frequent cloud cover, complete annual coverage required processing, filtering, and mosaicking numerous images. For instance, the 2018 Landsat 8 imagery alone involved processing 1,247 scenes. Data from the vegetation growing season (May-October) were selected, and temporal median filtering was applied to fuse annual datasets into single, cloud-free composites with balanced quality. Each annual composite was verified, and scenes with insufficient spatial coverage due to data gaps were excluded. Landsat 5 data showed more pronounced gaps in Central Asia, so data acquisition time was extended to improve large-scale spatial coverage. Temporal median filtering effectively reduced color differences between different path/row images caused by varying observation periods, enhancing image quality stability and temporal robustness.

2 Methods

2.1 Data Preprocessing

The preprocessing workflow differed from single-scene processing by adopting a dataset concept for pre-screening and processing. The LSR product eliminated the need for radiometric correction. The workflow (Fig. 2) included: (1) selecting all images covering Central Asia during the growing season (May–October); (2) applying cloud and shadow masking using the Fmask algorithm; (3) performing temporal median filtering to fuse annual datasets into comprehensive, cloud-free composites; (4) clipping and mosaicking images; and (5) verifying annual composites and rejecting those with low coverage due to insufficient data availability.

[Figure 2: see original paper]

2.2 Vegetation Coverage Estimation

NDVI is calculated as the ratio of the difference between near-infrared (NIR) and red (RED) reflectance to their sum (Equation 1), serving as a crucial parameter for vegetation monitoring. Compared to traditional field sampling, remote sensing enables spatially continuous, large-scale, low-cost monitoring. NDVI effectively extracts vegetation information and is widely applied in forest monitoring, grassland assessment, crop yield estimation, and drought monitoring.

For Landsat 5 TM, bands 3 and 4 correspond to red and near-infrared, respectively; for Landsat 8 OLI, bands 4 and 5 serve these functions.

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

The dimidiate pixel model assumes each pixel comprises vegetation and non-vegetation components. Though simple, it has clear physical meaning and has been validated for applicability in Central Asia. Fractional vegetation coverage (FVC) was estimated using Equation 2:

$$FVC = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}}$$

where FVC is fractional vegetation coverage, $NDVI$ is the normalized difference vegetation index, $NDVI_{soil}$ is the NDVI value for bare soil, and $NDVI_{veg}$ is the NDVI value for full vegetation cover. The highest vegetation coverage occurs in the Tianshan and Altai Mountains, where snowmelt sustains coniferous forests (Siberian larch and Schrenk' s spruce) with NDVI values approaching 0.8. Desert areas like the Karakum and Kyzylkum show NDVI < 0.1. Therefore, $NDVI_{veg}$ was set to 0.8 and $NDVI_{soil}$ to 0.1, with the latter derived from masking negative NDVI regions. Based on equal-interval principles and high-resolution Google Earth sample validation, vegetation coverage was classified into five levels: (1) bare soil (FVC < 0.1); (2) low vegetation (0.1 ≤ FVC < 0.3); (3) medium vegetation (0.3 ≤ FVC < 0.5); (4) high vegetation (0.5 ≤ FVC < 0.7); and (5) very high vegetation (FVC ≥ 0.7).

Linear regression analysis was applied to assess temporal trends in vegetation coverage. For each pixel, the slope (θ_{slope}) of the regression line was calculated (Equation 3), where positive values indicate increasing coverage and negative values indicate decreasing coverage.

$$\theta_{slope} = \frac{n \times \sum_{i=1}^{n}(Y_i \times FVC_i) - \sum_{i=1}^{n} Y_i \times \sum_{i=1}^{n} FVC_i}{n \times \sum_{i=1}^{n} Y_i^2 - (\sum_{i=1}^{n} Y_i)^2}$$

where n is the number of monitoring years and Y_i is the year corresponding to sequence i.

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3 Results and Analysis

3.1 Vegetation Coverage Estimation Results

The spatial distribution of vegetation coverage in Central Asia shows three typical patterns (Fig. 3): (1) The Turan Lowland exhibits extensive low coverage, with desert areas (covering half the plain) showing extremely sparse vegetation approaching bare soil, including the Karakum Desert (Turkmenistan) and Kyzylkum Desert (spanning Uzbekistan and Kazakhstan). (2) Mountain ranges from southeast to northeast—including the Pamir Plateau, Karakoram, Kunlun, Tianshan, and Altai Mountains—show better vegetation coverage due to summer glacial meltwater, appearing as light to dark green in the imagery. (3) The Kazakhstan Hills in the north form windward slopes that intercept warm, moist Atlantic airflows, generating precipitation and supporting relatively good vegetation cover.

[Figure 3: see original paper]

3.2 Spatial Pattern Evolution of Vegetation Coverage

The spatial pattern of vegetation coverage trends from 1993-2018 is shown in Figure 4 (blank areas represent cumulative data gaps). Most regions maintained stable vegetation trends during this period. Areas with increasing coverage include: (1) the Tianshan Mountains and Pamir Plateau; (2) the Fergana Basin; and (3) the central Kazakhstan Hills. Decreasing trends occurred mainly in the Ural River Basin and the Syr Darya River Basin north of the Kyzylkum Desert. Notably, the Aral Sea region (once the world' s fourth-largest lake) shows a significant apparent increase in vegetation coverage, but this reflects a land cover change from water to exposed lakebed sediments due to excessive agricultural and industrial water consumption, not actual vegetation growth.

[Figure 4: see original paper]

Significance testing using the F-test classified trends into five categories (Table 2). Non-significant changes ($P > 0.05$) covered 348.56×10^{4} km^2 (86.03% of the region). Significant decrease (slope < 0, $P \leq 0.05$) and extremely significant decrease (slope < 0, $P \leq 0.01$) totaled 4.85×10^{4} km^2 (1.19%). Significant increase (slope > 0, $P \leq 0.05$) and extremely significant increase (slope > 0, $P \leq 0.01$) covered 18.88×10^{4} km^2 (4.85%). The mean slope of 0.0007 indicates overall stable vegetation trends. Turkmenistan (containing the Karakum Desert) showed the most stable trends, while Kyrgyzstan and Tajikistan exhibited the strongest increasing trends.

3.3 Temporal Evolution of Vegetation Coverage by Country

Figure 5 shows the temporal variation of mean vegetation coverage for each country from 1993-2018. Ranked from highest to lowest coverage: Kyrgyzstan, Kazakhstan, Tajikistan, Uzbekistan, and Turkmenistan. Overall, Central Asian vegetation coverage showed an oscillatory increase, cumulatively rising by 3.96%. Tajikistan had the highest cumulative increase at 5.86%, while Turkmenistan, dominated by desert and bare land, showed virtually no change. Between 1993-2000, vegetation coverage decreased significantly at -0.0037/year, reflecting strong environmental degradation. After 2000, coverage increased oscillatory, cumulatively rising by 3.96% through 2018. The spatial distribution became more heterogeneous after 2000, particularly in Kyrgyzstan and Tajikistan, which contain the Tianshan Mountains and Pamir Plateau. Glaciers and snow in these areas are highly sensitive to global climate change, affecting local climate and causing strong temporal fluctuations in vegetation coverage. These results align with previous studies using MODIS data to estimate grassland coverage changes in Central Asia.

[Figure 5: see original paper]

3.4 Temporal Changes in Area of Different Vegetation Coverage Classes

Spatial statistics of water bodies, bare soil, and vegetation coverage classes show that bare soil area retreated by 25.9×10^{4} km^2 during 1993-2018 (Fig. 6). Low vegetation coverage area increased by 19.6×10^{4} km^2, while medium and high vegetation coverage areas increased by 9.5×10^{4} km^2 and 7.1×10^{4} km^2, respectively, showing oscillatory expansion. Water area decreased by 5.3×10^{4} km^2, primarily due to Aral Sea shrinkage. The most dramatic reduction occurred during 1993-2000 (4.3×10^{4} km^2), reflecting strong disturbance from the region' s arid climate. The subsequent increase in bare soil area by 28.1×10^{4} km^2 also indicates significant ecological degradation during this period.

[Figure 6: see original paper]

4 Conclusions

The "Belt and Road" national strategy, proposed in 2013, emphasizes building a "Silk Road Economic Belt" and "21st Century Maritime Silk Road," highlighting Central Asia' s geographical advantages and fostering a "community of shared destiny" with China. This requires development models that balance economic growth with ecological protection ("green mountains and clear waters"). This study utilized long-term Landsat data and the Google Earth Engine platform to achieve large-scale, moderate-resolution (30 m) vegetation coverage estimation for Central Asia from 1993–2018, analyzing spatiotemporal evolution patterns.

Key findings include: (1) Spatially, vegetation coverage shows strong heterogeneity, with typical regions including the low-coverage Turan Lowland (deserts), moderate-coverage Kazakhstan Hills, and high-coverage eastern Tianshan and Altai Mountains. (2) Temporally, most regions remained stable during 1993–2018, with increasing trends in the eastern Fergana Basin and central Kazakhstan Hills, and decreasing trends in the Ural and Syr Darya River Basins. (3) Overall vegetation coverage increased by 3.96%, with Kyrgyzstan and Tajikistan showing significant increases of 5.86% and 3.96%, respectively, while Turkmenistan remained unchanged. (4) Bare soil area retreated by 25.9×10^{4} km^2, while low, medium, and high vegetation coverage areas showed oscillatory expansion. Water area decreased by 5.3×10^{4} km^2 due to Aral Sea shrinkage.

This study demonstrates that combining remote sensing big data with geospatial cloud computing enables effective monitoring of vegetation dynamics at regional scales, providing a spatially extensive ecological reference and data foundation for the sustainable implementation of the "Belt and Road" initiative.

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