Research on the change of vegetation loss and gain in Shenyang based on NDVI index

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Abstract. Monitoring long time series of vegetation cover changes is essential to investigate the vegetation gain/loss and ecological conservation of an area. This paper first calculates and synthesizes the maximum NDVI image based on Landsat data of Google Earth Engine platform. Secondly, the vegetation cover is obtained using the dimidiate pixel model. Thirdly, the temporal and spatial trends of vegetation cover are analyzed using linear regression analysis method. Finally, with the support of random pre algorithm, the land cover types are obtained, and the gain / loss change types of vegetation are analyzed. The results show that the overall vegetation cover in Shenyang is mainly high cover. Vegetation cover change was dominated by significant gain, with minimal significant loss and an overall upward trend. Large areas of land cover in the study area were converted to vegetation, while vegetation in some areas of the district was converted to construction land.

1. Introduction

The monitoring of dynamic changes in vegetation and the relationship between ecological changes and sustainable human development has become one of the important topics of ecological and environmental research [1]. With the rapid development of urbanization, the scale of cities continues to expand, and the impact of related policies on returning farmland to forests and human factors has changed the vegetation coverage pattern of the original city [2]. The spatial distribution of changes in vegetation gain and loss types are not known to the public, and this has become an urgent issue to be addressed.

Changes in vegetation include losses and gains, a concept developed by Huang [3], which is important for this paper's vegetation study. Current studies mostly use NDVI to analyze the spatio-temporal characteristics and influencing factors of vegetation, but there are relatively few studies on vegetation gains and losses and their types of changes. For example, Pei used NDVI time series data to analyze the spatio-temporal variation characteristics of vegetation [4], Piao studied the influencing factors of vegetation dynamic changes [5], and Mynini studied the fluctuation factors of vegetation coverage based on AVHRR NDVI data [6], Wang used MODIS data to study vegetation degradation and improvement areas in Shenyang [7]. Zhang used the GEE (Google Earth Engine) platform to analyze the increase and decrease of vegetation coverage in the Beijing-Tianjin-Hebei region [8]. These studies have failed to spatially visualize the types of changes in vegetation cover gains and losses, making it difficult to provide criteria for the overall planning of urban vegetation.
Therefore, based on the advantages of the GEE remote sensing big data platform, this paper studies the spatiotemporal changes and types of vegetation coverage in Shenyang from 2001 to 2017. First extract the vegetation to obtain the spatial distribution of vegetation coverage. Second, analyze the trend of vegetation coverage in the study area. Finally, the classification results are combined with the maximum vegetation coverage to analyze the changes in vegetation gains and losses.

2. Study area and data

2.1. Study area
Shenyang is located in northeast China and central Liaoning, the geographical centre of Northeast Asia. Shenyang is under the jurisdiction of 10 municipalities, 2 counties, and 1 county-level city. The total area of Shenyang is 12980 km², and the built-up area is 553.00 km². By the end of 2016, the city’s forest coverage rate was 28%.

2.2. Data access and processing
This paper uses pre-processed Landsat TOA (top-of-atmosphere) data from the GEE database. Select all images between 2001-2017 (except 2012). De-clouding, cropping, stitching and calculating the NDVI of each image. Errors due to cloudiness are eliminated by maximum-value synthesis, and the synthesized images are used as NDVI data for that year.

3. Research methods

3.1. Dimidiate pixel model
The basic principle of the pixel dichotomy model is to assume that the information of each pixel observed by the remote sensing sensor is composed of the vegetation part and the bare soil part, and its weight size is the percentage of the area occupied by the two parts of the pixel, and thus the proportion occupied by the vegetation part in each pixel can be calculated [9]. The specific formula is as follows:

\[
FVC = \frac{\text{NDVI} - \text{NDVI}_{\text{soil}}}{\text{NDVI}_{\text{veg}} - \text{NDVI}_{\text{soil}}}
\]  

(1)

Where FVC (Fractional Vegetation Cover) is the vegetation cover [10], NDVI is the normalized vegetation index, \( \text{NDVI}_{\text{soil}} \) is the bare soil pixel values and \( \text{NDVI}_{\text{veg}} \) is the pure vegetation pixel values.

3.2. Linear regression analysis method
The linear regression analysis method [11] is based on the least squares method, which regresses variables on time scales to model the trends of the variables. Trend analysis was performed on the raster pixels in the study area, reflecting the different temporal trends of NDVI characteristics for each pixel. The formula is:

\[
k = \frac{n \times \sum_{i=1}^{n} i \times FVC_i - (\sum_{i=1}^{n} i) \left( \sum_{i=1}^{n} FVC_i \right)}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}
\]  

(2)

where \( k \) is the slope of change in vegetation cover in the study area, characterizing the trend in vegetation cover over the study period. \( n \) is the number of years of monitoring, \( FVC_i \) is the maximum vegetation cover in year \( i \).

For each pixel in the study area, a goodness-of-fit test is performed using the determination coefficient \( R^2 \). The closer \( R^2 \) is to 1, the closer the actual pixel value is to the regression line, the better the goodness-of-fit is.

\[
R^2 = k^2 \frac{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}
\]  

(3)
where $x_i$ is the time series, $y_i$ is the NDVI value of the $i$ year.

3.3. Random forest algorithm

Random Forest [12] is a machine learning method proposed in 2001 as an integrated classifier with multiple decision trees as the base classifier. In this paper, a random forest algorithm was used to supervise the classification of 2017 Landsat 8 TOA images, dividing the study area into three categories: built-up area, vegetation, and water.

4. Analysis of results

4.1. Characterization of the spatial distribution of vegetation cover

![Image]

**Figure 1.** Distribution of vegetation cover in Shenyang city, 2001-2017.

Each pixel of the study area, by calculating the vegetation cover of the 2001-2017 time series of Shenyang city, according to the Soil Erosion Classification Grading Criteria classifies the vegetation cover of the study area into the following five classes: $<10\%$ is non-vegetated, $10\% \sim 30\%$ is low coverage, $30\% \sim 45\%$ is low to medium coverage, $45\% \sim 60\%$ is medium coverage, $>60\%$ is high coverage.

From Figure 2 and Table 2, it can be seen that the overall vegetation cover in the study area is good, with medium and high cover being more prevalent, and over all more stable. Non-vegetated areas continued to increase slightly by 1.56 percent, other cover fluctuated widely, high-coverage areas changed the most. A significant reduction of 17.02% from 2007-2017. There are only small overall changes in vegetation cover across all grades in Shenyang, with the most significant changes occurring in areas of high cover vegetation, but maintaining a Dynamic Balance.

**Table 1.** Shenyang city vegetation cover classification area statistics, 2001-2017.

| Year | Non-vegetated | Low coverage | Low to medium coverage | Medium coverage | High coverage |
|------|---------------|--------------|------------------------|-----------------|--------------|
| 2001 | 8.98          | 9.63         | 15.21                  | 20.25           | 45.92        |
| 2007 | 9.53          | 5.86         | 7.40                   | 11.92           | 65.29        |
| 2010 | 9.35          | 8.32         | 11.79                  | 17.23           | 53.31        |
| 2017 | 10.54         | 9.93         | 13.94                  | 18.29           | 47.27        |

4.2. Analysis of temporal and spatial trends in vegetation cover

For each pixel in the study area, the inter-annual trend in FVC values is computed by Formula (2), grading the slope $k$ values. The trends of vegetation change were as follows: $k < -0.005$ for clear loss, and $-0.005 < k < -0.001$ for mild loss, $-0.001 < k < 0.001$ is unchanged, $0.001 < k < 0.005$ is mild gain, $k > 0.005$ for clear gain.
Figure 2. (a) Trends of vegetation cover change in Shenyang, (b) Spatial distribution of the coefficient of variability $R^2$.

Table 2. Shenyang vegetation change trend graded area statistics, 2001-2017.

| Trends          | Clear loss | Mild loss | Unchanged | Mild gain | Clear gain |
|-----------------|------------|-----------|-----------|-----------|------------|
| Area (10000 $km^2$) | 1414.30    | 1867.20   | 2529.06   | 2854.20   | 4190.23    |
| Percentage (%)  | 10.94      | 14.84     | 21.10     | 21.87     | 31.25      |

Figure 2(a) shows clear gain in west and east clearly vegetation in Shenyang, clear loss in large areas of the central part of the city, and losses in all other regions slight change. Table 3 shows that the trend of vegetation change in Shenyang from 2001 to 2017 is dominated by clear gain, followed by mild gain. Areas of clear loss were the least. Shenyang city showed more gain than loss of vegetation, indicating an increasing trend of vegetation. Figure 2(b) shows that more than 38% of the area within the study area has a decision factor greater than 0.4, indicating that the results of the analysis of the trend of change more accurate.

4.3. Analysis of vegetation loss and gain types under the random forest algorithm

Figure 3. (a) Land cover type in Shenyang city, 2017, (b) Vegetation loss type, (c) Vegetation gain type.

Table 3. Land cover classification accuracy statistics.

| Category     | Built-up area | Vegetation | Water | Producer accuracy (%) |
|--------------|---------------|------------|-------|-----------------------|
| Built-up area| 144           | 8          | 7     | 73.07                 |
| Vegetation   | 3             | 431        | 10    | 97.07                 |
| Waters       | 12            | 5          | 203   | 92.27                 |
| User accuracy (%) | 90.57    | 89.62      | 92.27 |
Overall accuracy: 90.36%, Kappa statistic: 0.84.

Figure 4. Histogram of proportional change in vegetation loss type in Shenyang.

The classification accuracy of this forest stochastic algorithm was high (Table 3). The proportion of built-up land was 16.76%, the proportion of vegetation was 81.37%, and the proportion of water area was 1.87%. The classification results were overlaid with the 2017 vegetation cover distribution, resulting in six types of cover: construction land, water, low cover, low-moderate cover, medium cover, and high cover. See Figure 3. (b,c).

The conversion of vegetation to construction land accounted for 45.56% of the total vegetation loss (Figure 4). The conversion lands types into vegetation accounted for 97.34% of the total vegetation gain in the gain change. The loss of vegetation is mainly due to the destruction of vegetation on construction sites. The main forms of vegetation gain are vegetation growth and agricultural land reclamation, which are distributed in the north, where the region is mountainous and has a high vegetation cover.

5. Conclusions
This article analyses the types of vegetation gains and losses in Shenyang from 2001 to 2017. Conclusions are as follows: (1) The GEE cloud platform uses code programming, which can efficiently realize batch collection, processing operations and result output of remote sensing big data. (2) The method of this study has high practicality. The judgement coefficient fit is excellent, and the random forest Kappa coefficient is 0.84, which is of high precision. (3) The vegetation loss in Shenyang City is mainly distributed around the urban area, and the overall vegetation coverage shows a gain trend. Land cover change is the main reason for the change of vegetation cover, among which urban expansion and vegetation destruction are the main factors leading to vegetation loss. Afforestation and conversion of farmland to forest are the main factors for vegetation gain.

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