Analysis of Landscape Change Characteristics of Drought Severity Levels in the Interior of Mu Us Sandy Land Based on Remote Sensing Data (Postprint)

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Abstract

Currently, numerous remote sensing methods are available for monitoring soil moisture content. This study selected three monitoring methods characterized by good stability, wide applicability, and minimal meteorological data requirements—the SWEPDI index method, energy index method, and TVDI index method. Using medium-to-high resolution Landsat8 data from two periods (April and September 2016) as the data source, linear regression was performed between each of the three methods (SWEPDI spectral method, energy index method, and TVDI index method) and field-measured soil moisture data across different temporal periods and soil depths, and inter-model comparisons were conducted to identify the most suitable model. Concurrently, landscape indices were employed to analyze soil moisture variation trends between the two temporal phases at the patch-type level. The results demonstrate that the TVDI method significantly outperforms both the SWEPDI spectral method and the energy index method. Moreover, this method resolves the limitation of other methods in continuously monitoring soil water content and is applicable for soil moisture retrieval under diverse vegetation cover conditions and across various soil depths. Furthermore, six landscape indices were utilized to analyze landscape pattern changes associated with different drought severity levels in April and September 2016, revealing that the PLAND index reached 58.76% in April, while the PLAND index for light drought level attained 44.16% in September, both representing dominant proportions, wherein the values of LPI, AREA_CV, and AI indices also reached their maximum values, indicating a significant improvement in drought conditions.

Full Text

Preamble

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Abstract: Remote sensing technology has become increasingly popular for monitoring soil moisture content. This study selected three monitoring methods with good stability and minimal meteorological data requirements: the SWEPDI index method, the energy index method, and the TVDI index method, to better understand landscape change characteristics under hinterland drought conditions in Mu Us Sandy Land, Inner Mongolia, China. Using Landsat 8 data from April 2016 and September 2016 as data sources, each method was linearly fitted with field survey data according to sampling time, soil depth, and corresponding soil moisture content. Model comparison determined the most suitable approach. Simultaneously, soil moisture change trends across two time phases were analyzed by plaque type using landscape indices. Results showed that the TVDI index method outperformed both the SWEPDI index method and the energy index method, and also solved problems existing in continuous soil moisture monitoring. The TVDI index method is suitable for all vegetation conditions and various soil depths in drought monitoring. Additionally, six landscape indices were selected to analyze landscape pattern changes in April 2016 and September 2016 at different drought levels. It was found that PLAND reached 58.76% in April, decreasing to 44.16% in September at light drought grade, while both remained dominant as other indices like LPI, AREA_CV, and AI reached maximum values, indicating obvious drought condition improvement.

Keywords: SWEPDI index method; energy index method; temperature vegetation drought index; landscape pattern

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2. Methods

2.1 Data Collection

The study area is located in Mu Us Sandy Land, Inner Mongolia. Landsat 8 OLI/TIRS imagery from April 9 and September 9, 2016, was selected as the primary data source. The images were preprocessed using ENVI software, including radiometric calibration, atmospheric correction with FLAASH, and geometric correction. Field sampling was conducted synchronously with satellite overpass times. A total of 80 sampling points were established, each covering a 10 km × 10 km area, with three soil layers (0–10 cm, 10–20 cm, and 20–30 cm) measured at each point using a soil auger. Soil moisture content was determined using the drying method, with measurements taken at 10 cm intervals. The geographic location of the study area and sampling point distribution are shown in [FIGURE 1].

2.2 SWEPDI Index Method

The SWEPDI (Soil Water Evaporation and Plant Drought Index) method is based on the NIR-Red spectral feature space. The index is calculated as:

$$SWEPDI = 1 - EPDI$$

where EPDI is calculated according to the formula:

$$EPDI = \frac{\rho_{red} + M\rho_{nir} - L \times (DVI - M\rho_{red})}{EVI \times \sqrt{1 + M^2}}$$

In this equation, ρ_{red} and ρ_{nir} represent red and near-infrared reflectance after FLAASH atmospheric correction; M is the slope of the soil line; EVI is the Enhanced Vegetation Index; and L is the soil line intercept, typically set to 0.6 for sandy land areas.

The variable D is defined as:

$$D = \frac{1 - A1}{TS}$$

where $A1$ is the reflectance of the first thermal infrared band (10.60–11.19 m) and TS is the surface temperature.

2.3 TVDI Index Method

The TVDI (Temperature Vegetation Drought Index) method, based on the principle that surface temperature and vegetation index are negatively correlated, uses the dry and wet edges of the NDVI-TS feature space to calculate drought conditions. The dry and wet edge equations are:

$$TS_{max} = a_1 + b_1 \times NDVI$$
$$TS_{min} = a_2 + b_2 \times NDVI$$

where TS_{max} and TS_{min} represent the maximum and minimum surface temperatures, respectively, corresponding to the dry and wet edges in the NDVI-TS feature space. The coefficients a_1, b_1, a_2, and b_2 are obtained through linear fitting of the dry and wet edges.

TVDI is then calculated as:

$$TVDI = \frac{TS - TS_{min}}{TS_{max} - TS_{min}}$$

TVDI values range from 0 to 1, where values closer to 0 indicate wetter conditions and values closer to 1 indicate drier conditions. Generally, TVDI < 0.2 represents wet conditions, 0.2–0.4 represents normal conditions, 0.4–0.6 represents light drought, 0.6–0.8 represents moderate drought, and >0.8 represents severe drought.

2.4 Energy Index Method

The energy index method establishes a relationship between soil moisture and remote sensing-derived energy indices. Common indices include the Crop Water Stress Index (CWSI), Water Deficit Index (WDI), and others. This study employed a linear regression model between soil moisture content and various energy indices to establish an inversion model.

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3. Results

3.1 Model Fitting and Validation

Linear regression models ($W = a + bQ$) were established between measured soil moisture content (W) and the three index methods (Q) for different soil layers (0–10 cm, 10–20 cm, 20–30 cm) in April and September 2016. The fitting and validation results are presented in [TABLE 1], [TABLE 2], and [TABLE 3].

TABLE 1 shows the SWEPDI method results. For April, the correlation coefficients (R^2) were 0.606, 0.541, and 0.502 for the three soil layers, with average relative errors of 14.96%, 21.96%, and 23.45%, respectively. For September, R^2 values were 0.641, 0.594, and 0.571, with average relative errors of 14.91%, 18.37%, and 19.14%.

TABLE 2 presents the energy index method results. April R^2 values were 0.652, 0.621, and 0.566, with average relative errors of 13.84%, 16.27%, and 21.41%. September R^2 values were 0.749, 0.670, and 0.661, with average relative errors of 12.24%, 15.67%, and 16.65%.

TABLE 3 shows the TVDI method results. For April, correlation coefficients were -0.865, -0.840, and -0.723, with average relative errors of 8.97%, 10.95%, and 15.13%. September values were -0.752, -0.703, and -0.679, with average relative errors of 10.85%, 11.01%, and 14.23%.

3.2 Method Comparison

The TVDI method demonstrated the highest accuracy among the three approaches, with the lowest average relative errors across all soil layers and both time periods. The correlation coefficients for TVDI were negative because TVDI is inversely related to soil moisture (higher TVDI values indicate drier conditions). The TVDI method successfully addressed limitations in continuous soil moisture monitoring and proved suitable for various vegetation conditions and soil depths.

The energy index method performed second best, while SWEPDI showed the lowest correlation coefficients and highest errors. The performance of all methods was generally better for surface layers (0–10 cm) than deeper layers, and better in September than in April.

3.3 Landscape Pattern Analysis

Based on TVDI inversion results, drought conditions were classified into five levels: wet ($0 < TVDI < 0.2$), normal ($0.2 < TVDI < 0.4$), light drought ($0.4 < TVDI < 0.6$), moderate drought ($0.6 < TVDI < 0.8$), and severe drought ($0.8 < TVDI < 1$). Landscape pattern indices were calculated for each drought level in April and September 2016.

TABLE 4 and **TABLE 5** show the landscape indices for different drought patches. The Percentage of Landscape (PLAND) index, which represents the proportion of each drought level area, revealed that light drought patches dominated in April (58.76% of total area) and decreased to 44.16% in September. The Largest Patch Index (LPI), Area-Weighted Mean Shape Index (AREA_CV), and Aggregation Index (AI) all reached maximum values at the light drought level, indicating that light drought was the dominant landscape type.

The spatial distribution of TVDI in 2016 ([FIGURE 4]) shows that drought conditions were more severe in April, with larger areas of moderate and severe drought, while September showed improved conditions with expanded wet and normal areas. The landscape pattern analysis demonstrates that TVDI not only effectively monitors soil moisture but also captures the spatial heterogeneity of drought conditions.

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4. Discussion

The TVDI method' s superiority stems from its physical basis in the energy balance principle and its consideration of both vegetation status and surface temperature. Unlike SWEPDI, which relies solely on spectral information, TVDI integrates thermal information, making it more sensitive to soil moisture variations. The energy index method, while effective, requires more complex parameterization and meteorological data.

The seasonal variation in model performance reflects vegetation phenology. In April, sparse vegetation cover in Mu Us Sandy Land reduces the sensitivity of spectral-based methods, while the thermal-based TVDI remains robust. By

September, increased vegetation cover improves the performance of all methods, but TVDI maintains its advantage.

Landscape pattern analysis revealed that drought conditions in Mu Us Sandy Land are spatially aggregated, with light drought forming the dominant patch type. The decrease in PLAND for light drought patches from April to September, coupled with increases in wet and normal patches, indicates significant drought alleviation during the growing season. The high AI values at light drought levels suggest that drought patches are highly aggregated, which has important implications for water resource management and ecological restoration.

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5. Conclusion

This study compared three remote sensing methods for soil moisture monitoring in Mu Us Sandy Land. The TVDI index method demonstrated the highest accuracy and stability across different soil depths and time periods, making it most suitable for drought monitoring in this region. The method effectively solved problems in continuous monitoring and performed well under various vegetation conditions.

Landscape pattern analysis based on TVDI classification revealed that light drought was the dominant condition in April 2016, covering 58.76% of the area, but decreased to 44.16% by September. The improvement in drought conditions was evident across all landscape indices. These findings provide valuable insights for drought monitoring and ecological management in arid and semi-arid regions.

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