Post-print: Crop Planting Structure Extraction Based on Landsat 8 Time Series NDVI

Authors: Bai Yanying, Gao Julin, Zhang Baolin, Gao Julin

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Abstract

To improve the accuracy and efficiency of remote sensing monitoring of crop planting structures in the Inner Mongolia Plain irrigation areas, a method for extracting crop planting structures based on time-series NDVI curves is proposed. Taking the Tumote Right Banner Plain region in Inner Mongolia as the study area and multi-temporal Landsat imagery from 2015 covering the crop growth period as the data source, the land surface in the study area was classified into three categories—vegetated surface, non-vegetated surface, and water body—according to the different NDVI value ranges of various land cover types. Within the vegetated area, forest land and barren grassland were extracted based on the characteristics of their time-series NDVI curves, with the remaining area designated as farmland. A classification decision tree model was constructed based on the differential characteristics of time-series NDVI curves for wheat, maize, sunflower, and zucchini to extract the spatial planting distribution information of these crops within the farmland area. The remote sensing extracted areas of various land cover types and crops in the study area were close to the actual statistical areas, with the overall land use classification accuracy reaching 85.71% and the overall crop classification accuracy reaching 82.69%. The research results demonstrate that this method achieves high accuracy in extracting crop planting information and enables efficient and accurate monitoring of regional crop planting information.

Full Text

Preamble

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1. Study Area

1.1 Overview

The study area, Tumote You County, is located in the Hetao Irrigation District of Inner Mongolia, China, covering a total area of 2369.18 km². The county lies between 110°13 -110°13 E longitude and 40°14 -40°39 N latitude, with the core research zone encompassing 1667.5 km² [Figure 1: see original paper]. The region features a temperate continental climate characterized by distinct land use types including farmland, woodland, grassland, water bodies, and built-up areas. Cropland dominates the landscape, accounting for approximately 91% of the total area, with spring wheat, corn, sunflower, and zucchini being the primary crops.

1.2 Data Sources and Preprocessing

Multi-temporal Landsat imagery from the 2015 growing season served as the primary data source, comprising 12 scenes with cloud cover below 20% . The dataset included both Landsat 8 OLI and Landsat 7 ETM+ images. Preprocessing involved atmospheric correction using the FLAASH algorithm and geometric correction with 50 m × 50 m ground control points, achieving sub-pixel registration accuracy.

A total of 510 sampling points were collected across the study area: 329 training samples (49 wheat, 120 corn, 70 sunflower, 42 zucchini, and 31 other land cover types) and 181 validation samples (53 wheat, 40 corn, 55 sunflower, 24 zucchini, and 9 other types) [Figure 2: see original paper].

1.3 Decision Tree Classification Methodology

The classification framework employed a hierarchical decision tree structure based on temporal NDVI profiles. The methodology sequentially separated land cover types by exploiting characteristic differences in their NDVI time series signatures.

2. NDVI Time Series Analysis

2.1 NDVI Profile Characteristics

The Normalized Difference Vegetation Index (NDVI) was calculated using the standard formula:

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

where NIR and Red represent the near-infrared and red band reflectance values, respectively.

Distinct temporal patterns emerged among different land cover types [FIGURE:3, FIGURE:4]. Forest areas exhibited consistently high NDVI values throughout the growing season, while grasslands showed moderate values with gradual seasonal decline. Croplands displayed dynamic NDVI trajectories corresponding to crop phenological stages, with each crop type possessing unique temporal signatures .

2.2 Decision Tree Construction

The decision tree classification followed a multi-level rule set:

1. **Vegetation vs. Non-vegetation Separation**: Pixels with maximum NDVI values below 0.35 were classified as non-vegetation (water, built-up, bare land). This threshold effectively eliminated non-vegetated surfaces while preserving all crop types.
2. **Forest and Grassland Extraction**: Within vegetated areas, forest and grassland were distinguished based on their distinct NDVI temporal patterns. Forest maintained NDVI > 0.5 throughout the season, whereas grassland showed lower values and different seasonal dynamics.
3. **Crop Type Discrimination**: The remaining vegetated pixels (cropland) were classified into specific crops using phenology-based rules:
   - **Wheat**: Peak NDVI occurred in late May, with rapid senescence in June
   - **Corn**: NDVI remained low in May, increased steadily through July, and peaked in August
   - **Sunflower**: Characterized by delayed green-up (late June) and peak NDVI in mid-August
   - **Zucchini**: Showed early growth (May) but lower peak NDVI values compared to other crops

Key temporal nodes included May 30, July 25, and August 26, which captured critical phenological differences among crops [Figure 5: see original paper].

2.3 Classification Results and Validation

The decision tree classification achieved an overall accuracy of 85.71% with a Kappa coefficient of 0.75 for land cover types. The crop-specific classification yielded an overall accuracy of 82.69% with a Kappa coefficient of 0.77. Confusion analysis revealed that 66.70% of the study area was correctly classified as cropland, with forest and grassland comprising 9.58% and 17.82%, respectively. Mixed pixels and spectral similarity among certain crop types accounted for the majority of classification errors [Figure 6: see original paper].

The results demonstrate that time-series NDVI analysis effectively captures crop phenological differences, enabling accurate and efficient extraction of planting structure information in irrigated agricultural regions.

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