Postprint of Land Use and Land Cover Classification in the Horqin Sand Dune-Meadow Interspersed Region

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Date: 2021-04-23T00:00:00+00:00

Abstract

To achieve identification of land use and land cover (LULC) types in the Horqin dune-meadow interlaced area based solely on optical remote sensing data, 64 scenes of Sentinel-2 imagery from 2018 were selected. Combined with image segmentation techniques and utilizing vegetation phenological information and habitat characteristics, a community-level LULC decision tree classification rule was established, achieving an overall classification accuracy of 0.91 and a Kappa coefficient of 0.89. Classification results show that dryland has the largest distribution area in the study region, accounting for 33.79%; shrub communities rank second, accounting for 25.03%; high-diversity semi-shrub communities and arboreal forests are similar, representing 14.54% and 10% respectively; low-diversity semi-shrub communities, meadowlands, and mobile sandy lands each account for approximately 5%; and the total proportion of remaining types is less than 5%. This method can not only accurately reflect the spatial distribution of cover types in the study area, but also provide the growth and development status of different cover types, thereby providing basic data for material cycle research in this region while also offering threshold references for historical LULC identification in this region.

Full Text

Land Use and Land Cover Classification in the Dune-Meadow Interlaced Area of Horqin Sandy Land

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Abstract

To achieve identification of land use and land cover (LULC) types in the dune-meadow interlaced area of Horqin Sandy Land based solely on optical remote sensing data, Sentinel-2 imagery was selected. Combining image segmentation techniques with vegetation phenology information and habitat characteristics, a decision tree recognition rule was established at the community level. The overall classification accuracy was 0.91 and the Kappa coefficient was 0.89. Classification results show that dryland has the largest distribution area in the study region, accounting for 33.79%, followed by shrub communities at 25.03%. High-diversity semi-shrub communities and arbor forests have similar distribution areas, accounting for 14.54% and 10% respectively. Low-diversity semi-shrub communities, meadowlands, and mobile sand lands each account for approximately 5%. The total proportion of remaining LULC types is less than 5%. This method can not only accurately reflect the spatial distribution of cover types in the study area, but also provide growth and development status information for different cover types, offering basic data for material cycle research in this region and threshold references for historical LULC identification.

Keywords: remote sensing; land use/land cover; multi-scale segmentation; decision tree; classification; Sentinel-2 satellite; multi-temporal; Horqin Sandy Land

1. Introduction

Horqin Sandy Land is the largest of China' s four major sandy lands, characterized by fragile ecosystems that serve as a primary source of sandstorms in North China [?]. With the rapid development of computer technology, using remote sensing data to obtain land use and land cover (LULC) information has become the primary means for LULC identification. Previous studies on Horqin Sandy Land have mostly focused on classification based on vegetation coverage [?]. As local desertified land continues to be restored, research emphasis should shift to refined classification of vegetation cover types and vegetation diversity monitoring. Detecting early warning signals of habitat structure modification by invasive species and changes in key species occurrence and propagation is crucial for ecosystem management [?]. Additionally, studies have shown complex relationships between sandy land water balance and vegetation [?]. For example, in Zhanggutai in southern Horqin Sandy Land, increased broadleaf forest and farmland planting area has led to groundwater table decline, causing large-scale dieback of originally introduced *Pinus sylvestris* var. *mongolica* plantations [?]. Therefore, identifying LULC types in Horqin Sandy Land is important for local land management and sustainable development research.

With continuously enriched remote sensing data sources and advances in remote sensing applications, using multi-temporal remote sensing data to achieve community-level LULC precise identification has become feasible. The Sentinel-2 satellite, launched under the European Space Agency' s Copernicus program, not only has higher spatial resolution than Landsat satellite products but also includes 13 spectral bands covering visible light, near-infrared (NIR), vegetation red edge, and short-wave infrared (SWIR) [?]. Additionally, it has a high temporal resolution with a revisit cycle as short as five days [?]. Thus, using multi-temporal Sentinel-2 satellite data holds promise for achieving community-level LULC precise identification.

This study takes a dune-meadow interlaced area on the southeastern edge of Horqin Sandy Land as an example. Based on Sentinel-2 data from the 2018 vegetation growing season and ground survey data, we utilized vegetation phenology information and habitat characteristics combined with multi-resolution segmentation (MRS) based on object-oriented image segmentation technology to establish community-level LULC decision tree recognition rules. The goal is to provide a distribution pattern that reflects underlying surface vegetation growth and development information for subsequent ecosystem health evaluation in this region.

2. Data Sources

2.1. Study Area Overview

The study area is located on the southeastern edge of Horqin Sandy Land, within a closed drainage area of the West Liao River Basin. It belongs to Horqin Left Wing Rear Banner, Tongliao City, Inner Mongolia Autonomous Region, representing a typical desertified dune-meadow interlaced area. Geographic coordinates are 122°10 ~123°10 E, 42°50 ~43°46 N, with a total area of approximately 5787.32 km^2. The region has a semi-arid, semi-humid continental monsoon climate. In winter, the area is mainly controlled by cold high pressure from Mongolia, with prevailing north or west winds. In summer, it is controlled by continental low pressure and subtropical high pressure, with prevailing south and southwest winds. Surface water and groundwater resources are relatively abundant, with dense distribution of lakes, swamps, and ponds (Figure [Figure 1: see original paper]). The entire surface consists of multiple similar small units randomly combined to form a gently undulating plain, where each small unit comprises meadow patches surrounding lakes and dune patches around them [?].

2.2. Sentinel-2 Remote Sensing Imagery

This study used Sentinel-2 Level 1C image products (top-of-atmosphere reflectance after orthorectification and sub-pixel geometric correction) as the original analysis data. Images were retrieved from the European Space Agency' s https://scihub.copernicus.eu, totaling 64 scenes from the 2018 vegetation growing season. Figure [Figure 2: see original paper] lists the specific transit dates and climate conditions of the test area. Using the Sentinel Application Platform (SNAP) and Sen2cor2.4, Level 1C products were radiometrically calibrated and atmospherically corrected to generate Level 2A data. The 10 m, 20 m, and 60 m bands were resampled to generate 10 m spatial resolution for all bands, where bands 2, 3, 4, and 8 are 10 m resolution; bands 5, 6, 7, 8a, 11, and 12 are 20 m resolution; and bands 1, 9, and 10 are 60 m resolution. Then, linear interpolation was applied to the initial time-series data of each band to obtain daily NDVI time-series data. For example, $NDVI_5 = NDVI_5 + (NDVI_{15} - NDVI_5)$ (10/15). To further remove noise from the time-series data and make it more consistent with vegetation growth and development processes, a Double Logistic filter was applied. All operations were performed in TIMESAT 3.1 software [**?**].

2.3. Ground Survey Data

In August 2018, multiple survey points were established in the test area based on the geomorphological types of dune-meadow interlaced distribution. During the survey, farmland and arbor forests with uniform distribution were only visited for point verification, while other vegetation with irregular distribution was surveyed in detail. At each detailed survey point, a 10 m × 10 m large quadrat was first established for shrub and semi-shrub investigation, followed by five 1 m × 1 m small quadrats at the four corners and center of the large quadrat for herbaceous investigation. Vegetation species, height, and density were surveyed in each quadrat. For vegetatively propagated species, ramets were considered the basic unit of species density [**?**]. Finally, the harvest method was used to obtain aboveground biomass for each plant species in the quadrats. Standard plants were collected, placed in sealed plastic bags, and taken back to the laboratory. After oven-drying, dry mass was measured and multiplied by density to obtain aboveground biomass for each species. Using the obtained biomass, density, and height, the Shannon diversity index was calculated for each survey point [**?**].

3. Methods

3.1. LULC Classification System

Based on previous vegetation classification studies in the test area [**?**], the LULC types were divided into nine categories: (1) Dryland, with corn as the main crop; (2) Paddy field, with rice as the main crop; (3) Water body; (4) Arbor forest, with poplar as the representative species; (5) Shrub community, with *Caragana microphylla* as the dominant species; (6) Low-diversity semi-shrub community, with *Artemisia halodendron* as the dominant species; (7) High-diversity semi-shrub community, with dominant species including *Artemisia frigida*, *Ephedra sinica*, and *Agropyron cristatum*; (8) Meadowland, with dominant species including *Carex duriuscula* and *Phragmites communis*; and (9) Mobile sand land, including both unvegetated areas and sparsely vegetated areas. When vegetation is present, dominant species are *Agriophyllum squarrosum* and *Artemisia* *halodendron*, with low species richness, biomass, and diversity. Table presents the composition and structural characteristics of different vegetation community types.

3.2. Methodology Overview

The community-level LULC identification process consists of two steps. First, decision tree recognition rules are constructed based on measured data from the test area. The optimal image segmentation method is explored, then training samples are imported to analyze temporal variation patterns of the Normalized Difference Vegetation Index (NDVI) and reflectance in each band, establishing recognition rules. These rules are debugged using validation samples to make interpretation results as close to reality as possible. Training samples are from 2018 ground survey data, while validation samples are from 2017 ground survey points [?], with specific sample allocation shown in Table . For features with obvious characteristics like water bodies and residential areas, manual digitization was used to add validation samples. Second, the established recognition rules are applied to interpret LULC in the study area, with coarse evaluation using Google Earth.

3.2.1. Multi-scale Image Segmentation Image segmentation in the interpretation process is implemented through the Multi-Resolution Segmentation (MRS) algorithm [?]. This algorithm has three user-defined parameters: scale, shape, and compactness. The scale parameter is the criterion for determining whether examined pixels should be merged into adjacent image objects. The shape parameter value equals 1 minus the color parameter, and the compactness parameter equals 1 minus the smoothness parameter [?]. Different object layers generated by different segmentation parameters have attribute inheritance relationships. Determining appropriate segmentation parameters is important for correct LULC identification [?]. First, through visual interpretation, residential areas, water bodies, and vegetation with significantly different characteristics were selected to choose data sources for image segmentation. The Estimating the Scale Parameter (ESP) 2 optimal scale tool [?] was used combined with manual parameter debugging and comparison to obtain optimal segmentation parameters.

3.2.2. Growing Season Time-Series Analysis NDVI is the most widely used vegetation index, calculated as follows:

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

where R_{NIR} is near-infrared band reflectance and R_{RED} is red band reflectance, corresponding to Sentinel-2 bands 8 and 4, respectively.

To remove noise from the calculated initial time-series data and make it more consistent with vegetation growth and development processes, a Double Logistic filter was applied (Figure [Figure 3: see original paper]). The TIMESAT 3.1 software [?] was used to simulate vegetation growth processes, with parameters set to obtain seasonal maximum value (NDVI$_{max}$), start time, and end time of the growing season.

The Normalized Difference Water Index (NDWI) is calculated as:

$$NDWI = \frac{R_{GREEN} - R_{NIR}}{R_{GREEN} + R_{NIR}}$$

where R_{GREEN} is green band reflectance and R_{NIR} is near-infrared band reflectance, corresponding to Sentinel-2 bands 3 and 8, respectively.

For mobile sand land classification, the Vegetation Coverage Index (VCI) derived from the pixel dichotomy model was used [?], calculated as:

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

where $NDVI_{soil}$ is the pixel value corresponding to bare land, and $NDVI_{veg}$ is the pixel value when fully covered by vegetation. In this study, $NDVI_{max}$ was used as $NDVI_{veg}$, and based on ground survey data, $NDVI_{soil}$ was set to 0.1.

3.2.3. Non-Vegetation Identification Water bodies were identified using the Normalized Difference Water Index (NDWI). Residential area identification is challenging because residential areas contain both bare land with low NDVI and green/planted land with high NDVI, making it difficult to separate using NDVI and band reflectance time-series changes. First, true-color images from May 15 were used to select samples based on house colors (R\$ $200, G$ $150, B$ \$150). Then, based on image segmentation, residential areas were classified using a sample-based classification function. The workflow is shown in Figure [Figure 4: see original paper].

4. Results

4.1. LULC Decision Tree Recognition Rules

Figure [Figure 5: see original paper] shows the remote sensing inversion information characteristics of different cover types. The NDVI time-series curves reflect vegetation phenology information. Arbor forests and meadowlands have earlier green-up times than other vegetation, so their NDVI values are higher than other vegetation from early April to late May. Paddy fields and drylands have later green-up times and rapid growth periods than other vegetation, so their NDVI values are higher from late June to early August. Shrub communities have earlier green-up times and more vigorous growth than semi-shrubs, so their NDVI values are greater than semi-shrubs during the study period.

The SWIR band reflectance time-series curves reflect moisture conditions of vegetation underlying surfaces. During the study period, paddy fields had the lowest average reflectance, followed by meadowlands, while low-diversity semi-shrub communities had the highest reflectance. Other cover types had relatively similar reflectance values.

Although remote sensing characteristics of various cover types differ significantly on average, development variations exist within the same cover type. Therefore, appropriate classification rules and thresholds must be found to make interpretation results closest to reality.

After repeated debugging and comparison, the study area LULC decision tree recognition rules were established as shown in Figure [Figure 6: see original paper]. The process involves three segmentation steps:

1. **Residential area extraction**: Based on four bands (blue, green, red, NIR) with segmentation scale, shape parameter, and smoothness set to 50, 0.1, and 0.5, respectively. Classification is performed based on imported house samples.

2. **Water body extraction**: Based on four bands with segmentation scale, shape parameter, and smoothness set to 30, 0.1, and 0.5, respectively. Objects with NDWI > 0.2 are defined as water bodies. To avoid interference from aquatic vegetation and considering cloud cover in some images, objects with NDWI > 0.2 on both May 15 and August 23 are defined as water bodies.

3. **Detailed cover type identification**: Based on six bands (blue, green, red, red edge, NIR, SWIR) with segmentation scale, shape parameter, and compactness set to 30, 0.2, and 0.5, respectively.

    - **Mobile sand land**: Objects with VCI < 0.1 are defined as mobile sand land.
    - **Farmland**: Objects with green-up time > 150 days and growth rate > 0.01 are defined as farmland. Using moisture-sensitive SWIR reflectance, farmland is divided into dryland and paddy field.
    - **Meadowland**: Objects with SWIR reflectance < 1500 are defined as meadowland.
    - **Arbor forest**: Objects with green-up time < 110 days are defined as arbor forest.
    - **Semi-shrub communities**: Using fuzzy rules based on membership functions [**?**], semi-shrub communities are identified. The fuzzy interval from small to large at NDVI_{max} 0.25-0.3 represents the transition from semi-shrub to shrub communities. Because dunes with high-diversity semi-shrub communities have better restoration status and soil water-holding capacity than those with low-diversity semi-shrub communities [**?**, **?**], SWIR reflectance is used for discrimination. Objects with SWIR reflectance > threshold are defined as low-diversity semi-shrub communities; otherwise, they are high-diversity semi-shrub communities.

4.2. LULC Identification Results

The total interpreted area of the study region is 5558.91 km^2. The spatial distribution is shown in Figure [Figure 7: see original paper]. Dryland has the largest distribution area, accounting for 33.79% of the total area. Shrub communities rank second, accounting for 25.03%. High-diversity semi-shrub communities and arbor forests have similar distribution areas, accounting for 14.54% and 10% respectively. Low-diversity semi-shrub communities, meadowlands, and mobile sand lands have relatively small distribution areas, accounting for 5.67%, 5.66%, and 4.79% respectively. Water bodies, residential areas, and paddy fields have the smallest proportions, accounting for 2.91%, 0.94%, and 0.51% respectively. High-diversity semi-shrub communities are mainly distributed in the northwestern part of the study area, while low-diversity semi-shrub communities are mainly distributed around water bodies.

4.3. Classification Accuracy Assessment

To verify the accuracy and application potential of the constructed classification rules, accuracy assessment was first performed on the test area classification results using validation samples. Evaluation metrics include Kappa coefficient, overall classification accuracy, user accuracy, and producer accuracy. Google Earth was then used for coarse evaluation of the study area classification results. User accuracy represents the proportion of true samples among all samples classified as a particular class. Producer accuracy represents the proportion of samples of a particular class that are correctly classified. Overall classification accuracy represents the total number of correctly classified pixels divided by the total number of pixels.

The Kappa coefficient comprehensively evaluates classification results by considering all factors, more accurately reflecting overall accuracy. As shown in Table , the overall classification accuracy for training samples is 0.91. User accuracy is above 85% for all classes except arbor forest and shrub communities. Producer accuracy is above 85% for all classes except high-diversity semi-shrub communities. This may be because some arbor forests have abnormal phenology—for example, some artificially planted poplar forests grow poorly under water stress and may be interpreted as shrub communities.

Water bodies, residential areas, and paddy fields have user accuracy and producer accuracy of 100%, indicating that the test area classification results are quite close to reality. For the study area classification results, Google Earth was used to randomly select 50 locations for fuzzy verification of identifiable water bodies, mobile sand lands, residential areas, arbor forests, and shrub communities, also achieving almost perfect agreement.

5. Conclusion

Using Sentinel-2 data with high temporal, spatial, and spectral resolution, vegetation in the study area was identified based on vegetation phenology information and habitat conditions. According to green-up time, cover types can be divided into three categories: early green-up (arbor forest and meadowland), late green-up (farmland), and intermediate green-up (other vegetation communities). Additionally, based on moisture conditions of vegetation growth environments, cover types can be divided into: rice planted in water, vegetation distributed around water bodies with relatively good moisture conditions (corn fields and meadow communities), and vegetation distributed on sandy land with relatively poor moisture conditions. Furthermore, based on the relationship between vegetation diversity levels and surface soil moisture conditions in sandy land, semi-shrub communities were divided into high-diversity and low-diversity types.

Based on these vegetation characteristics and using the multi-resolution segmentation algorithm, decision tree recognition rules were established with an overall classification accuracy of 0.91 and Kappa coefficient of 0.89. This method not only achieves fine classification of LULC types in the study area but also reflects phenology information and habitat conditions of different underlying surfaces, providing basic data for future ecosystem health evaluation in this region.

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