An object-based hierarchical classification method for nature reserve land cover classification

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Abstract. This study presents an object-based hierarchical classification method for nature reserve land cover classification using hyperspectral and multi-spectral data. The method firstly extracts several indices to identify non-vegetation land covers that are distinguishable with these indices, and then classify vegetation into grass land and crop. The classified land covers were finally assigned to image objects. In this study we obtained an overall classification accuracy of 95.05, with a Kappa of 0.89, which indicates the potential of this method in nature reserve change monitoring and management.

1. Introduction
The purpose of nature reserves is to protect special ecosystems where species are rare or endangered. It is of great significance to the protection of the natural environment and resources \cite{1}. However, natural disasters such as fires, earthquakes, mudslides, droughts as well as human activities such as urban expansion, overgrazing, and tourism resource development will cause irreversible losses to nature reserves \cite{2-4}. Human activities are the main causes to the interruption of nature reserve ecological balance, thus spatio-temporal land cover change monitoring is the key task for nature reserve management.

Remote sensing technology-based monitoring of nature reserves land cover change is highly efficient, accessible, and repeatable. However, human disturbance-induced land cover changes are fragmented, rapid and hidden. Such changes are difficult to be detected with single feature derived from remote sensing data. By contrast, multi-source remote sensing images originated features would be more qualified. Studies have shown that multi-source data can outperform the single-feature-used classification in tree species identification\cite{5}, forest surveys\cite{5-8}, alien invasive vegetation identification\cite{9-11}, aquatic vegetation classification\cite{12}, and tropical savanna forest mapping\cite{13}, which indicates multi-source remote sensing data can effectively make up the deficiencies of single data source used land cover classification.

Different from the concept of pixel-based classification, the object-based image analysis (OBIA) segments image to generate image objects that are basic units to be classified or analyzed. Compared with pixel-based remote sensing image analysis method, object-based classification method can make full use of statistical information and even semantic information of the internal pixels within image objects during the classification \cite{14}. Therefore, object-based classification can combine more features obtained by different remote sensing sensors to improve the classification accuracy for land cover types\cite{15-17}.

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In the application of land cover classifications, the hierarchical classification poses the manner of solving problems hierarchically, in which classification targets with distinguishable features would be labeled to the corresponding classes, different features and identification methods would be used during this procedure. Finally, a particular classification structure will be generated. Such kinds of classifications are common but effective, for example, Gavis et al. \cite{19} used hierarchical classification method based on random forests to map different quality land covers within protected habitats, this method divides complex spatial feature information into different types to reduce data dimensions. Their results show the hierarchical model could improve the classification accuracy and readability, compared with plane models. Haest et al. \cite{18} classified land covers in barren land into four levels for finer classification, the result was used to describe the habitat protection status. Although the hierarchical method can provide some valuable information for the target objects, there is no obvious difference in performance between the hierarchical model and the typical plane classification model. They also showed that the best results may need a more complicated hierarchy, so there is still room to improve the methodology.

This paper proposes an object-based hierarchical classification method based on the spatial structure and land cover indices that derived from hyperspectral data and multispectral data. We used the method in nature reserve land cover classification to analyse the applicability of our method in nature reserve change monitoring and management.

2. Study area and data

1. Study Area

The chosen study area locates in National Nature Reserve of Xilin Gol Grassland, Inner Mongolia, China. The reserve was about 20 kilometres southeast of Xilinhot city (43°26’ - 44°33’ N, 115°32’ - 117°12’ E). The reserve was built in 1985 and was upgraded to a national nature reserve in 1997 with a total area of approximately 5800 square kilometres. It is bounded by the natural watershed of Xilin River Basin (as shown in Figure 1). Biodiversity in this protected area is relatively abundant. Besides grassland, there are barren sand, forest, farmland, and wetland in this area. The grassland ecosystem is the dominant ecosystem, accounting for about 90% of the total area.

Figure 1. study area schematic (image on bottom right is Sentinel-2A image in standard false colour composite)
2. Data

The hyperspectral data was Hyperion data with a resolution of 30 m and spectral resolution of 10 nm (spectral ranges from 355nm to 2577 nm, 242 bands in total). Hyperion data used in this study was acquired on August 21, 2016. This data was downloaded from the USGS data distribution site: https://earthexplorer.usgs.gov/.

Although Hyperion could capture the spectral information of land covers, the low spatial resolution may cause mixed pixels. In order to overcome this defect, we employed Sentinel-2A image with higher spatial resolution (20m) to generate image objects (short wave infrared band was 20 m, so we resampled visible and near-infrared bands to 20m). The Sentinel L1C level data was downloaded from: https://earthexplorer.usgs.gov/. The data acquisition time was August 1, 2016, with 0 percent of cloud coverage.

The ground control points (GCPs) were from ground station monitoring and selected in conjunction with GoogleEarth imageries. These samples were used to train the classifier and assess the classification accuracy. Half samples were used for training and half were used for accuracy assessment in this study.

3. Methodology

This paper proposes an object-based hierarchical classification method that combines the spectral feature of hyperspectral data and vegetation index information with the land cover geometry information that derived from multispectral data. The specific process is shown in figure 2.

![Figure 2. Workflow of the hierarchical classification.](image_url)

Atmospheric corrections to Sentinel-2A and Hyperion images were conducted using Sen2Cor and FLAASH modules that integrated with SNAP and ENVI software respectively. We used the Sentinel-2A image to generate image objects for the study area, because the landscape of this study area is relatively uniform and less fragmented. We used the FNEA (Fractal Net Evolution Approach) algorithm in e-Cognition software to segment Sentinel-2A image, the generated image objects were used to extract the shape information of image objects. Hyperion data was used to calculate the narrow band index such as MNDWI, SAVI, NDBI, and NDVI. MNF (minimum noise fractional) transformation was performed to Hyperion to extract spectral features, the transformed data retained the spectral characteristics but reduced the dimensions which reduced the computation burden. Indices were used to identify the corresponding ground land covers. In this paper, we used OTSU's method, which was used to reduce the grayscale image to obtain the threshold to separate image into targets.
and background [20], to identify non-vegetation types such as road, water, buildings and bare soil. And then used MNF feature to classify vegetation types into grassland and woodland employing SVM classifier.

Table 1. Indices used in this study.

| Item        | Formula | Description                                                                                           | Author (Year) |
|-------------|---------|-------------------------------------------------------------------------------------------------------|---------------|
| NDVI        | NDVI = \( \frac{NIR - Red}{NIR + Red} \)                                                        | To detect vegetation growth status, it is sensitive to vegetation coverage. | Rouse, et. al. (1974) |
| SAVI        | SAVI = \( \frac{NIR - Red}{NIR + Red + L(1 + L)} \)                                              | A modified vegetation index based on NDVI to correct the influence of soil background. | Huete, et. al. (1988) |
| MNDWI       | MNDWI = \( \frac{Green - Mir}{Green + Mir} \)                                                     | An improved waterbody index based on NDWI. | Xu (2005) |
| NDBI        | NDBI = \( \frac{MIR - NIR}{MIR + NIR} \)                                                        | To enhance the impervious surface coverage. | Zha, et al. (2003) |
| SAVI-NDBI   | SAVI-NDBI                                      | An enhanced method to identify the impervious surface. | Pan, et al. (2013) |

4. Results and analysis

Each index was used to extract a single class following the threshold derived from the OTSU algorithm. Thresholds and classes classified by each index are shown in Table 2. As shown in Figure 3, the presented index the enhanced contrast between the corresponding land cover type and others.

![Figure 3. Indices extracted from Hyperion data.](image)

Table 2. Indices and the thresholds.

| Index       | Threshold | Description                                      |
|-------------|-----------|--------------------------------------------------|
| NDVI        | 0.0       | Vegetation: NDVI > 0.0; Non-vegetation: ≤0.0          |
| Length/Width| 9.5       | Road: Length/Width > 9.5; Non-road ≤ 9.5            |
| MNDWI       | 0.0       | Waterbody: NDVI > 0.0; Non-waterbody: ≤0.0          |
| SAVI-NDBI   | -0.5215   | Built-up: SAVI-NDBI > -0.5215; Non-built-up: ≤ -0.5215 |

Following the Indices and the thresholds, we identified waterbody, built-up, road and bare soil. The bare soil was identified with this rule: NDVI ≤ 0.0 and Length/width ≤ 9.5 and MNDWI ≤ 0.0 and
SAVI-NDBI $\leq -0.5215$. We employed the shape index feature that extracted from segmented image objects, to identify roads which have greater shape index than 3.5. Results of the identified classes are shown in Figure 4.

![Figure 4](image)

Figure 4. Land covers of (a) study area (partial) that was classified to (b) waterbody, (c) built-up, (d) bare soil, and (e) road using indices.

We further classified vegetation into two classes (grass and crop) using the SVM (Support vector Machine) classifier. The training samples were ground investigated control points, 205 points for crops and 6945 points for grass which is the main land cover type in this area. Existing researches show that the pixel-based classification may introduce the salt and pepper noise into the classification results, so we assigned each classified types to the segmented image objects following the method presented by Liu and Bo (2015) to generate the object-based classification results [21].

![Figure 5](image)

Figure 5. Classification result of the study area.

The classification result was assessed using the confusion matrix. The assessment results showed that the total classification accuracy was 95.05%, with a Kappa of 0.89. Misclassifications were mainly found between the water body and built-up, bare soil and built-up, grass and bare soil. The spectral and spatial features of low coverage vegetation, built-up area and bare soil in this area are similar.
Table 3. Confusion matrix of the classification results.

| Ground Truth | Total |
|--------------|-------|
| Crop         | 393   |
| Grass        | 9249  |
| Waterbody    | 298   |
| Road         | 178   |
| Built-up     | 0     |
| Bare Soil    | 233   |
| Total        | 1308  |

| Classification results | Crop | Grass | Waterbody | Road | Built-up | Bare Soil | Total |
|------------------------|------|-------|-----------|------|----------|-----------|-------|
| Crop                   | 393  | 17    | 0         | 0    | 0        | 0         | 410   |
| Grass                  | 6    | 9249  | 54        | 2    | 24       | 15        | 9350  |
| Waterbody              | 0    | 0     | 298       | 0    | 110      | 0         | 408   |
| Road                   | 0    | 0     | 0         | 178  | 32       | 7         | 217   |
| Built-up               | 0    | 0     | 0         | 19   | 1177     | 0         | 1196  |
| Bare Soil              | 0    | 233   | 41        | 3    | 85       | 1139      | 1501  |
| Total                  | 399  | 9499  | 393       | 202  | 1428     | 1161      | 1308  |

Producer's Accuracy: 98.50% 97.37% 75.83% 88.12% 82.42% 98.11%
Producer's Accuracy Percentage: 95.05%
Kappa: 0.89

5. Conclusion
In this study we propose an object-based hierarchical classification method which applies multi-features that extracted from hyperspectral data and image objects. This method identifies land covers that can be identified by single feature such as indices or image object geometry features. We got a high classification result (OA: 95.05%, with a Kappa of 0.89) in the National Nature Reserve of Xilingol Grassland in Inner Mongolia, China.

Our further work will focus on a finer scale classification of more fragmented land covers to test the robustness of this method. Comparison with the state-of-the-art methods will also be necessary to assess our method.

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