Combining Object-Oriented Segmentation and Mixed Pixel Decomposition for Desertified Land Information Extraction [Postprint]

Authors: Hua Yongchun, Li Zengyuan, Gao Zhihai, Gao Zhihai

Date: 2020-12-17T00:00:00+00:00

Abstract

Taking Minqin County, Gansu Province as the study area, this research utilized three scenes of Landsat 8 OLI data to extract sandy land information and proposed a novel method combining mixed pixel decomposition (FCLSU) with object-oriented image segmentation techniques. This method not only achieved classification and identification of sandy land, saline-alkali land, and bare soil, but also realized quantitative differentiation of mobile sandy land, semi-fixed sandy land, and fixed sandy land. The overall sandy land classification accuracy of the new method reached 87.23%, higher than the 84.82% achieved by object-oriented image classification, demonstrating more pronounced advantages in quantitative sandy land classification.

Full Text

Extraction of Sandy Land Information by Combining Object-Oriented Segmentation with Mixed Pixel Decomposition

HUA Yong-chun[1], LI Zeng-yuan[2], GAO Zhi-hai[2]
[1]Forestry College of Inner Mongolia Agricultural University, Hohhot 010011, Inner Mongolia, China
[2]Research Institute of Resource Information, Chinese Academy of Forestry, Beijing 100091, China

Abstract

Taking Minqin County in Gansu Province as the study area, this study utilized Landsat 8 OLI data to extract sandy land information and proposed a novel method combining fully constrained least squares-based linear unmixing

(FCLSU) with object-oriented image segmentation. This approach not only achieved the classification and identification of sandy land, saline-alkali land, and bare soil, but also enabled the quantitative distinction among shifting sandy land, semi-fixed sandy land, and fixed sandy land. The overall classification accuracy for sandy land using the new method reached 87.23%, significantly higher than the 84.82% achieved by conventional object-oriented image classification, demonstrating a clear advantage in the quantitative partitioning of sandy land.

Keywords: sandy land classification; quantitative; mixed pixel decomposition; object-oriented polygon segmentation

1 Introduction

Sandy land refers to degraded land where sand materials constitute the primary surface indicator under various climatic conditions, formed by both natural and anthropogenic factors. Land desertification not only deteriorates ecological environments but also causes substantial economic losses, making monitoring and assessment of sandy land essential. Traditional sandy land surveys rely primarily on field reconnaissance routes and sample plot measurements, where characteristic data from specific locations are used to delineate mapping units on topographic maps or other base maps to generate regional distribution charts of sandy land types. However, these methods are constrained by time, budget, transportation, and subjective human factors. Most sample points are established along river valleys and roads, resulting in limited and unevenly distributed data that cannot accurately capture the spatial distribution of different desertification types.

Remote sensing technologies have proven effective for improving the timeliness and accuracy of sandy land monitoring. Currently, multispectral, hyperspectral, and radar data with various spatial and temporal resolutions have been extensively applied to extract desertification information. Research on sandy land information extraction using remote sensing primarily includes three aspects: vegetation information extraction, sandy land classification, and retrieval of sandy land soil characteristic parameters. Vegetation extraction methods include vegetation index approaches, mixed pixel decomposition, and artificial neural networks. Sandy land classification methods mainly comprise pixel-based classification, object-oriented classification, and mixed pixel decomposition. Soil characteristic parameter retrieval focuses on quantitative inversion of soil texture, organic matter content, particle size composition, moisture, and nutrient elements. Among these, soil particle size composition serves as the best indicator of sandy land conditions and is crucial for evaluating desertification phenomena and their severity.

Despite the diversification of remote sensing data sources and research methods, quantitative extraction of sandy land remains a hot and challenging issue. Minqin County is located in an arid region where sparse vegetation is difficult to extract using conventional vegetation index methods. The complex land cover types, including sandy land, saline-alkali land, and bare land, as well as the subtle distinctions among shifting, semi-fixed, and fixed sandy lands, pose significant challenges for quantitative classification. Therefore, this paper proposes a method integrating mixed pixel decomposition with object-oriented polygon segmentation to achieve quantitative extraction of these difficult-to-distinguish land categories.

2 Study Area and Data Preprocessing

2.1 Study Area

Minqin County in Gansu Province is located in the northeastern part of the Hexi Corridor and the lower reaches of the Shiyang River Basin, adjacent to the Badain Jaran Desert to the west and the Tengger Desert to the east [Figure 1: see original paper]. The total land area is approximately 1.60$\times10^{4}$ km^2, predominantly covered by the Tengger and Badain Jaran deserts composed of shifting, fixed, and semi-fixed dunes. The county comprises diverse geographic landscapes including deserts, gobi, eroded mountains, and oases. Natural vegetation mainly includes *Nitraria schoberi*, *Nitraria sphaerocarpa*, *Phyllanthus urinaria*, *Hololachne soongarica*, *Ephedra przewalskii*, *Alhagi sparsifolia*, and *Artemisia desertorum*, while artificial vegetation consists primarily of *Haloxylon ammodendron*, *Elaeagnus angustifolia*, and *Hedysarum scoparium*.

2.2 Data and Preprocessing

The remote sensing data consisted of three Landsat 8 OLI scenes covering the study area. Preprocessing included band composition, radiometric correction, geometric correction, and image mosaicking and clipping [Figure 2: see original paper]. Field spectral measurements of major vegetation and land types in Minqin County were obtained using an ASD FieldSpec Pro spectrometer to support subsequent analysis.

3 Research Methods

The sandy land use and cover classification system in this study was based on the "Technical Regulations for the Fourth National Desertification and Sandification Monitoring" combined with actual land categories in Minqin. The final classification included mountains, water bodies, cultivated land, gobi, sandy land (shifting, semi-fixed, fixed), saline-alkali land, bare soil, and others. According to the characteristics of each land category, the classification was implemented in three steps:

1. **Step 1:** Classify easily distinguishable categories including mountains, water bodies, cultivated land, and gobi using object-oriented methods and create masks.

2. **Step 2:** Apply a combined approach of mixed pixel decomposition and object-oriented multi-scale segmentation to quantitatively delineate boundaries among sandy land, saline-alkali land, and bare soil with fuzzy boundaries.
3. **Step 3:** Utilize the vegetation fraction from mixed pixel decomposition to quantitatively distinguish among sandy land types (shifting, semi-fixed, and fixed).

3.1 Image Segmentation and Object-Oriented Classification

Remote image segmentation algorithms primarily fall into three categories: threshold-based, edge-based, and region-based methods. To improve segmentation quality and automation, researchers have explored multi-scale segmentation and functional interpolation approaches. However, due to variations in imagery and land categories, finding a universally applicable automatic parameter calculation method remains challenging. This study employed a multi-scale segmentation algorithm on Landsat 8 OLI' s seven bands. Through repeated visual comparison of segmentation results, optimal scale, shape, and compactness parameters were determined for each land category .

Object-oriented classification methods include Classification and Regression Tree (CART), K-Nearest Neighbor (KNN), Bayesian (BAYES), and Support Vector Machine (SVM). This study selected SVM to classify mountains, water bodies, cultivated land, and gobi, with the radial basis function (RBF) kernel parameter (γ) and margin parameter (C) configured appropriately.

3.2 FCLSU Mixed Pixel Decomposition

Previous research in Minqin using Hyperion imagery compared vegetation indices, partial least squares regression, artificial neural networks, and mixed pixel decomposition for retrieving sparse vegetation cover, finding that mixed pixel decomposition, particularly fully constrained least squares-based linear unmixing (FCLSU), performed best. Studies comparing linear, kernel-based nonlinear, and bilinear spectral mixture models for *Nitraria* extraction in Minqin found no significant advantage of nonlinear models over linear models. Therefore, this study selected the mature and operational FCLSU linear mixed pixel decomposition model to extract sparse vegetation information in Minqin.

The FCLSU algorithm is expressed as:

$$X_i = \sum_{j=1}^{n} f_j X_{ij} + \varepsilon_i$$

where X_i is the pixel spectral reflectance in band i; n is the number of endmembers; f_j is the proportion of endmember j within the pixel; X_{ij} is the reflectance of endmember j in band i; and ε_i is the error term for band i.

Alternatively, in matrix form:

$$DN = M\alpha + E$$

where DN is an L-dimensional grayscale value vector; M is an L×p endmember grayscale value matrix; α is a p-dimensional vector of endmember proportions within the pixel; and E is the error vector.

The Lagrange function is:

$$J = \frac{1}{2}(DN - M\alpha)^T(DN - M\alpha) + c^T\alpha$$

where c is an unknown p-dimensional non-negative constraint constant vector.

Endmembers were determined using field-measured spectral curves. Although various sparse vegetation types were measured with different growth conditions and coverage, their spectral reflectance patterns were generally consistent across wavelengths. Since sparse vegetation mixed pixels were difficult to directly extract from the imagery, the vegetation endmember reflectance was represented by the average of all measured vegetation spectra. Sandy land spectral reflectance showed consistent patterns where fine sand exceeded coarse sand and windward slopes exceeded leeward slopes, so the sand endmember used the average of measured sand spectra. Similarly, the bare soil endmember was determined from the average of bare soil and depression crust soils. Saline-alkali land was special, as light and severe saline-alkali lands showed significantly different reflectance, requiring separate endmembers that were later merged.

The implementation process involved: (1) creating a spectral library from averaged endmember spectra using the Spectral Library Builder tool; (2) resampling the library to match Landsat 8 OLI's seven band central wavelengths using Spectral Library Resampling; and (3) applying the FCLSU model for decomposition [Figure 3: see original paper].

3.3 Sandy Land Type Classification

In arid Minqin County, the complex land categories make it difficult to distinguish among sandy land, saline-alkali land, and bare land, as well as among shifting, semi-fixed, and fixed sandy lands. Traditional classification methods can only achieve qualitative partitioning, and the uncertainty in sample selection prevents accurate classification. This study combined mixed pixel decomposition with object-oriented polygon segmentation to quantitatively classify sandy land types.

The method calculated the mean values of FCLSU components (sand, saline-alkali, bare soil) within each multi-scale segmentation polygon. The land category corresponding to the maximum mean fraction was assigned to the polygon, enabling quantitative delineation of sandy land, saline-alkali land, and bare soil.

Based on sandy land definitions, vegetation fraction was used for density slicing: 0–0.1 for shifting sandy land, 0.1–0.3 for semi-fixed sandy land, and 0.3–1.0 for fixed sandy land [Figure 4: see original paper].

3.4 Accuracy Assessment

3.4.1 Root Mean Square Error (RMSE) RMSE was used to evaluate the deviation between estimated and measured sparse vegetation cover:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_{\text{obs},i} - X_{\text{model},i})^2}{n}}$$

where $X_{\text{obs},i}$ is the observed value; $X_{\text{model},i}$ is the model-retrieved value; and n is the number of validation samples.

3.4.2 Classification Accuracy Metrics A confusion matrix was employed to assess sandy land classification accuracy, with primary metrics including overall accuracy, Kappa coefficient, producer' s accuracy, and user' s accuracy. Overall accuracy represents the proportion of correctly classified samples. The Kappa coefficient evaluates agreement between classification results and reference data, with all factors in the error matrix contributing to a more comprehensive accuracy assessment. Producer' s accuracy is the ratio of correctly classified pixels to the total reference pixels for a class, while user' s accuracy is the ratio of correctly classified pixels to the total pixels classified as that class.

4 Results and Analysis

4.1 Sparse Vegetation Accuracy Validation

The accuracy of vegetation cover extraction directly determines sandy land type classification. To validate FCLSU' s accuracy for sparse vegetation cover retrieval, linear regression analysis was performed using 30 field vegetation survey samples [Figure 5: see original paper]. Results demonstrated that FCLSU effectively extracted sparse vegetation with R^2 reaching 0.86, indicating that the vegetation fraction from FCLSU decomposition reliably reflects actual sparse vegetation cover.

4.2 Classification Results and Accuracy Validation

To compare the effectiveness of the new method, both object-oriented classification and the FCLSU-segmentation hybrid approach were implemented [Figure 6: see original paper]. Accuracy validation using field survey data showed that object-oriented classification achieved 84.86% overall accuracy (Kappa = 0.85), while the new method reached 86.60% overall accuracy (Kappa = 0.87).

The study focused on high-precision extraction of different sandy land types. The new method achieved 91.43% producer' s accuracy and 90.69% user' s accuracy for shifting sandy land, significantly higher than object-oriented classification (85.24% and 87.65%, respectively). Shifting sandy land showed the highest classification accuracy because Minqin contains large areas of nearly vegetation-free shifting sands that are easily extracted. Semi-fixed sandy land showed the lowest accuracy (producer' s: 83.58%, user' s: 76.59% for the new method; 82.68% and 78.87% for object-oriented) due to the difficulty in accurately delineating sparse vegetation boundaries. Fixed sandy land accuracy fell between the two, with the new method achieving 86.67% producer' s and 88.14% user' s accuracy, compared to 86.53% and 88.01% for object-oriented classification. The overall sandy land classification accuracy of the new method was 87.23%, superior to the 84.82% from object-oriented classification, demonstrating clear advantages in quantitative sandy land partitioning.

5 Conclusion and Discussion

In arid regions, sparse vegetation occupies a small proportion within mixed pixels, creating significant uncertainty in establishing interpretation keys for sandy land classification based on pixel or object-oriented methods. Conventional approaches struggle to strictly follow quantitative desertification classification standards (e.g., shifting sandy land: vegetation cover <10%; semi-fixed: 10–30%; fixed: >30%). This study successfully achieved quantitative extraction of desertification land types by combining mixed pixel decomposition with object-oriented segmentation. The main conclusions and existing issues are summarized in six points:

1. **Scale Determination in Sandy Land Classification**: The research scale (patch size) significantly influences sandy land classification outcomes. For example, a *Nitraria* shrub patch might be classified as fixed sandy land at the individual shrub scale, while the inter-shrub sand could be considered shifting sandy land. At a larger scale encompassing both, the area might be classified as semi-fixed sandy land. This study employed object-oriented multi-scale segmentation technology, adjusting parameters to achieve optimal patch delineation for sandy land classification at the remote sensing scale.

2. **Sparse Vegetation Retrieval**: The FCLSU method effectively extracted sparse vegetation information in the study area, with R^2 reaching 0.86. The vegetation fraction from FCLSU decomposition reliably reflects actual sparse vegetation cover.

3. **Advantage for Vegetated Areas**: The new method shows clear superiority in classifying land categories beneath vegetation cover. While traditional methods can only classify these areas as vegetation types, the proposed approach can accurately determine the underlying land category based on the magnitude of decomposed fractions.

4. **Quantitative Extraction Accuracy**: From a quantitative extraction perspective, the FCLSU-segmentation hybrid method achieved higher accuracy than object-oriented classification for different sandy land types. Shifting sandy land extraction reached the highest accuracy (producer' s >90%), followed by fixed sandy land (>86.67%). Semi-fixed sandy land extraction accuracy was the lowest (83.58%) but still higher than object-oriented classification (82.68%). The overall sandy land classification accuracy of 87.23% significantly exceeded the 84.82% from object-oriented methods, demonstrating that the proposed approach effectively enables quantitative partitioning of sandy land.

5. **Endmember Selection**: This study used field-measured spectral curves to determine endmembers, with average reflectance values representing each endmember category. However, each endmember encompasses numerous subcategories, and using average values may cause spectral mismatches in mixed pixel decomposition. Future research will explore variable endmember mixed pixel decomposition for improved extraction of land categories or vegetation types in arid regions.

6. **Segmentation Parameter Optimization**: This study applied uniform segmentation parameters to sandy land, without fully considering that shifting sandy land patches are typically larger while fixed and semi-fixed patches are smaller with slightly different compactness and shape characteristics. Future research will refine segmentation parameters for different sandy land types.

References

[1] State Forestry Administration. The National Desertification Monitoring Technical Regulations[R]. Beijing: State Forestry Administration, 1998.

[2] Wu Jian, Peng Daoli. Research advances in remote sensing monitoring technology for desertification[J]. World Forestry Research, 2009, 22(4): 47-52.

[3] Yang Yi, Wu Shixin, Zhuang Qingwei, et al. Spatiotemporal change of EVI in the Gurbantunggut Desert from 2000 to 2018[J]. Arid Zone Research, 2019, 36(6): 1512-1520.

[4] Hua Yongchun, Li Zengyuan, Gao Zhihai. Variation of vegetation coverage in Minqin County since 2001[J]. Arid Zone Research, 2017, 34(2): 337-343.

[5] Li Xiaosong. Qualitative Retrieval of Sparse Vegetation Cover in Arid Regions Using Hyperspectral Data[D]. Beijing: Chinese Academy of Forestry, 2008.

[6] Ballantine J A C, Okin G S, Prentiss D E, et al. Mapping North African landforms using continental scale unmixing of MODIS imagery[J]. Remote Sensing of Environment, 2005, 97(4): 470-483.

[7] Fan W, Hu B, Miller J, et al. Comparative study between a new nonlinear model and common linear model for analysing laboratory simulated forest

hyperspectral data[J]. International Journal of Remote Sensing, 2009, 30(11): 2951-2962.

[8] Somers B, Cools K, Delalieux S, et al. Nonlinear hyperspectral mixture analysis for tree cover estimates in orchards[J]. Remote Sensing of Environment, 2009, 113(6): 1183-1193.

[9] Ji Cuicui, Jia Yonghong, Li Xiaosong, et al. Research on linear and nonlinear spectral mixture models for estimating vegetation fractional cover of *Nitraria* bushes[J]. Journal of Remote Sensing, 2016, 20(6): 1402-1412.

[10] Chen Tao, Niu Ruiqing, Li Pingxiang, et al. An artificial neural network method for vegetation cover retrieval with Beijing-1 microsatellite data[J]. Remote Sensing Technology and Application, 2010(1): 24-30.

[11] Silva Junior C A, Nanni M R, Teodoro P E, et al. Comparison of mapping soybean areas in Brazil through perceptron neural networks and vegetation indices[J]. African Journal of Agricultural Research, 2016, 11(43): 4413-4424.

[12] Long Jing. The application of remote sensing technique to sandy desertification assessment[J]. Remote Sensing for Land and Resources, 2005, 17(1): 17-19.

[13] Liu B, Coulthard T J. Mapping the interactions between rivers and sand dunes: Implications for fluvial and aeolian geomorphology[J]. Geomorphology, 2015, 231: 246-257.

[14] Wu Junjun. Quantitative Extraction of Land Sandification Information Using BJ-1 Multispectral Data[D]. Beijing: Chinese Academy of Forestry, 2012.

[15] Wahidin N, Siregar V P, Nababan B, et al. Object based image analysis for coral reef benthic habitat mapping with several classification algorithms[J]. Procedia Environmental Sciences, 2015, 24: 473-483.

[16] Xu Erjing. Remote Sensing Image Segmentation Based on Mean Shift[D]. Urumqi: Xinjiang University, 2014.

[17] Wu C Y, Jacobson A R, Laba M, et al. Accounting for surface roughness effects in the near infrared reflectance sensing of soils[J]. Geoderma, 2009, 152(1-2): 171-180.

[18] Montzka C, Moradkhani H, Weihermüller L, et al. Hydraulic parameter estimation by remotely sensed top soil moisture observations with the particle filter[J]. Journal of Hydrology, 2011, 399(3-4): 410-421.

[19] Curcio D, Ciraolo G, D' Asaro F, et al. Prediction of soil texture distributions using VNIR-SWIR reflectance spectroscopy[J]. Procedia Environmental Sciences, 2013, 19: 494-503.

[20] Lu P, Wang L, Niu Z, et al. Prediction of soil properties using laboratory VIS-NIR spectroscopy and Hyperion imagery[J]. Journal of Geochemical Exploration, 2013, 132: 26-33.

[21] State Forestry Administration. A Bulletin of Status Quo of Desertification and Sandification in China[R]. Beijing: State Forestry Administration, 2011.

[22] Haralick R, Shaprio L G. Image segmentation technique[J]. Computer Vision Graphics and Image Processing, 1985, 12: 100-132.

[23] Johnson Brain, Xie Zhixiao. Unsupervised image segmentation evaluation and refinement using a multi-scale approach[J]. International Society for Photogrammetry and Remote Sensing, 2011, 2: 473-483.

[24] Song Y, Wu Y, Dai Y. A new active contour remote sensing river image segmentation algorithm inspired from the cross entropy[J]. Digital Signal Processing, 2016, 48: 322-332.

[25] Su T, Zhang S. Local and global evaluation for remote sensing image segmentation[J]. ISPRS Journal of Photogrammetry and Remote Sensing, 2017, 130: 256-276.

[26] Ji C, Jia Y, Gao Z, et al. Nonlinear spectral mixture effects for photosynthetic/non-photosynthetic vegetation cover estimates of typical desert vegetation in Western China[J]. PloS One, 2017, 12(12): e0189292.

[27] Chang C I, Heinz D C. Constrained subpixel target detection for remotely sensed imagery[J]. IEEE Transactions on Geoscience and Remote Sensing, 2000, 38(3): 1144-1159.

[28] Li Xiaoqin, Zhang Zhende, Zhang Peimin. Remote sensing survey and monitoring of desertification in Golmud Area[J]. Remote Sensing for Land and Resources, 2006, 18(2): 61-63.

[29] Wang Zhibo. Extraction of Sandy Land Information Based on Object-Oriented Method from Remote Sensing Data[D]. Beijing: Chinese Academy of Forestry, 2012.