

## Postprint of Desert Land Surface Type Information Extraction Based on UAV Imagery

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### Abstract

Based on UAV visible light imagery, surface type information was extracted for the Gurbantunggut Desert by employing object-oriented multi-scale segmentation. On the basis of extracting spectral, shape, texture, and vegetation index features from samples, rules were established to extract surface type information. The results show that: Different desert surface types have different optimal segmentation scales; Surface types with different degrees of desertification have similar features that cannot be distinguished using a single feature, requiring the selection of multiple feature combinations for surface type extraction; The object-oriented multi-scale segmentation method demonstrates significant improvement compared to pixel-based maximum likelihood classification, with overall classification accuracies of 93.00% for lightly desertified areas, 91.83% for moderately desertified areas, and 93.50% for severely desertified areas, representing improvements of 10.34%, 11.86%, and 12.50%, respectively, over the pixel-based maximum likelihood method. This demonstrates that the object-oriented multi-scale segmentation method can extract desert surface type information from UAV visible light imagery with high precision.

### Full Text

## Preamble

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**Abstract:** Based on unmanned aerial vehicle (UAV) imagery, this study extracted surface type information from the Gurbantunggut Desert using object-oriented multi-scale segmentation to derive spectral, shape, texture, and vegetation index features from sample plots. The results demonstrated that: (1) The optimal segmentation scale varied among different desert surface types; (2) Features of surface types at different desertification levels exhibited similarity and could not be distinguished using single characteristics; (3) Compared with the pixel-based maximum likelihood method, the object-oriented multi-scale segmentation approach achieved significant improvements. The overall classification accuracies for slightly, moderately, and severely desertified areas reached 93.00%, 91.83%, and 93.50% respectively—representing improvements of 10.34%, 11.86%, and 12.50% over the pixel-based maximum likelihood method. These findings reveal that the object-oriented multi-scale segmentation method can accurately extract desert surface type information from UAV visible imagery.

**Keywords:** UAV imagery; desert; land surface type; information extraction; Gurbantunggut Desert

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## 1 Introduction

### 1.1 Study Area

The Gurbantunggut Desert, located in the central Junggar Basin of Xinjiang, represents a typical temperate arid zone desert. Geographically situated between 44°11′–46°20′ N and 84°31′–90°00′ E, it covers an area of  $4.88 \times 10^4$  km<sup>2</sup>, making it the largest fixed and semi-fixed desert in China. The region is characterized by an arid climate with annual precipitation of 70–150 mm, annual evaporation exceeding 2000 mm, and mean annual temperatures ranging from 6 to 10°C. The dominant vegetation includes *Haloxylon ammodendron*, *Ephedra distachya*, *Calligonum mongolicum*, and *Reaumuria songarica*, accompanied by herbaceous species such as *Erodium oxyrrhynchum*, *Carex physodes*, *Eremurus nderiensis*, and *Ceratocarpus arenarius* [21].

Three distinct desertification levels were established for this study: (1) Slightly desertified areas, (2) Moderately desertified areas, and (3) Severely desertified areas [22]. Sample plots measuring 1.5 km × 1.5 km were established for each desertification level.

[Figure 1: see original paper] shows the geographical location of the study area.

### 1.2 Data Source

UAV images were acquired in July 2013 using a SONY NEX-5R camera with a resolution of  $(cid : 138)(cid : 128)H.L.(cid : 143)(cid : 133)Z[KL(cid : 153), j \%_o(cid : 190)/18(cid : 242) \ddagger w(cid : 230)(cid : 231) E_i E (cid :$

138)(cid : 223) (cid : 217)(cid : 236)(cid : 237)(cid : 238)(cid : 147)01<sup>-i0</sup> 5(cid : 135)L(cid : 143)(cid : 217)¶ (cid : 151)fH2 34@Af(cid : 217)B(cid : 239)(cid : 240)cKMKL(cid : 160)...(cid : 242)(cid : 154)cK(cid : 127) (cid : 243)(cid : 147)(cid : 152)500m (cid : 244)(cid : 221)(cid : 243)a(cid : 153)if(cid : 152)65 (cid : 246)a(cid : 153)if(cid : 152)40 2013(cid : 135)7(cid : 136)18—20(cid : 242)(cid : 201)]6j, j-r (cid : 131)G(cid : 247)J(cid : 212)(cid : 213)(cid : 152)1 1600s W(cid : 152)SONYNEX 7 i@A(cid : 136) > 4g(cid : 240) (cid : 135)j(cid : 136)(cid : 240)(cid : 221)(cid : 156)10(cid : 135)7(cid : 228)@(cid : 221)»(cid : 243)(cid : 147)(cid : 128)KL(cid : 239)(cid : 213)g6(cid : 219)(cid : 152)0 15m EFG(cid : 201)A(cid : 136)qW > 4c20m × 20mj(cid : 142) j(cid : 142)()¶9]HIJKL o < (cid : 252) (cid : 253)3(cid : 135)(cid : 254)(cid : 255) M(cid : 243) < T-GPS \* (cid : 230) > 4VW (cid : 131)/89(cid : 238) !KLZ["# 01. The imagery underwent geometric and radiometric correction preprocessing.

### 1.3 Methods

### 1.3.1 UAV Image Preprocessing

GPS measurements provided ground control points for geometric correction. Structure-from-Motion (SfM) photogrammetry generated three-dimensional terrain data. The image objects were segmented using object-oriented multi-scale segmentation based on spectral, shape, and texture characteristics.

### 1.3.2 Feature Extraction

Four categories of features were extracted for classification: spectral features (Mean Red, Mean Green, Mean Blue, Brightness), shape features (Maximum difference, Length/Width ratio, Shape index), texture features (GLCM Homogeneity), and vegetation indices (NGRDI, NGBDI) [19, 28].

### 1.3.3 Multi-scale Segmentation

The segmentation process employed a bottom-up region-merging algorithm that minimized heterogeneity. Scale parameters were optimized through visual interpretation and quantitative evaluation, with shape and compactness weights set at 0.1 and 0.5 respectively [16].

### 1.3.4 Classification Rules

Decision tree classification rules were developed based on the statistical characteristics of sample plots. The rules incorporated thresholds for spectral values, vegetation indices, and texture measures to discriminate among surface types.

### 1.3.5 Accuracy Assessment

Classification accuracy was evaluated using confusion matrices, overall accuracy, and Kappa coefficients derived from validation samples.

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## 2 Results

### 2.1 Segmentation Scale Analysis

The segmentation scale significantly influenced information extraction accuracy. Scales ranging from 10 to 100 were tested, with optimal values identified for different surface types. For slightly desertified areas, the optimal scale parameters were 75–80, while moderately desertified areas performed best at 80–90, and severely desertified areas at 85–90.

[Figure 2: see original paper] illustrates the research workflow. [Figure 3: see original paper] presents segmentation results at different scales. [Figure 4: see original paper] shows the classification accuracy across scales.

The relationship between segmentation scale and object heterogeneity followed a predictable pattern: smaller scales produced numerous objects with high internal homogeneity but excessive fragmentation, while larger scales created fewer objects that risked merging distinct features. The optimal scale balanced these competing effects.

### ### 2.2 Feature Analysis

Statistical analysis of eigenvalues revealed distinct characteristic ranges for each desertification level. , , and summarize the eigenvalue distributions for slightly, moderately, and severely desertified areas respectively.

Key observations include: (1) Spectral means (Red, Green, Blue) decreased with increasing desertification severity; (2) Texture homogeneity values were lowest in severely desertified areas; (3) Vegetation indices (NGRDI, NGBDI) showed progressively narrower ranges as desertification intensified.

The feature analysis demonstrated that single characteristics could not reliably separate desertification levels due to substantial overlap in value ranges. This necessitated the use of multi-feature rule sets for accurate classification.

### ### 2.3 Classification Accuracy Evaluation

The object-oriented multi-scale segmentation method achieved overall accuracies of 93.00%, 91.83%, and 93.50% for slightly, moderately, and severely desertified areas, with corresponding Kappa coefficients of 0.89, 0.84, and 0.89 .

In contrast, the pixel-based maximum likelihood method yielded lower accuracies of 82.66%, 78.16%, and 81.00%, with Kappa values of 0.80, 0.72, and 0.79 respectively . The object-oriented approach improved accuracy by 10.34%, 11.86%, and 12.50% across the three desertification levels.

[Figure 7: see original paper] and [Figure 8: see original paper] compare classification results between the two methods, visually demonstrating the superior performance of object-oriented segmentation in maintaining spatial continuity and reducing salt-and-pepper effects.

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## ## 3 Discussion

### ### 3.1 Methodological Considerations

The object-oriented multi-scale segmentation method addresses limitations of pixel-based approaches by incorporating spatial context and object geometry. Three key advantages emerged from this study:

First, the multi-scale framework accommodates the inherent scale dependency of desert surface features. Different surface types exhibit optimal representation at different segmentation scales, and the hierarchical approach allows simultaneous processing across these scales.

Second, the integration of spectral, shape, and texture features captures the comprehensive characteristics of desert surfaces. The rule-based classification system, , effectively distinguished surface types that spectrally similar but texturally distinct.

Third, the method significantly reduced classification noise. Pixel-based methods suffer from high-frequency variation within homogeneous areas, while object-oriented segmentation preserves meaningful boundaries and produces cartographically superior results.

### ### 3.2 Application Implications

This study demonstrates that UAV imagery combined with object-oriented analysis provides an effective tool for high-resolution desert surface mapping. The achieved accuracies exceed 90% across all desertification levels, meeting the requirements for detailed land degradation monitoring.

The methodology is particularly valuable for: (1) Monitoring vegetation restoration efforts in desertified regions; (2) Assessing the effectiveness of sand stabilization measures; (3) Supporting precision management of fragile arid ecosystems.

Future research should explore automated scale selection algorithms and investigate the transferability of classification rules to other desert regions. Integration with hyperspectral imagery could further enhance discrimination capabilities.

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