Multi-feature-Assisted Hawthorn Recognition Using GF-6 WFV Imagery in the Junggar Basin: A Postprint

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Abstract

To address the relatively weak research foundation in the application of GF-6 WFV data and the deficiencies in algorithms and data sources for Zungarian hawthorn remote sensing identification, this study combined GF-6 WFV and ZY-3 image data to extract multiple classification features. Based on methods including object-oriented segmentation, feature selection, feature importance evaluation and combination, and multi-classifier ensemble, research was conducted on the remote sensing identification of Zungarian hawthorn, and an object-oriented multi-classifier combination algorithm for Zungarian hawthorn identification assisted by optimized features was proposed. The results indicate that: (1) GF-6 WFV data can effectively identify Zungarian hawthorn, with the newly added red-edge band playing a significant role in tree species identification; (2) object-oriented segmentation, feature selection, and multi-feature combination all positively enhance the accuracy of Zungarian hawthorn identification; (3) the multi-classifier combination algorithm can compensate for errors caused by differences in representation capability among single classifiers, significantly improving identification accuracy and algorithm stability.

Full Text

Abstract

Remote sensing identification of *Crataegus songarica* remains relatively underdeveloped, with limitations in both algorithms and data sources. To address these gaps, this study investigates the recognition of *C. songarica* using GF-6 WFV imagery by integrating multiple classification features, object-oriented segmentation, feature selection, feature importance evaluation, and multi-classifier combination methods. We propose an object-oriented multi-classifier combination algorithm for *C. songarica* identification assisted by optimized features.

The results demonstrate that: (1) GF-6 WFV data can effectively identify *C. songarica*, with the newly added red-edge bands playing a crucial role in tree species discrimination; (2) Object-oriented segmentation, feature selection, and multi-feature combination all positively enhance identification accuracy; (3) The multi-classifier combination algorithm compensates for errors caused by differential representation capacity of single classifiers, significantly improving both identification precision and algorithm stability.

Keywords: GF-6; feature selection; object-oriented; multi-classifier combination; *Crataegus songarica*

1 Study Area

The study area is located on the southern slope of the Keguqin Mountain in Daxigou, Huocheng County, Xinjiang, covering a region of 10.96 km × 10.21 km (80°45 00 E–80°52 30 E, 44°25 N–44°30 N) [Figure 1: see original paper]. The imagery shown in the figure is a false-color composite of ZY-3 multispectral data. Situated in a valley modified by Quaternary glaciers at 800–1500 m elevation, the area experiences a temperate humid climate with an average annual temperature of 8.7°C and average precipitation of 266.9 mm. The growing season lasts 165 days. Soils are primarily sandy loam and meadow soil, with moderate fertility. Under these favorable conditions, vegetation grows densely with tree heights of 3–4 m, forming a community dominated by *C. songarica*.

2 Data and Methods

2.1 Data Sources and Processing

To explore the advantages of multi-feature joint identification and improve *C. songarica* recognition accuracy, this study utilized ZY-3 data and concurrent GF-6 WFV panchromatic and multispectral data. The high spatial resolution ZY-3 data enabled superpixel segmentation and texture feature extraction, while GF-6 WFV data provided rich spectral and vegetation index features. Specific sensor parameters are listed in Table 1 .

Image preprocessing included several steps: First, radiation calibration was performed using calibration parameters provided by the China Centre for Resources Satellite Data and Application, followed by atmospheric correction using the FLAASH method. Geometric precise correction was conducted using a digital elevation model (DEM) and rational polynomial coefficient (RPC) files to ensure root mean square error was controlled within one pixel, achieving spatial co-registration. Subsequently, the ZY-3 panchromatic and multispectral data were fused using the Gram-Schmidt Spectral Sharpening method. Principal component analysis (PCA) was applied to compress the fused data, concentrating usable information into the first principal component for subsequent texture feature extraction and image segmentation.

2.2 Sample Set Construction and Division

To construct reliable training and validation sample sets ensuring classifier accuracy and validation reliability, we incorporated Class I forest inventory data and field survey data as auxiliary information. The Class I inventory data were updated annually by the Huocheng County Forestry Department based on the 8th national forest resource inventory, while field survey data were collected during August 2019 fieldwork. Since Class I inventory data are recorded at the subcompartment scale—relatively coarse compared to remote sensing imagery—and field survey points were limited, relying solely on these would cause insufficient samples and overfitting during training. To ensure uniform and representative sample distribution, the study area was divided into 182 m × 170 m rectangular grids. Referencing field survey data, forest inventory data, and object-oriented segmentation results, we performed overlay analysis. Within each rectangle, we selected one sample polygon with an area exceeding 900 m^2 and sufficiently pure land cover type. Considering accessibility and scientific rigor, 100 samples were ultimately selected, including 25 *C. songarica* samples, 25 grassland samples, 25 bare land samples, and 25 other forest samples. These were randomly divided into three subsets: 40% for feature optimization and classifier training, 30% for cross-validation during parameter selection, and 30% for final accuracy assessment.

3 Methods

3.1 Object-Oriented Multi-Scale Segmentation

Traditional pixel-based extraction suffers from low efficiency and "salt-and-pepper" effects. When fusing multi-scale classification features, pixel-level resampling causes information loss or computational waste. To address these issues, we employed object-oriented multi-scale segmentation using a trial-and-error approach to select the optimal scale, enabling feature fusion at the object level. The linear spectral clustering (LSC) algorithm, an improved normalized cut (NC) method, was used. LSC employs kernel similarity metrics to achieve normalized segmentation in pixel high-dimensional feature space, avoiding eigenmatrix decomposition and offering high memory efficiency and low computational complexity. The weighted k-means metric is defined as:

Where m represents cluster centers, denotes pixel weights in high-dimensional space, d represents multidimensional vector space features composed of color and spatial coordinates, k is the cluster center index, and K is the total number of cluster centers.

Considering the complex forest structure and unclear boundaries, we used Class I inventory and field survey data as references to determine the optimal segmentation scale through trial-and-error. An over-segmentation strategy was adopted —first ensuring no mixed land cover types within segments, then gradually reducing the scale. The final segmentation scale was set at 15, shape factor at 0.3, and compactness at 0.5. Segments within 5 pixels of boundaries were eliminated to reduce topographic effects. This approach effectively distinguished different land cover types [Figure 2: see original paper] and provided the foundation for subsequent feature fusion and *C. songarica* identification.

3.2 Multi-Feature Extraction

To fully leverage multi-source data advantages, we extracted spectral features and vegetation indices from GF-6 WFV data, and texture features from fused ZY-3 data. A total of 48 classification features were extracted: 8 spectral features including brightness values from 8 bands (B1–B8), maximum pixel value (MAX), and minimum pixel value (MIN); 10 vegetation index features including NDVI, RVI, DVI, Vogelmann red edge index (VRE), photochemical reflectance index (PRI), and two anthocyanin reflectance indices (ARI1, ARI2); and 30 texture features extracted using the gray-level co-occurrence matrix (GLCM) in 3 directions (0°, 45°, 90°) with 10 metrics: entropy (ENT), mean (MEA), variance (VAR), homogeneity (HOM), contrast (CON), angular second moment (ASM), correlation (COR), and dissimilarity (DIS). To eliminate scale effects, all features were normalized using min-max normalization. Texture extraction window size was set to 7$×$7 pixels based on trial-and-error, effectively reducing forest canopy and shadow effects while improving identification accuracy. Vegetation index formulas and meanings are listed in Table 2 .

3.3 Feature Optimization and Importance Evaluation

To reduce feature correlation and redundancy, recursive feature elimination (RFE) was applied for feature set optimization. Based on the random forest model, feature importance was evaluated using mean decrease impurity (MDI) for ranking and analysis. The relationship between selected feature count and overall classification accuracy shows strong correlation [Figure 3: see original paper]. Initially, accuracy increased positively with feature count. When 15 features were used, accuracy improvement peaked; beyond 20 features, accuracy reached maximum at 96.8% and began fluctuating. Therefore, 20 features were selected for the optimal feature set.

The optimal features, ranked by importance, were: spectral features SKE_3, SKE_6, MAX_5, MIN_4; vegetation index features NDVI, PRI, ARI1, VRE, RVI, DVI; and texture features ASM_{45}, COR_0, ENT_0, HOM_{90}, DIS_0. Spectral features from bands 3–6 were most important for species identification, while 45°-extracted texture features performed best. Vegetation index features were particularly crucial, with all six indices entering the optimal set and representing the most important classification features [Figure 4: see original paper].

3.4 Classifier and Classification Scheme Construction

To address performance variations of single classifiers across scenarios, we employed support vector machine (SVM) and random forest (RF)—both proven effective and stable—for *C. songarica* identification, then constructed a weighted adaptive voting combination classifier (WAVCC). SVM' s learning strategy maximizes margins, formulated as convex quadratic programming, performing well with small samples, nonlinearity, and high dimensions using radial basis kernel function. RF, based on decision tree ensembles, offers greater stability and generalization than single trees, with excellent noise reduction and overfitting prevention. Parameters were optimized via grid search: SVM with C=1500, gamma=0.005; RF with N=400 trees and mtry=4 features.

WAVCC uses the mean of user accuracy and producer accuracy as each algorithm' s weight for specific land cover identification. Each classifier has one vote weighted by its identification accuracy score. The final classification result is determined by combined voting of SVM and RF in parallel. The voting rule is:

Where C represents the object classified as class j, $T(C)$ is the score from classifier k for class j, P is the voting score (average of user and producer accuracy), and M is the total number of classes.

To evaluate the impacts of object-oriented segmentation, feature optimization, and WAVCC, we designed five classification schemes (Table 3) using controlled variables. Schemes 1-2 compare feature optimization effects; schemes 2-3 compare object- versus pixel-based scales; schemes 2, 4-5 validate WAVCC performance; and schemes 4-6 explore different feature combinations' impacts on accuracy.

4 Results and Analysis

Accuracy was assessed using confusion matrices to calculate producer accuracy (PA), user accuracy (UA), overall accuracy (OA), and Kappa coefficient for each scheme.

4.1 Impact of Feature Optimization and Combination

Under consistent algorithms and hardware, Scheme 2 (optimized features) achieved significantly higher OA and Kappa than Scheme 1 (all features), with *C. songarica* PA and UA also substantially improved. Kappa increased by 0.02 and ET decreased by 7.73 minutes. Feature selection effectively reduced computational load while maintaining accuracy and improving algorithm stability. Multi-feature combination achieved highest accuracy: spectral + texture + vegetation indices outperformed single-feature sets, though computation time increased accordingly. Scheme 4 (spectral + vegetation indices) performed slightly better than Scheme 5 (spectral + texture), indicating vegetation indices contributed more than texture features to accuracy improvement (Table 4).

4.2 Impact of Object-Oriented Segmentation

Comparing Schemes 2 and 3 reveals performance differences between object- and pixel-based methods. Pixel-based results showed obvious salt-and-pepper effects with fragmented patches and poor integrity, yielding significantly lower accuracy metrics. Since three spectral features only exist at object scale, Scheme 3 excluded them. WAVCC' s pixel-based version required voting 判定 per pixel, and with far more pixels than objects, computation time was markedly higher than object-based methods [Figure 5: see original paper].

4.3 Impact of Multi-Classifier Combination

Single classifiers inevitably produce errors due to algorithmic differences and varying representation capacities. WAVCC integrates SVM and RF advantages, avoiding partial "confusion" from single classifier limitations and improving accuracy. As shown in Table 4, WAVCC significantly outperformed single classifiers across all accuracy metrics. However, since WAVCC calculates weights per classification unit based on single classifier results, its computation time exceeds that of individual classifiers [Figure 6: see original paper].

5 Conclusions

This study investigated GF-6 WFV data for *C. songarica* identification using object-oriented segmentation, multi-source feature extraction, recursive feature elimination, and classifier combination. The impacts of classification scale, feature selection, feature combination, and algorithms were explored, yielding the following conclusions: (1) GF-6 WFV data demonstrate strong potential for forestry applications, with new red-edge bands crucial for species identification; (2) Feature optimization reduces redundancy, improves efficiency and stability, with vegetation indices contributing more than texture features; (3) Object-based classification effectively mitigates salt-and-pepper effects, improving accuracy by 2.86% and Kappa by 4.44% while reducing runtime by nearly 7.73% compared to pixel-based methods; (4) The weight-adaptive multi-classifier voting combination algorithm integrates different algorithm strengths, avoiding confusion from single classifier representation differences and improving accuracy—WAVCC increased OA and Kappa by 1.81% and 3.31% respectively over single classifiers.

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