Comparison of nearest neighbor and rule-based decision tree classification in an object-oriented environment

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Abstract **– Object-oriented classification is a useful tool for analysis of high-resolution imagery due to the incorporation of spectral, textural and contextual variables. However, feature selection and incorporation of appropriate training sites can be difficult. We compared two object-oriented image classification approaches, one using a decision tree (DT), the other a nearest neighbor classification (NN) with regard to classification accuracy, effort involved and feasibility for mapping similar areas. We used a QuickBird satellite image to map arid rangeland vegetation in a 1200 ha pasture in southern New Mexico. In the DT approach, we used ground truth data from plots (8.75 m^2) as input for a decision tree to create a rule base for classification. In the NN approach, larger polygons (mean=100 m^2) served as training areas for a nearest neighbor classification. Overall accuracy was 80% using the DT and 77% using the NN classification. The DT was a superior tool for reducing the number of input features, but this technique required more field data, export to a decision tree program and was more time consuming. With the NN approach, input features were selected within the image analysis program and were applied to the classification immediately. The use of larger polygons for training and test samples was more appropriate for use in an object-oriented environment than the small plots. We concluded that for arid rangeland classification from QuickBird data, the NN technique required less time in the field and for image analysis, had comparable accuracy to the DT approach, and would be appropriate for mapping similar areas. A combination of both methods would incorporate the advantages of feature selection in a DT with the object-oriented nature of the analysis.**

Keywords: Object-oriented classification; rangelands; decision tree; high-resolution satellite imagery

I. INTRODUCTION

For the classification of arid rangelands, an object-oriented approach can be more effective than pixel-based techniques for two reasons. First, spectral information alone is less meaningful in arid environments due to the mixture of green and brown senescent vegetation coupled with the high reflectance of the soil background [1]. Second, the addition of spatial and contextual information for each input band can greatly improve classification results, especially with high-resolution satellite imagery [2]. In an object-oriented image analysis approach, as implemented in the software eCognition [3], the image is segmented into discrete objects that are homogenous with regard to spatial or spectral characteristics. Spectral, spatial, and contextual information is then derived from those image objects, and the image is classified using either a rule-based or nearest neighbor fuzzy classification algorithm [4].

Object-oriented image classification techniques are successfully used with high resolution images for determining shrub encroachment [5,6], as well as for land use/land cover mapping projects [7,8]. With the addition of spatial and contextual variables, there are hundreds of features that can potentially be incorporated into the analysis. Therefore, feature selection can present a problem in object-based classification. Decision trees are commonly used in image analysis for variable selection, to reduce data dimensionality and to incorporate ancillary information [9]. Classification accuracies from decision tree classifiers are often greater compared to using maximum likelihood or linear discriminant function classifiers [10]. Combining decision tree analysis with object-based classification has proven successful in arid rangelands [7]. However, one disadvantage is that the decision tree analysis has to be performed outside of the image analysis program and rules derived from the tree have to be entered manually into eCognition. Another issue in object-oriented analysis is the incorporation of ground truth data. Because the analysis is based on objects and not pixels, the size of the ground plot can affect classification and accuracy assessment results.

To address these issues, we compared two object-oriented image classification approaches that differed in terms of feature selection and training data. In the first approach, a decision tree (DT) technique with rule-based classification was used, in the second approach a nearest neighbor classification (NN) was applied. The objective was to assess both approaches in terms of classification accuracy, effort involved and feasibility for mapping similar areas.

II. METHODS

We used a QuickBird satellite image to map vegetation in a 1200 ha pasture on the Jornada Experimental Range, operated by the USDA's Agricultural Research Service in southern New Mexico. The area is located at the northern end of the

Chihuahuan Desert and the dominant vegetation at the study site consists of mesquite shrubs (*Prosopis glandulosa*) with black grama (*Bouteloua eriopoda*) and tobosa (*Pleuraphis mutica*) as sub-dominants. For this study, we used the four bands multispectral image, a pansharpened band, the first principal component (PC1) and the soil adjusted vegetation index (SAVI). For both classification approaches, the image was segmented at a fine scale to classify and mask out shrubs, so that shrub interspace vegetation could be mapped separately. Due to the object-oriented approach, an image segment may contain one or many shrubs, which have lower spectral values than the surrounding vegetation. Masking out shrubs ensured that the low spectral values were not included in the image segments. The masked shrub image was segmented again at a coarser scale for classification with the DT and the NN approach. Segmentation parameters are shown in Table I.

TABLE I. SEGMENTATION PARAMETERS USED IN THE ANALYSIS

Segmentation level	Scale Parameter[a]	Color/ Shape[b]	Smoothness/ Compactness
Level 1	10	0.8/0.2	0.8/0.2
Level 2	100	0.9/0.1	0.5/0.5

[a]Scale parameter is without unit. [b]Color/shape and smoothness/compactness values are weighting factors ranging from 0 to 1.

For the ground sampling of the DT approach, we used a stratified proportional sampling approach, where the number of plots in each vegetation community was based on the proportional area of that vegetation community. We used 325 plots measuring 2.5 m x 3.5 m (8.75 m^2) and determined the dominant vegetation in the plot based on four classes: black grama, tobosa, mixed grasses and bare/sparse vegetation communities. (The plot size was determined by the size of a ground photo taken concurrently and used for additional studies.) Due to the object-oriented nature of analysis, the dominant vegetation type in the plot represented the vegetation in the larger image segment in which the plot was located (Fig. 1).

Spectral, spatial and textural features for half of the plot segments were extracted and used as input for the DT; the other half of the plots was used for accuracy assessment. DT analysis was performed in CART® [11], and the resulting rule base was applied in eCognition with membership functions. Due to the nature of the decision tree, the membership function was Boolean (either greater than or smaller than the number at the tree's node) and did not use eCognition's fuzzy classification algorithm.

For the NN approach, we collected GPS field data by walking around homogenous areas representing the dominant vegetation (n=84, mean=100 m^2), and used half of the polygons as training areas for a nearest neighbor classification, and the other half for accuracy assessment. In the NN approach in eCognition, the user chooses image objects as training areas and selects features that are used for classifying the image. In subsequent steps, unclassified or wrongly classified objects are assigned to the correct classes by adding samples of known vegetation. As the nearest neighbor feature space becomes more defined, the classification becomes more stable and, presumably, more accurate. As in all classifications, the quality of samples reflects the accuracy of the classification.

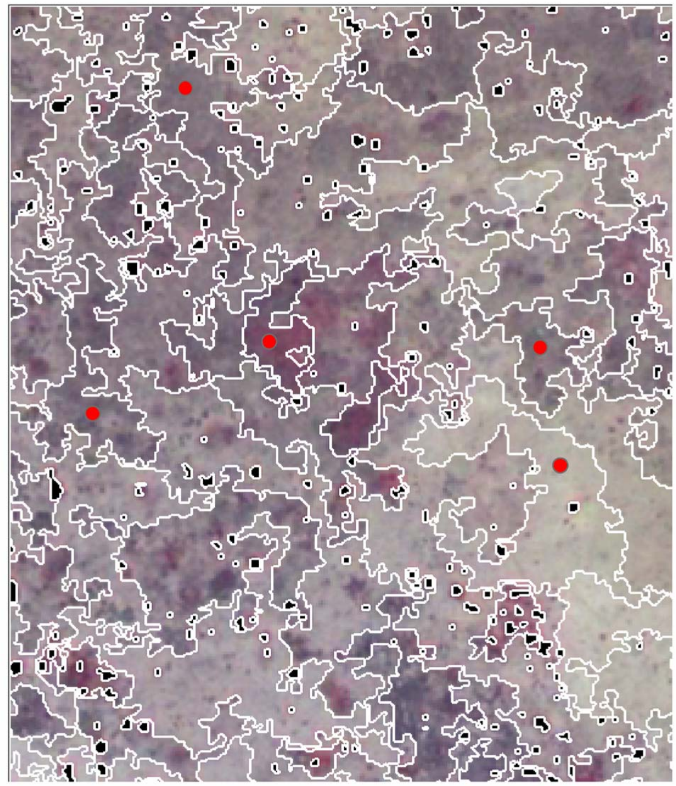

Figure 1. Portion of segmented QuickBird image showing selected plots (in red) used for DT analysis. Image extent is 190 m x 223 m. Shrubs excluded from segmentation appear as black objects.

Nearest Neighbor classification in eCognition is based on a fuzzy classification algorithm and classified image objects have a membership to more than one class. The smaller the difference is between sample objects and the object to be classified, the higher is the membership value. The greater degree of membership between the best and second best class assignment, the better the classification stability of an image object [3].

We selected input features (bands and indices) using the "feature view" and "feature space optimization" tools. "Feature view" allows for initial visual assessment of the usefulness of a feature by displaying the segmented image in grayscale. "Feature space optimization" is a tool that evaluates the distance in feature space between the samples of classes, and selects feature combinations that result in the best class separation distance. The results are solely based on the selected samples, and sufficient samples have to be chosen, so that the feature space for each class can be defined accurately. For that reason, samples have to be selected carefully. In spite of this drawback, feature space optimization serves as an additional tool for feature selection. We chose the mean and ratio of the four multispectral bands, PC1 and SAVI. The ratio in eCognition is calculated as the layer mean value of an image object divided by the sum of all layers (f. ex. Ratio Red: is Red/Red+Green+Blue+Near infrared).

III. RESULTS AND DISCUSSION

The DT was an excellent tool for reducing the number of input features. Out of 118 features, fourteen were selected by the classification tree. As others have shown, decision trees are useful tools for data reduction [12]. With the NN approach, we chose twelve input features based on the feature view and feature space optimization tools. This left out numerous other potentially useful features. Based on our experience with the feature space optimization tool, it is not advisable to input a large number of features with a limited number of samples, because it is impossible to assess the n-dimensional feature space appropriately with too many features and not enough samples. For those reasons, proper selection of features is still largely based on the image analyst's experience.

Although the DT approach was excellent for feature selection, this technique required more field data than the nearest neighbor approach (n=322 for DT vs. n=84 for NN) and was more time consuming. Export to a decision tree program was required, and after the tree was developed, the rule base had to be entered manually into eCognition. An advantage of eCognition's display was that classes could be displayed in an expanded version (1 class per node in the tree) or a collapsed version (1 class for each of the 4 vegetation communities). This allowed for fine tuning the classification by placing nodes into different vegetation communities. Accuracy assessment based on the 325 field plots in the DT approach had to be performed outside of eCognition and an error matrix was developed in Excel, because eCognition's error matrix is based on polygons, not points.

The advantage of the NN approach was that the entire image analysis process was contained in eCognition. Import of field samples, selection of input features, classification and accuracy assessment were all part of the built-in workflow. The accuracy assessment was simpler in the NN approach, because training and test sites were both object-based and fit better into the workflow than performing accuracy assessment outside of the image analysis program. Even though we used a fewer number of samples in the NN approach compared to the DT approach, the area used for accuracy assessment was actually larger for NN (3943 m^2) compared to DT (1340 m^2) due to the larger samples.

The accuracy assessment in eCognition is based on comparing training and test samples as objects but is expressed in number of pixels, therefore it is not a true object-based accuracy assessment. The accuracy statistics for NN and DT are shown in Table II. Overall accuracy was comparable for both methods. In the DT approach, producer's, user's and overall accuracy for all classes were equally high, while in the NN approach, the producer's accuracy for Mixed grasses and the user's accuracy for Bare/Sparse vegetation were considerably lower than the other classes. The producer's accuracy for Black grama was 100% in the NN classification and based on field visits, we determined that the NN approach was superior in mapping Black grama. The classification maps derived from both approaches are similar with the largest difference occurring in the Black grama class (Fig. 2). Black grama is a species that declines during droughts and it is highly palatable for livestock; therefore, mapping this species accurately is important at the Jornada Experimental Range.

TABLE II. ACCURACY STATISTICS FOR DECISION TREE (DT) AND NEAREST NEIGHBOR (NN) CLASSIFICATIONS

	Accuracy statistic	**Black grama**	**Mixed grasses**	**Bare/ Sparse**	**Tobosa**
NN	Producer's (%)	100	47	88	96
	User's (%)	61	92	55	98
	Overall (%)	78			
	Kappa	0.70			
DT	Producer's (%)	73	77	82	100
	User's (%)	85	71	85	80
	Overall (%)	80			
	Kappa	0.72			

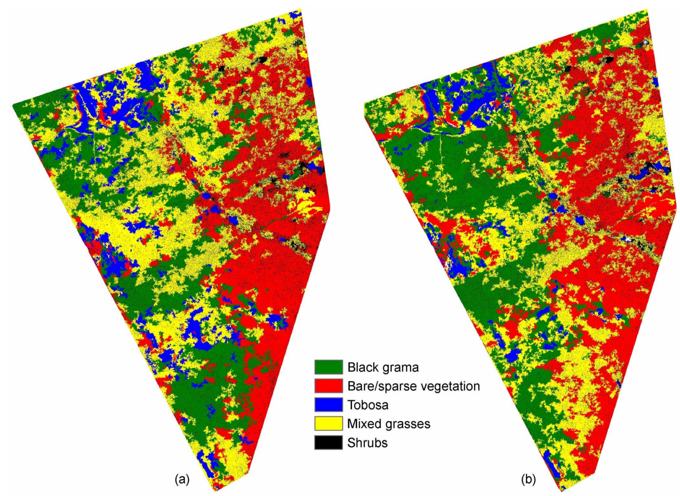

Figure 2. Classification maps derived from NN (a) and DT (b) approaches. Shrubs were classified separately at a fine segmentation level and overlaid on both maps.

Both classification approaches had advantages and disadvantages. The DT method was more objective in terms of feature selection, but was more time consuming because decision tree analysis and accuracy assessment were performed outside of the image analysis environment. The NN approach involved a less objective method of feature selection, but was advantageous because the entire workflow was carried out in one program. In addition, training and test samples were objects, which was more suitable than pixels in an object-oriented image analysis environment. A combination of both methods would incorporate the advantages of feature selection in a DT with the object-oriented nature of the analysis.

IV. CONCLUSIONS

In this paper, we compared two methods of object-oriented image analysis: DT and NN. The use of larger polygons for training and test samples in the NN method was considered more appropriate for use in an object-oriented environment than the smaller plots used for the DT approach. The DT method was more time consuming, but offered a more objective approach for feature selection than the NN approach. We concluded that for arid rangeland classification from QuickBird data, the NN technique required less time in the field and for image analysis, had comparable accuracy to the DT approach, and would be appropriate for mapping similar areas. The advantages of both approaches could be incorporated by conducting feature selection with a decision tree and by using objects as training samples and for accuracy assessment.

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