MULTI-SCALE, OBJECT-ORIENTED ANALYSIS OF QUICKBIRD IMAGERY FOR DETERMINING PERCENT COVER IN ARID LAND VEGETATION

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ABSTRACT

Efforts to remotely sense arid land vegetation are often hindered by high reflectance of the soil background, mixtures of green and senescent grasses, and the prevalence of shrubs in grasslands. These issues make it difficult to classify vegetation or estimate percent vegetation cover. Objectives of this study were to derive estimates of percent cover for several vegetation classes in a 1200 ha pasture at the USDA Agricultural Research Service's (ARS) Jornada Experimental Range (JER) in southern New Mexico. A stratified random sample approach was used to determine percent cover for 322 field plots. A QuickBird satellite image was segmented at different scales which resulted in image objects for which a multitude of spectral, spatial, and texture characteristics were extracted. We used regression trees to develop a rule base for image classification and performed conventional and fuzzy accuracy assessments. For classes with discrete boundaries, overall map accuracy was 73%, while accuracy values ranged from 81-86% using a 2.5%-5% cover boundary around each class (fuzzy accuracy assessment). This object-oriented multi-scale approach allowed us to extract shrubs at a fine scale and determine percent cover values for the shrub interspace at a coarser scale. The regression tree was an excellent tool for reducing the number of input variables derived from the image. Future research will include refining the predictive ability of the decision tree and determining the possibility of applying this model to other locations and/or to other scales.

INTRODUCTION

Current remote sensing research at the Jornada Experimental Range is focused on determining relationships between ground-based and remotely sensed information at multiple scales in order to improve the assessment and monitoring of arid land vegetation. Remote sensing in arid conditions is often hampered by high reflectance of the soil background, a variable mixture of green and senescent grasses, multiple scattering due to open canopies and bright soils, and the prevalence of shrubs in grasslands (Okin and Roberts, 2004). These attributes can make it difficult to determine the proportion of grass cover even from high-resolution satellite imagery such as QuickBird.

Our goal was to assess an approach using object-oriented, multi-scale image analysis with regression trees for mapping percent vegetation cover from a QuickBird image. Specific objectives were 1) to determine shrub cover at a fine scale, 2) to determine percent vegetation cover at a coarser scale, 3) to perform discrete and fuzzy accuracy assessments.

In object-based image analysis, the first step is image segmentation, whereby pixels are aggregated into objects that are homogenous with regard to spatial or spectral characteristics (Ryherd and Woodcock, 1996), whereby homogeneity refers to smaller within-object than between-object variance. In a second step, those objects rather than single pixels are classified. Object-based image analysis is proven to be very effective with high resolution imagery (Herold et al., 2003; Lennartz and Congalton, 2004; Thomas et al., 2003; van der Sande et al., 2003; Wang et al., 2004), and has been applied successfully for determining shrub encroachment (Hudak and Wessman, 1998; Laliberte et al., 2004). In ecological studies, object-based image analysis is advantageous, because landscape patches or ecological sites can often be detected and multi-scale image segmentation offers added insight into ecological processes (Burnett and Blaschke, 2003; Hay et al., 2002).

Classification and regression trees (or decision trees) are commonly used in remote sensing (DeFries et al., 1998; Hansen et al., 1996; Lawrence et al., 2004). Lawrence and Wright (2001) found that the decision tree approach facilitated the use of ancillary data in rule-based classification. Friedl and Brodley (1997) concluded that classification accuracies from decision trees were consistently greater than accuracies obtained using maximum likelihood and linear discriminant function classifiers. The decision tree approach uses binary recursive partitioning of the dataset, which is successively split into increasingly homogenous subsets until terminal nodes are reached. In remote sensing, the response variable for a classification tree is a categorical variable (land use/land cover class), and for a regression tree the response is a continuous variable (percent cover, percent canopy closure). Explanatory variables can be categorical or continuous (spectral response in bands, elevation, aspect, etc.). The terminal nodes of the tree represent the resulting land use/land cover classes; and as such, the tree results in a number of class prediction rules that are used to create a predictive map.

Combining object-based classification with decision tree analysis also serves as an efficient data reduction tool. The object-based image analysis program eCognition (Baatz and Schaepe, 2000; Definiens, 2003) used in this study outputs hundreds of features that describe image objects created in the segmentation process. Those features include spectral, spatial, textural, and contextual (relationships between neighboring objects and objects at multiple scales) information. The decision tree approach is well suited to sort through numerous features and determine which best describe a terminal class in the regression tree.

METHODS

Study Area

The Jornada Experimental Range (approx. elevation 1200 m) is located approximately 40 km northeast of Las Cruces, New Mexico in the northern part of the Chihuahuan Desert. Average monthly maximum temperatures range from 13° C in January to 36° C in June, and mean annual precipitation is 241 mm of which more than 50% occurs during July, August and September. Historically, this area was a desert grassland, but shrub encroachment by honey mesquite (*Prosopis glandulosa* Torr.), creosotebush (*Larrea tridentata* (Sess. & Moc. ex DC) Cov.), and tarbush (*Flourensia cernua* DC.) has led to a conversion to desert scrub. Our study occurred in a 1200 ha pasture, which represented most of the major vegetation communities on the basin floor of the JER. Dominant grass species included black grama (*Bouteloua eriopoda* (Torrey) Torrey), tobosa (*Pleuraphis mutica* Buckley), dropseed (*Sporobolus* spp.), threeawn (*Aristida* spp.), and burrograss (*Scleropogon brevifolius* Phil.). Dominant shrub species included honey mesquite, four-wing saltbush (*Atriplex canescens* (Pursh) Nutt.), soap-tree yucca (*Yucca elata* Engleman.), mormon tea (*Ephedra torreyana* (Wats.), and broom snakeweed (*Gutierrezia sarothrae* (Pursh) Britt. & Rusby). While black grama and tobosa tend to occur in pure stands, dropseed and threeawn are often intermixed and not easily identified with remote sensing, even in high-resolution imagery. Mesquite occurs both as an encroaching shrub to grasslands and as a monoculture within mesquite coppice dune systems. In these latter areas, mesquite plants are quite large (approx. 6-8 m canopy diameter) and easily distinguished because the shrub interspace typically lacks vegetation except following pulses of effective rainfall. A stratified random field sample approach was used to determine percent cover and dominant vegetation for 322 field plots (2.5 x 3.5 m).

Image Segmentation and Analysis

The panchromatic (0.61 cm) and multispectral (2.4 m) bands of a QuickBird image acquired on Nov. 4, 2004 were pansharpened using the principle components method in Erdas Imagine 8.7. The pansharpened image allowed us to detect single mesquite shrubs and differentiate broader vegetation classes. Derived image products from the multispectral bands included a principle components analysis (PCA) image and a soil adjusted vegetation index (SAVI) image (Huete, 1988). Other data layers included a soil map, a digital elevation model (DEM), and aspect and slope layers.

Imagery was analyzed with eCognition, an object-based image analysis program (Definiens, 2003). In this approach, an image is segmented based on 3 parameters: scale, color (spectral information), and shape. Color and shape can be weighted from 0 to 1. Within the shape setting, smoothness or compactness can be defined and also weighted from 0 to 1. The scale parameter is unit-less and controls the size of image objects, with a larger scale parameter resulting in larger image objects. The image was segmented at three different levels: level 1 at scale 10 (fine scale for detecting single shrubs), level 2 at scale 100 (coarser scale for broader vegetation patches), and level 3 at scale 200 (scale for extracting broadest vegetation patches). Color/shape and smoothness/compactness were set at 0.8/0.2 and 0.8/0.2 respectively for level 1 and at 0.9/0.1 and 0.5/0.5 for levels 2 and 3.

Shrubs were classified at level 1 using the methods described in Laliberte et al. (2004), then masked out and the image was segmented again at level 2. If shrubs were included in the segmentation, their low spectral values would reduce the overall mean spectral value for an object. By masking the shrubs, we were able to obtain image object attributes that described only shrub interspace vegetation, because our main objective was to map grass cover.

For each image object that contained a field plot, we extracted the following spectral, spatial, texture and contextual features from eCognition, resulting in a total of 118 input variables for the decision tree:

- Mean, ratio, and standard deviation of each band (near infrared, red, green, blue, PCA, SAVI)
- Relationship to neighboring, super- or sub-object (objects on other levels)
- Texture measures (Gray-level co-occurrence matrix)
- Aspect, slope, soil layers, and an elevation model

Decision Tree Analysis

For the decision tree analysis, we used CART® by Salford Systems (Steinberg and Colla, 1997), a program that uses the classification and regression tree algorithm originally develop by Breiman et al., 1984). Half of the field plots were used to grow the regression tree, half were reserved to perform independent accuracy assessments of the resulting predictive maps. A maximal tree was grown, and then pruned back to obtain the optimal tree by determining the lowest misclassification error, which was achieved with 10-fold cross validation. In decision trees, an optimal tree has the lowest cross validated relative error, which is the error rate of the tree relative to the root node. In our decision tree, the response variable was percent vegetation cover, and the explanatory variables included the 118 variables extracted from eCognition. The rule base obtained from CART® was applied in eCognition to create predictive maps of percent vegetation cover.

Accuracy Assessment

We performed two types of accuracy assessments of the predictive maps: a conventional accuracy assessment using discrete class boundaries, and an accuracy assessment using fuzzy class boundaries. Class boundaries were determined from the regression tree based on the midpoints between the node mean values, while in the fuzzy accuracy assessment, we allowed for a 2.5% or a 5% vegetation cover buffer around the class boundary. Using fuzzy class boundaries was considered to be more appropriate in this case, because the regression tree outputs mean percent cover values for the nodes, and for a continuous variable such as percent cover it is difficult to determine exact cutoff values for discrete classes. Although our accuracy assessment with fuzzy boundaries is not a fuzzy accuracy assessment in the strict sense as described by Gopal and Woodcock (1994) as applied to landcover/landuse classes, it is nevertheless a variation of fuzzy set theory that describes imprecision or vagueness in complex environments (Zadeh, 1973).

RESULTS

Multiresolution Image Segmentation

The results of the image segmentation on level 1 (fine scale) with the resulting shrub classification, and subsequent segmentation on level 2 (coarse scale) are depicted in Figure 1. The approach of classifying shrubs, masking shrubs, and segmenting the image again has the advantage that the spectral values of image objects are not affected by the relative low spectral values of shrubs. This allowed us to obtain a better relationship between percent cover measured in the field and the estimate obtained from the image. The classified shrub layer was combined with the level 2 classification in a classification-based segmentation, a procedure in eCognition that allows for merging of classification results from different levels.

Decision Tree and Map Output

The optimal tree provided by CART® had 10 nodes, but we decided to develop classification maps of percent cover using 4, 5, and 6 nodes for two reasons: 1) we felt that using 10 classes for percent cover was excessive in arid land vegetation, and 2) the cross validated relative error of the tree increased only slightly from 0.381 (10 nodes) to 0.391 (4 nodes) (Figure 2). The decision tree in Figure 3 depicts the rule base used for creating the predictive vegetation cover maps. Shown is the regression tree with 6 end nodes. Pruning node 5 resulted in the 5-node tree and further pruning of node 2 resulted in the 4-node tree. Out of 118 input variables, 5 were chosen for this tree. The mean of the NIR band was the first split in the tree and was selected twice. The 3 other variables included the mean difference to the neighboring object of the SAVI band, the standard deviation of the SAVI band, and the standard deviation difference to the super object of the blue band.

The maps created from the regression trees with 4, 5, and 6 nodes are shown in Figure 4. The class means were determined by the regression tree and the class boundaries were established based on the midpoints between the node mean values.

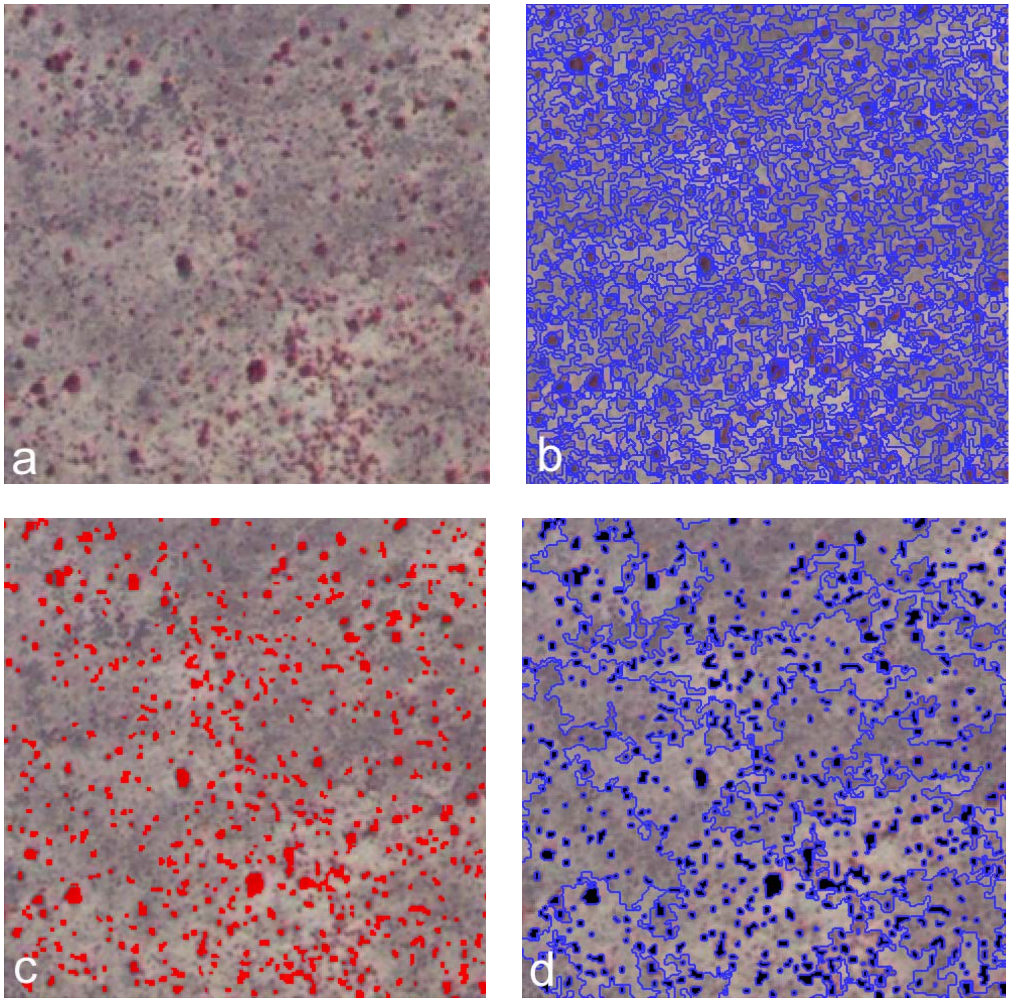

Figure 1. A subset of the pansharpened QuickBird image (a), the level 1 segmentation for detection of shrubs (b), the classified shrubs image (c), and the level 2 segmentation of the image with masked-out shrubs (d). Spectral, spatial and contextual object features for input to the regression tree were extracted from the level 2 segmentation.

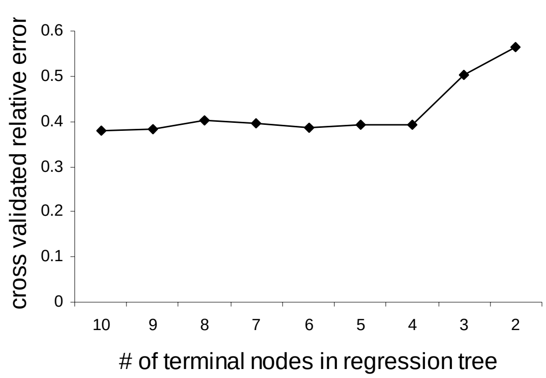

Figure 2. Cross validated relative error for regression trees with 2-10 nodes. The optimal tree chosen by the CART® program had 10 nodes; classified maps were developed from trees with 4, 5, and 6 nodes.

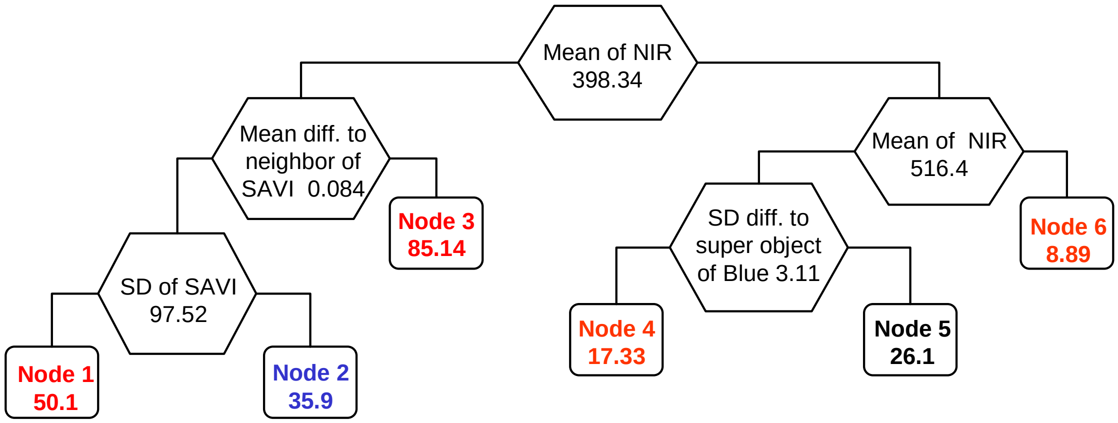

Figure 3. Regression tree with 6 end nodes. The hexagonal boxes show the variable and its threshold value used in the split. Terminal nodes are shown in bold, and values at terminal nodes are the mean percent cover for that node. Node 5 (in black) was pruned for the 5-node tree, and node 2 (in blue) was pruned for the 4-node tree (in red).

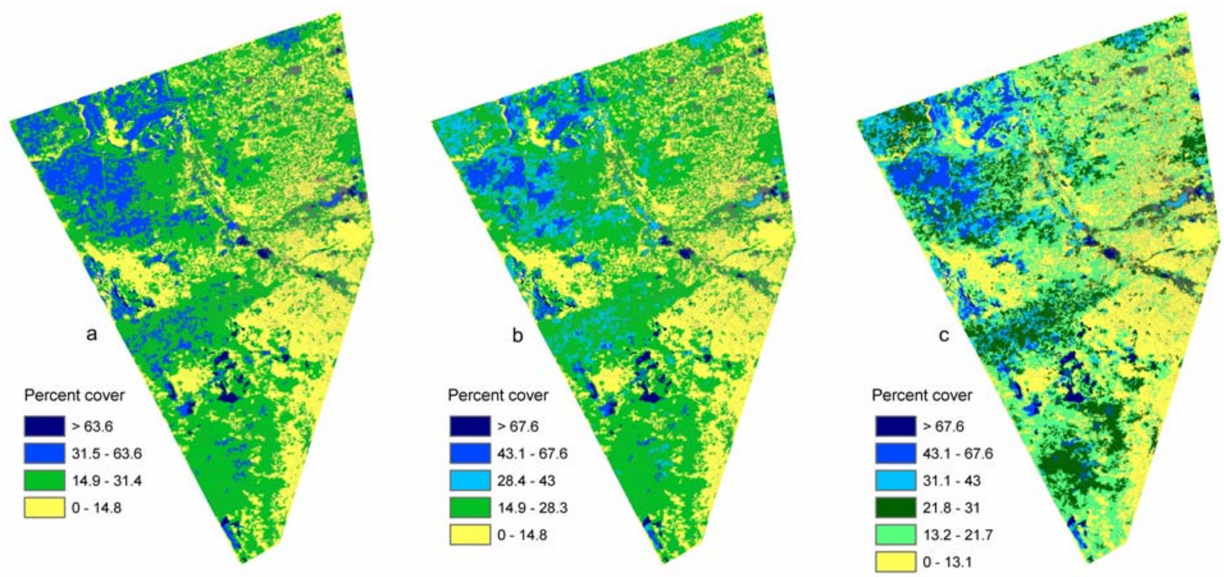

Figure 4. Classification of percent cover based on regression trees with 4 (a), 5 (b), and 6 (c) end nodes. Shrubs (in black) were derived from a separate classification at the finest segmentation level and overlaid on the maps.

Accuracy Assessment

Overall classification accuracy and Kappa Index of Agreement decreased with increasing class size and increased as the buffer size around the classes increased (Figure 5). Producer's and user's accuracy for the maps with 4, 5, and 6 classes are shown in Table 1. With the exception of class number 3 in the 5- and 6-class maps, all classes showed an improvement in producer's and user's accuracy by adding the 2.5% cover buffer and then increasing it to a 5% buffer. Class number 3 has the highest percent vegetation cover (>67.6%), and is composed exclusively of tobosa grass and high cover black grama grass. Both vegetation types have a unique signature and are easily detected. For that reason, no improvement in accuracy was seen by adding the buffers. In fact, except for the producer's accuracy for the discrete boundary analysis, all producer's and user's accuracies for class number 3 were lower in the 5- and 6-class map compared to the 4-class map.

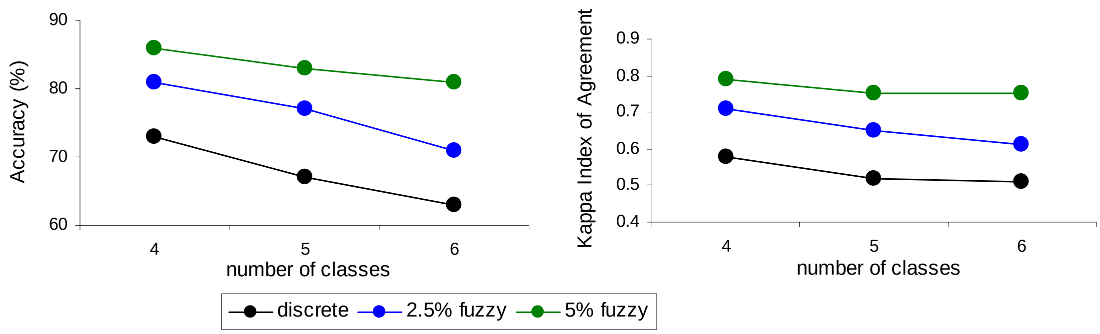

Figure 5. Overall classification accuracies and Kappa Index of Agreement for percent cover maps shown in Figure 3 with 4, 5, and 6 classes using discrete or fuzzy accuracy assessments. For the fuzzy accuracy assessment, a 2.5% or 5% cover buffer was placed around the class boundaries.

Table 1. Producers and user's accuracy (in %) for maps with 4, 5 and 6 classes based on discrete class boundaries, a 2.5% and a 5% cover buffer around class boundaries. Class numbers correspond to node numbers in regression tree in Figure 3

Class number: 4-class map % cover values	**6 0-14.8**	**4 14.9-31.4**	**1 31.5-63.6**	**3 >63.6**
Producer's accuracy discrete	76	72	67	73
User's accuracy discrete	80	63	76	89
Producer's accuracy 2.5% fuzzy	84	81	75	90
User's accuracy 2.5% fuzzy	85	75	86	100
Producer's accuracy 5% fuzzy	86	88	83	90
User's accuracy 5% fuzzy	93	79	86	100

Class number: 5-class map % cover values	**6 0-14.8**	**4 14.9-28.3**	**2 28.4-43**	**1 43.1-67.6**	**3 >67.6**
Producer's accuracy discrete	76	73	32	64	89
User's accuracy discrete	80	55	57	73	89
Producer's accuracy 2.5% fuzzy	84	82	43	67	89
User's accuracy 2.5% fuzzy	85	70	61	82	89
Producer's accuracy 5% fuzzy	86	91	56	72	89
User's accuracy 5% fuzzy	93	75	68	95	89

Class number: 6-class map % cover values	**6 0-13.1**	**4 13.2-21.7**	**5 21.8-31**	**2 31.1-43**	**1 43.1-67.6**	**3 >67.6**
Producer's accuracy discrete	81	55	47	39	64	89
User's accuracy discrete	77	54	44	50	73	89
Producer's accuracy 2.5% fuzzy	83	65	64	48	67	89
User's accuracy 2.5% fuzzy	80	66	54	57	82	89
Producer's accuracy 5% fuzzy	91	80	76	60	72	89
User's accuracy 5% fuzzy	87	83	67	64	95	89

DISCUSSION AND CONCLUSIONS

In our part of the Chihuahuan Desert, it is difficult to map vegetation with high resolution satellite or aerial imagery, because shrubs dominate many areas and are present in most vegetation communities, which complicates identifying non-shrub vegetation. The object-based multi-scale classification approach solved some of those problems and helped to detect and map vegetation at different scales. Shrubs were classified at a fine scale and shrub interspace vegetation at a coarser scale, and the decision tree rule base was applied only at the coarser scale.

The regression tree approach proved to be an excellent tool for reducing the numerous input variables created in eCognition and for identifying relationships between input variables and percent vegetation cover. Correlation between variables was not a problem, because decision trees are non-parametric. Applying the rules from the regression tree in eCognition was very straightforward, because the interface allows for creating, combining and modifying rule-based information.

The more frequent and earlier in a decision tree a variable is used, the greater explanatory power it has (Lagacherie and Holmes, 1997). The mean of the near infrared band represented the first and second split in the tree. Two other variables incorporated information about neighboring objects on the same level (mean difference to the neighboring object in the SAVI band) and on a coarser level (the standard deviation difference to the super object in the blue band). The near infrared band and the SAVI band were selected twice. The occurrence of spectral and contextual variables in the regression tree and the use of more than 1 segmentation level illustrate the usefulness of object-based multi-scale analysis for mapping percent cover. Similar findings were encountered mapping vegetation classes in the same pasture with object-based analysis and classification trees (Laliberte et al., in review). In that study, the near infrared band appeared in 3 segmentation levels as the first variable in the classification tree, the SAVI was the most frequently selected band, and the blue band was selected more frequently than the red or green band, with most of the blue band selections (5 of 9) as relationships to neighbor and super objects.

A fuzzy accuracy assessment was considered to be more appropriate than a conventional accuracy assessment under our conditions. First, although the regression tree yielded distinctive classes from a continuous variable and the means of those classes were known, discrete class boundaries are not easily defined. Second, even if discrete class boundaries were known, a predictive map for percent cover is better assessed by using fuzzy class boundaries, because of the uncertainty associated with estimating percent cover in the field. Third, we used an object-based analysis and related a field plot to a larger image object, which implies that there is some type of variability in percent cover within each object.

Our accuracy results compare favorably with similar studies. Lawrence et al. (2004) reported an overall classification accuracy of 84% for a comparable decision tree approach using IKONOS data. In that study, 4 classes were used: tree, water, meadow, rock. Shupe and Marsh (2004) used various combinations of Landsat TM, elevation and radar data and determined that the highest overall accuracy for relative cover in southwest Arizona was 88%

In terms of accuracy, our 4-class map would be most reliable for further analysis and use in management purposes. Splitting out a percent cover classification into more than 4-5 classes reduces not only the accuracy, but may not be ecologically meaningful, which was the reason that we chose to use fewer classes than the 10 classes suggested by the Cart® program for the optimal tree. We conclude that a 4-or 5-class map would be appropriate for our use, which will include determination of livestock movement and activities in the pasture.

This approach proved to be an effective method for mapping arid land vegetation cover from high-resolution satellite imagery at the pasture-level scale. The selection of variables in this study and the classification tree study (Laliberte et al., in review) can potentially guide future object-based classifications using nearest neighbor analysis and field sampling. Future research will focus on applying this approach over larger areas and incorporating satellite imagery and aerial photography of varying resolutions.

REFERENCES

Baatz, M., and A. Schaepe, (2000). Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation, *Angewandte Geographische Informationsverarbeitung* (J. Strobl, and T. Blaschke, Eds.), Vol.XII ed., Wichmann, Heidelberg, Germany, pp. 12-23.

Breiman, L., J.H. Friedman, R.A. Olshen, and C.J. Stone, (1984). *Classification and Regression Trees.* Wadsworth International Group, Belmont, CA.

Burnett, C., and T. Blaschke, (2003). A multi-scale segmentation/object relationship modelling methodology for

landscape analysis. *Ecological Modelling*, 168(3):233-249.
Definiens, (2003). Definiens Imaging, eCognition, URL: http://www.definiens-imaging.com, (last day accessed: 7 July 2005)
DeFries, R. S., M. Hansen, J.R.G. Townshend, and R. Sohlberg, (1998). Global land cover classifications at 8 m spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. International *Journal of Remote Sensing*, 19(16):3141-3168.
Friedl, M. A., and C. E. Brodley, (1997). Decision tree classification of land cover from remotely sensed data. Remote Sensing of Environment, 61:399-409.
Gopal, S., and C. Woodcock, (1994). Theory and methods for accuracy assessment of thematic maps using fuzzy sets. *Photogrammetric Engineering and Remote Sensing*, 60(2): 181-188.
Hansen, M., R. Dubayah, and R. DeFries, (1996). Classification trees: an alternative to traditional land cover classifiers. *International Journal of Remote Sensing*, 17(5):1075-1081.
Hay, G. J., P. Dube, A. Bouchard, and D.J. Marceau, (2002). A scale-space primer for exploring and quantifying complex landscapes. Ecological Modelling, 153:27-49.
Herold, M, X. Liu, and K.C. Clarke, (2003). Spatial metrics and image texture for mapping urban land use. *Photogrammetric Engineering and Remote Sensing*, 69(9):991-1001.
Hudak, A. T., and C. A. Wessman, (1998). Textural analysis of historical aerial photography to characterize woody plant encroachment in South African savanna. *Remote Sensing of Environment*, 66:317-330.
Huete, A. R., (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25:295-309.
Lagacherie, P., and S. Holmes, (1997). Addressing geographical data errors in a classification tree for soil unit prediction. *International Journal of Geographical Information Science*, 11(2):183-98.
Laliberte, A. S., A. Rango, K.M. Havstad, J.F. Paris, R.F. Beck, R. McNeely, and A.L Gonzalez, (2004). Object-oriented image analysis for mapping shrub encroachment from 1937-2003 in southern New Mexico. *Remote Sensing of Environment*, 93:198-210.
Laliberte, A.S., E.L. Fredrickson, and A. Rango. Combining decision trees with hierarchical object-oriented image analysis for mapping arid rangelands. *Photogrammetric Engineering and Remote Sensing* (In review).
Lawrence, R., A. Bunn, S. Powell, and M. Zambon, (2004). Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. *Remote Sensing of Environment*, 90:331-336.
Lawrence, R. L., and A. Wright, (2001). Rule-based classification systems using classification and regression trees (CART) analysis. *Photogrammetric Engineering and Remote Sensing*, 67(10):1137-42.
Lennartz, S. P., and R. G. Congalton, (2004). Classifying and mapping forest cover types using Ikonos imagery in the northeastern United States. *Proceedings of the ASPRS 2004 Annual Conference*, Denver, CO, American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland. CDROM.
Okin, G. S., and D. A. Roberts, (2004). Remote Sensing in Arid Regions: Challenges and Opportunities, Manual of Remote Sensing, Vol. 4, *Remote Sensing for Natural Resource Management and Environmental Monitoring* (S. L. Ustin, Ed.), John Wiley and Sons, New York, pp. 111-46.
Ryherd, S., and C. Woodcock, (1996). Combining spectral and texture data in the segmentation of remotely sensed images. *Photogrammetric Engineering and Remote Sensing*, 62(2):181-94.
Shupe, S. M., and S. E. Marsh, 2004. Cover and density based vegetation classifications of the Sonoran Desert using Landsat TM and ERS-1 SAR imagery. *Remote Sensing of Environment*, 93:131-49.
Steinberg, D., and P. Colla, (1997). CART - *Classification and Regression Trees*. Salford Systems, San Diego, CA.
Thomas, N., C. Hendrix, and R.G. Congalton, (2003). A comparison of urban mapping methods using high-resolution digital imagery. *Photogrammetric Engineering and Remote Sensing*, 69(9):963-72.
van der Sande, C. J., S.M. de Jong, and A.P.J. de Roo, (2003). A segmentation and classification approach of IKONOS-2 imagery for land cover mapping to assist flood risk and flood damage assessment. *International Journal of Applied Earth Observation and Geoinformation*, 4:217-229.
Wang, L., W.P. Sousa, and P. Gong, (2004). Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. *International Journal of Remote Sensing*, 25(24):5655-68.
Zadeh, L., (1973). Outline of a new approach to the analysis of complex or imprecise concepts. IEEE *Transactions on Systems, Man and Cybernetics*, SMC-3:28-44.