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Global Marketing Insights delivered a comprehensive review of the international remote sensing market for aerial and spaceborne sensors based on NOAA's specific requirements. Turn to page 14 for an exclusive state of the industry report.

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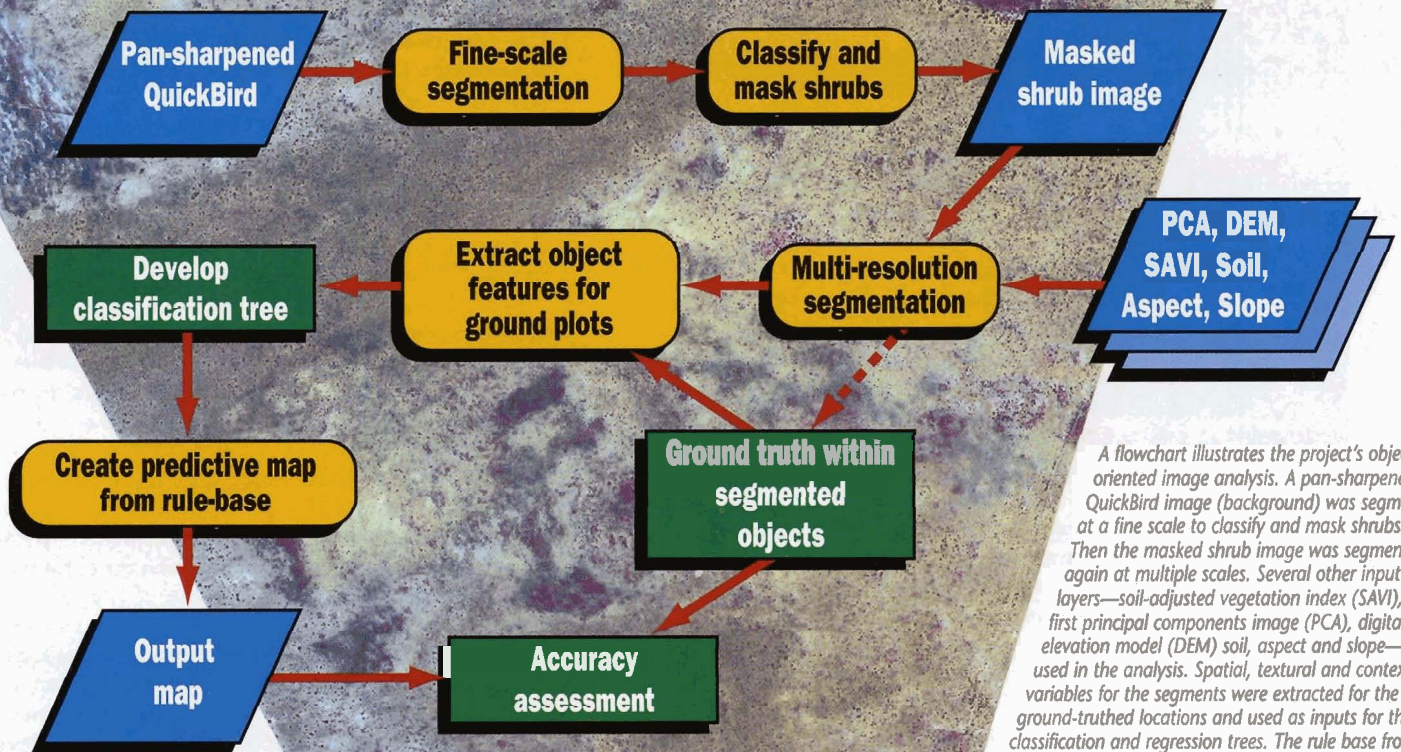
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RANGELAND M

Ease Classification with an Object-Oriented Approach and Satellite Imagery

By Andrea S. Laliberte, remote sensing scientist, Albert Rango, research hydrologist, and Ed L. Fredrickson, rangeland scientist, USDA-Agricultural Research Service, Jornada Experimental Range (<http://usda-ars.nmsu.edu>), New Mexico State University, Las Cruces, N.M.



A flowchart illustrates the project's object-oriented image analysis. A pan-sharpened QuickBird image (background) was segmented at a fine scale to classify and mask shrubs. Then the masked shrub image was segmented again at multiple scales. Several other input layers—soil-adjusted vegetation index (SAVI), the first principal components image (PCA), digital elevation model (DEM) soil, aspect and slope—were used in the analysis. Spatial, textural and contextual variables for the segments were extracted for the ground-truthed locations and used as inputs for the classification and regression trees. The rule base from the decision trees was used to create a predictive map.

MAPPING

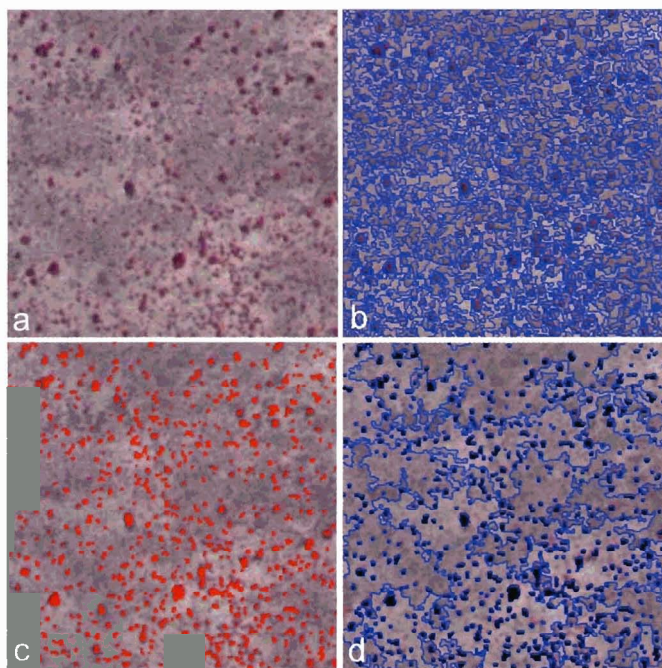
Determining detailed vegetation characteristics to classify arid rangelands often presents unique problems due to the high reflectance of the soil background, a mixture of green and senescent grasses, and the prevalence of shrubs in grasslands. These components can make it difficult to determine the proportion of grass cover. On the Jornada Experimental Range (JER), operated by the U.S. Department of Agriculture Agricultural Research Service near Las Cruces, N.M., ongoing research is aimed at determining the relationship between ground-based observations and remotely sensed data.

The goal of a recent study was to develop a detailed vegetation classification of a 1,200-hectare pasture to determine the extent of grassland and identify locations, extent and percent cover values for several grass species. Specific objectives were to develop and evaluate near-Earth photography for ground truthing a QuickBird satellite image from DigitalGlobe (www.digitalglobe.com); conduct a multiscale analysis, including ground sampling, near-Earth photography and satellite imagery; and combine object-oriented classification with classification and regression trees to analyze the satellite image.

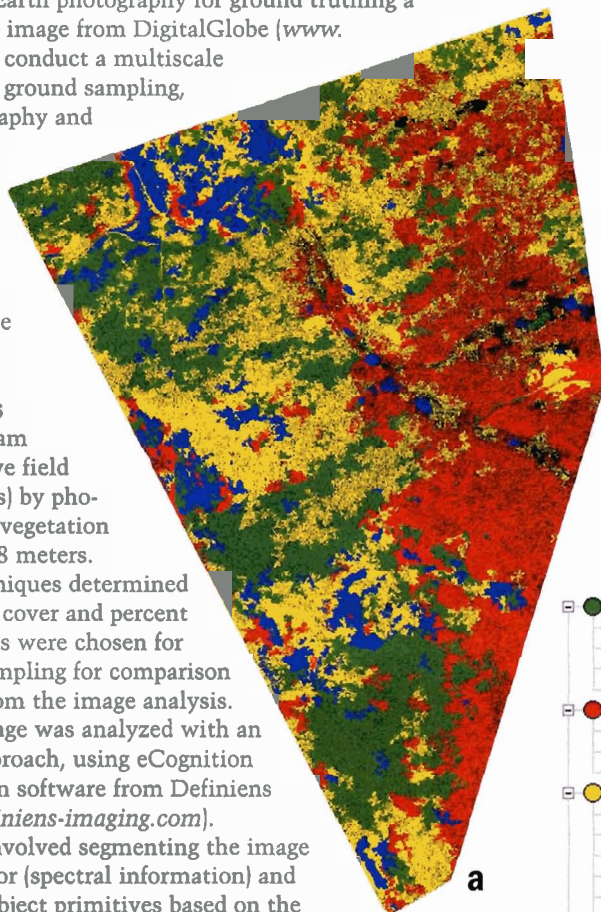
Research Methods

The research team conducted extensive field sampling (325 plots) by photographing ground vegetation from a height of 2.8 meters. Thresholding techniques determined percent vegetation cover and percent bare soil. Fifty plots were chosen for detailed ground sampling for comparison with the results from the image analysis. The QuickBird image was analyzed with an object-oriented approach, using eCognition image-classification software from Definiens Imaging (www.definiens-imaging.com).

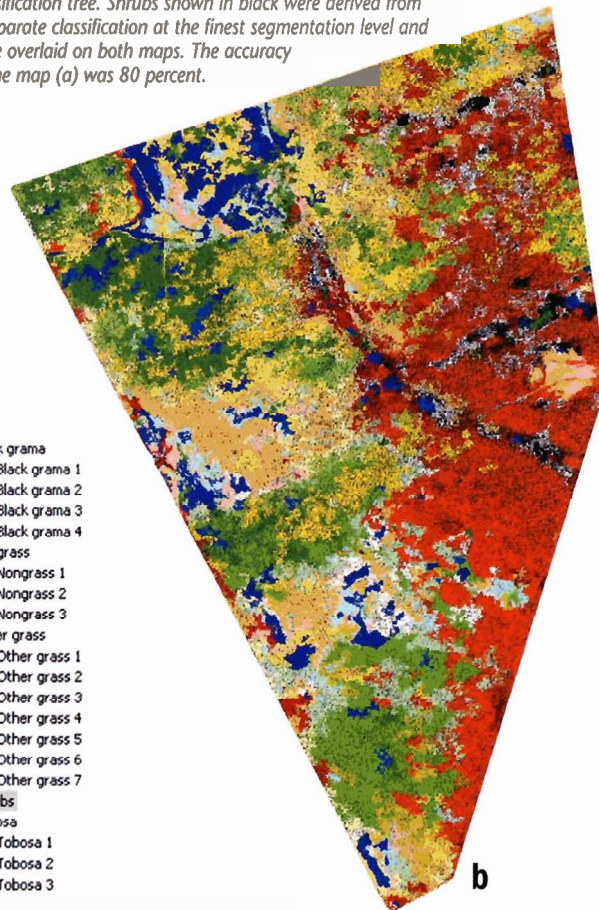
The first step involved segmenting the image based on scale, color (spectral information) and shape to identify object primitives based on the chosen parameters. Classification is then performed using those objects rather than single pixels. The classification is based on fuzzy logic theory combined with user-defined rules. The segmentation was performed at two



To extract shrubs from the QuickBird image, the pan-sharpened image (a) was segmented in the eCognition software at a fine scale to capture shrubs (b). Shrubs were classified (c), masked out, and the masked shrub image was segmented again at a coarser scale for mapping intershrub vegetation (d). This approach allowed for excluding the relatively low mean spectral values for shrubs from the image segments.

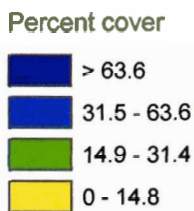
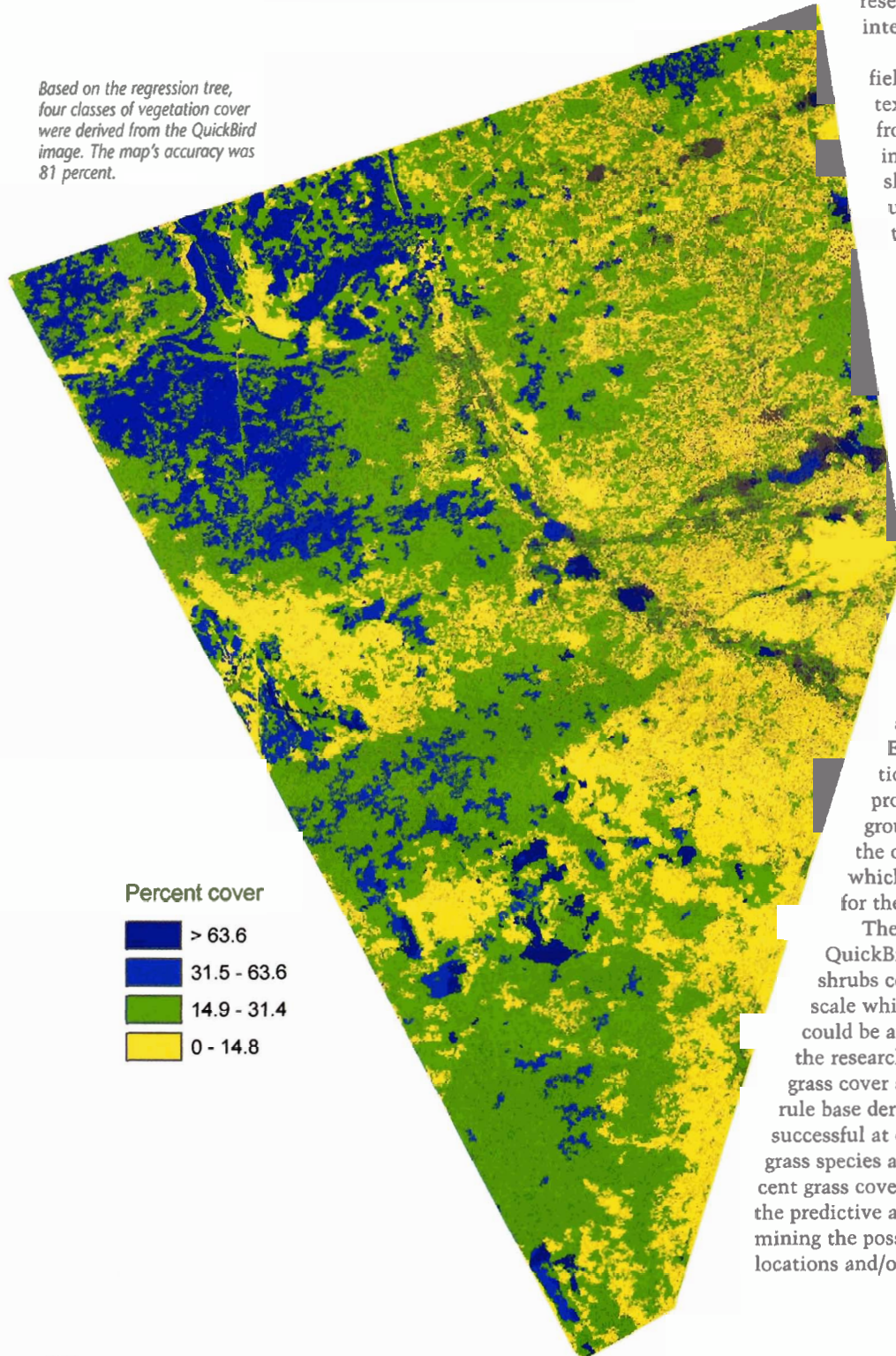


To classify the QuickBird image based on the classification tree, the map was collapsed into the four main vegetation classes (a). The main classes are expanded to show the results for 17 classes (b), one for each terminal node in the classification tree. Shrubs shown in black were derived from a separate classification at the finest segmentation level and were overlaid on both maps. The accuracy of the map (a) was 80 percent.



The object-oriented classification of the QuickBird image worked favorably, because shrubs could be classified separately at a finer scale while the shrub-interspace vegetation could be analyzed at a coarser scale.

Based on the regression tree, four classes of vegetation cover were derived from the QuickBird image. The map's accuracy was 81 percent.



different scales to construct a hierarchical network of image objects representing the image information in different spatial resolutions simultaneously. This allowed the research team to differentiate individual shrubs on a lower level and delineate broader landscape classes on a higher level. After the shrubs were classified, they were "removed" from the image so the segmentation at the higher level didn't include their spectral values. This approach allowed the researchers to determine the shrub-interspace vegetation.

For each image object containing the field plot, several spectral, spatial and texture characteristics were extracted from the image. Ancillary information included soils, elevation, aspect and slope layers. The data were analyzed using classification and regression trees to determine correlations between features of the segmented image objects and the measured field plot parameters. A decision tree is a tool for determining which features are most appropriate for predicting a particular class based on ground-plot information. With the help of a decision tree, one can quickly sift through numerous features associated with the image objects and select the best ones. Because eCognition offers hundreds of spectral, spatial and textural features, a decision tree is a useful tool for reducing the large number of input variables.

Favorable Results

Results for percent vegetation cover and bare soil calculated from the near-Earth photography showed close correlation to the ground-based sampling and proved to be a faster assessment tool than ground sampling. One disadvantage was the occurrence of shadow in the photos, which could be eliminated by using shading for the plot.

The object-oriented classification of the QuickBird image worked favorably, because shrubs could be classified separately at a finer scale while the shrub-interspace vegetation could be analyzed at a coarser scale. This allowed the research team to get a reliable estimate of grass cover and shrub density in the pasture. The rule base derived from the decision tree proved to be successful at differentiating between the dominant grass species as well as defining several classes of percent grass cover. 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. EJ