INCORPORATION OF TEXTURE, INTENSITY, HUE, AND SATURATION FOR RANGELAND MONITORING WITH UNMANNED AIRCRAFT IMAGERY

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ABSTRACT:

Aerial photography acquired with unmanned aerial vehicles (UAVs) has great potential for incorporation into rangeland health monitoring protocols, and object-based image analysis is well suited for this hyperspatial imagery. A major drawback, however, is the low spectral resolution of the imagery, because most lightweight cameras suitable for UAVs only acquire imagery in the red, green, and blue bands (RGB). Potential solutions include the incorporation of intensity, hue, and saturation (IHS) and/or texture measures. The use of texture had improved classification results in a related study, but we wanted to investigate whether IHS would yield similar results, because texture calculations in object-based analysis are computer intensive. Our objectives were to determine the optimal analysis scale and optimal band combinations: RGB, RGB+texture, RGB+IHS, or RGB+IHS+texture. Eight aerial photos were mosaicked and segmented at 15 consecutively coarser scale parameters (from 10 to 80) using the object-based image analysis program Definiens Professional. Class separation distances, classification accuracies and Kappa Index of Agreement were used to assess the classifications. The highest classification accuracies were achieved at segmentation scales between 50 and 70 and were consistently in the high 90% range, regardless of which bands were included. The inclusion of texture measures increased classification accuracies at nearly all segmentation scales, but the use of RGB+IHS alone resulted in comparable accuracies at most scales and with considerably less computation time. Techniques used in this study offer an objective approach for determining segmentation scale, and for selecting bands useful for rangeland mapping with hyperspatial, low spectral resolution imagery.

1. INTRODUCTION

Aerial photography acquired with piloted aircraft is commonly used for rangeland mapping and monitoring (Booth and Tuller, 2003; Rango and Havstad, 2003; Naylor et al., 2005; Petersen et al., 2005), but in many cases a higher resolution is desirable for quantifying spatial patterns of vegetation and soil, and for deriving landscape fragmentation metrics used in rangeland assessment and ecosystem models (Bestelmeyer et al., 2006). Unmanned aerial vehicles (UAVs) offer an alternative platform for image acquisition with several advantages: UAVs can be deployed rather quickly and repeatedly to assess effectiveness of rangeland restoration treatments, they are less costly and safer than piloted aircraft, and they can be deployed at low altitudes for acquiring sub-decimeter resolution imagery. This hyperspatial imagery, images with a resolution finer than the objects of interest, allows for mapping of small shrubs, grass and soil patches not detectable with conventional aerial photography or satellite imagery (Rango et al., 2006; Laliberte et al., 2007a), and thus bridges the gap between ground-based plot information and lower resolution remotely sensed data.

Although the spatial resolution of this UAV imagery is rather fine, this is often not true for the spectral resolution due to low payload capabilities, because low-cost, off-the-shelf digital cameras are commonly used for acquiring the imagery. Potential solutions for imagery with very high spatial and low spectral resolution include the incorporation of intensity, hue, and saturation (IHS) and/or texture measures, as well as exploitation of shape and contextual information using object-based image analysis (OBIA) (Carleer and Wolff, 2006; Yu et al., 2006; Laliberte et al., 2007b). Texture has been used widely in pixel-based image analysis (Ryherd and Woodcock, 1996; Wulder et al., 1998; Franklin et al., 2000), but the use of texture in OBIA has not been as well covered (Herold et al., 2003; Carleer and Wolff, 2006), especially the investigation of texture across multiple segmentation scales. This may be due to the fact that texture calculations in OBIA are relatively computer intensive.

In a related study (Laliberte and Rango, in review), texture had improved classification accuracy at all segmentation scales, but we wanted to investigate whether the use of IHS would yield similar accuracy results with lower computation costs. While band inter-correlation is relatively high in the RGB space, it is lower in the IHS space, and we have used this approach successfully for object-based analysis of ground plot photography (Laliberte and Rango, 2007b).

Our objectives were to determine the optimal analysis scale and optimal band combinations (RGB, RGB+texture, RGB+IHS, or RGB+IHS+texture) for differentiating vegetation structure groups (bare ground, grasses, shrubs) in an arid rangeland from UAV imagery. This study is part of ongoing research at the USDA Agricultural Research Service (ARS) Jornada Experimental Range (JER) in southern New Mexico, aimed at determining the utility of UAVs for rangeland mapping and monitoring and developing a workflow for processing and analyzing UAV imagery in a production environment.

2. METHODS

2.1 Image Acquisition

The UAV imagery was acquired in October 2006 at the JER in southern New Mexico over arid rangeland with a mixture of

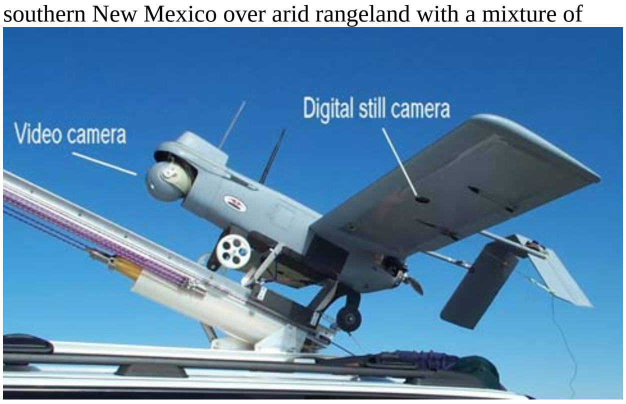


Figure 1. BAT 3 UAV on catapult on roof of launch vehicle. The video camera is located at the front; the digital still camera used in this study is located in the left wing.

shrubs, grasses, and bare soils representative of the northern part of the Chihuahuan desert. The platform used was a MLB BAT 3 UAV, a fully autonomous GPS-guided unmanned aircraft with a weight of 10 kg and a wingspan of 1.8 m (Figure 1). The UAV flies to pre-determined waypoints according to flight plans designed with the mission planning and flight software, and acquires imagery at 60% forward lap and 30% side lap for photogrammetric processing. For this mission, the UAV flew at 150 m above ground and acquired imagery with a Canon SD 550 seven-megapixel digital camera, resulting in an image footprint of approximately 152 m x 114 m. Eight images from this flight were orthorectified and mosaicked into a single image with 5 cm pixel resolution for further analysis.

2.2 Image Analysis

The image mosaic was segmented at 15 consecutively coarser scale parameters (from 10 to 80) in increments of 5, using the object-based image analysis program Definiens Professional (Definiens, 2006). Color/shape and compactness/smoothness were set to 0.9/0.1 and 0.5/0.5 respectively, based on previous research with this type of imagery in this area (Laliberte et al., 2007a). The cut-off for the coarsest scale was determined by our objective to retain individual shrubs with the segmentation.

The bands (or features, as they are called in Definiens Professional) used in this study are shown in Table 1. The optimal texture features for each segmentation scale had been determined in a related study (Laliberte and Rango, in review) by using a decision tree and assessing prediction success and cross-validated error rate of the tree, in conjunction with class separability and classification accuracy. The pre-selection reduced computer calculation times. Entropy, contrast, and standard deviation were consistently chosen by the decision tree at scales 65-80, and entropy received the highest score in most segmentation scales.

For this follow-up study, we used the previously selected texture measures for each segmentation scale and then assessed the following band combinations: 1) RGB, 2) RGB+texture, 3) RGB+IHS, and 4) RGB+IHS+texture with regard to classification accuracy and class separability. The Image was classified using a standard nearest neighbour classification, using samples for the three classes of interest collected in the field with differentially corrected GPS. Samples were collected

Band	Type
Mean Blue	Spectral
Mean Green	Spectral
Mean Red	Spectral
Mean Intensity	Spectral
Mean Hue	Spectral
Mean Saturation	Spectral
GLCM Homogeneity	Texture
GLCM Contrast	Texture
GLCM Dissimilarity	Texture
GLCM Entropy	Texture
GLCM Angular 2^{nd} moment	Texture
GLCM Mean	Texture
GLCM Standard Deviation	Texture
GLCM Correlation	Texture
GLDV Angular 2^{nd} moment	Texture
GLDV Entropy	Texture

Table 1. Spectral and texture bands used in the analysis

in polygon format to be consisted with object-based image analysis. Half of the 300 samples were used for classifying the map, half were retained for performing an accuracy assessment.

2.3 Class Separability and Accuracy Assessment

Evaluation of the band combinations was done by determining class separability and performing a classification accuracy assessment. We used the Feature Space Optimization tool in Definiens Professional for determining class separation distances. For each sample of class 1, the sample of class 2 with the smallest Euclidean distance is calculated. The process is repeated for samples of class 2 compared to class 1, and the Euclidean distances are finally averaged over all samples. Classification accuracy was assessed by determining Kappa Index of Agreement (KIA) as well as overall, producers, and users accuracies (Congalton, 1991).

3. RESULTS AND DISCUSSION

3.1 Class Separability

As a general trend, we observed increasing class separability as the segmentation scale became coarser for all four band combinations, with a notable increase after scale 50 for comparisons with the Bare class (Figure 2). The inclusion of texture measures as chosen by the decision tree for each scale increased the class separability compared to using only RGB bands. Only at scale 60 was the separability slightly greater for RGB than for RGB+texture for Bare-Shrub comparisons. RGB+IHS increased class separability considerably over using RGB alone for all three class comparisons at all segmentation scales, and it outperformed RGB+texture for Grass-Bare and Bare-Shrub at all scales. Using all band combinations (RGB+IHS+texture) resulted in the highest class separabilities for Grass-Bare and Bare-Shrub at scales greater than 50, while for Grass-Shrub, using RGB+texture had comparable results to using RGB+IHS+texture at those scales. A slight reduction in separability was noticeable around scale 70-75 for comparisons involving shrubs. This points to the requirement to keep the segmentation large enough to capture shrubs, but small enough to retain individual shrubs, which occurred between scale parameters 50-70.

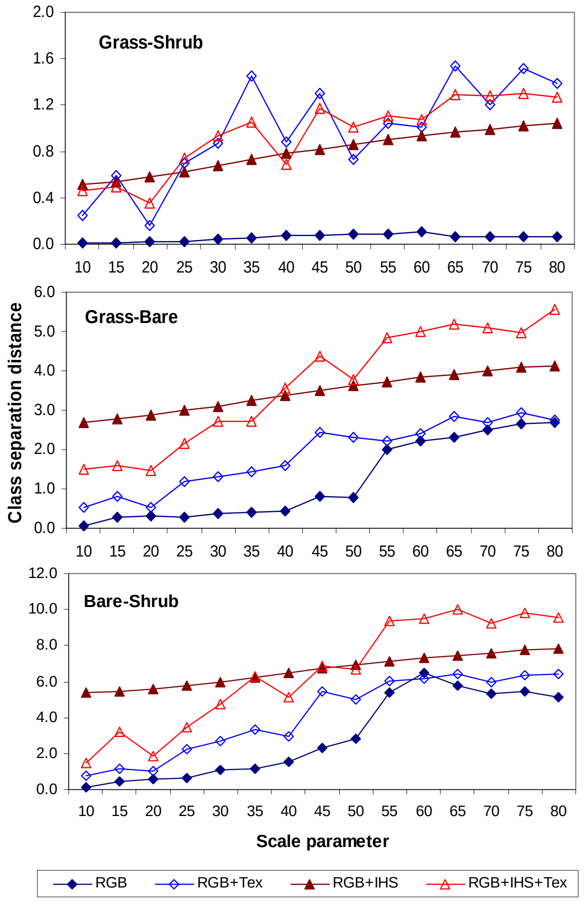


Figure 2. Class separability for Grass-Shrub, Grass-Bare, and Bare-Shrub for four different band combinations at varying scale parameters.

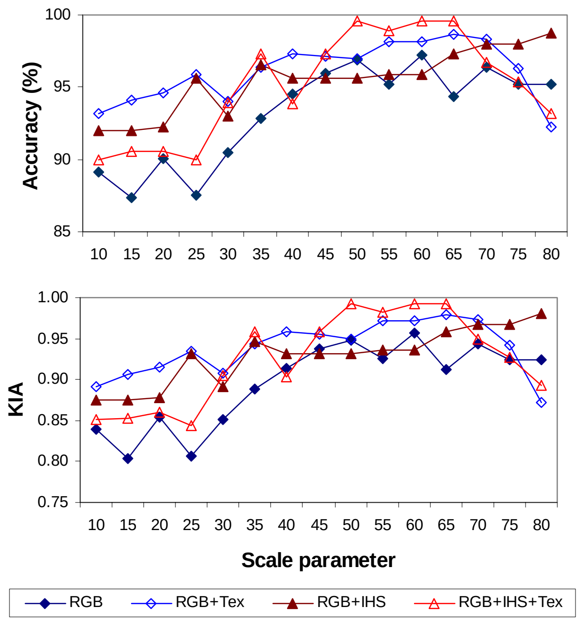


Figure 3. Classification accuracy and Kappa Index of Agreement for four different band combinations at varying scale parameters.

For RGB+IHS, class separability showed a steady increase with increasing segmentation scale. For RGB+IHS+texture for Grass-Bare and Bare-Shrub comparison, there was a marked increase in separability after scale 50. We attribute this to the fact that at coarser scales, the image objects are larger, and the ratio between edge pixels of an image object and the number of pixels in an image object is lower than at finer scales, making texture a more effective tool at relatively coarser segmentation scales to separate vegetation from bare ground. The separability values were much lower for Grass-Shrub comparisons, although adding texture increased the separability regardless of whether IHS was included or not.

While we used class separability tools built into the Definiens software for this study, there are other options for feature selection and/or optimal segmentation scales. Carleer and Wolff (2006) used the Bhattacharyya distance for calculating class separability and feature selection for mapping urban areas with QuickBird satellite imagery. Nussbaum et al. (2006) developed a tool called SEaTH (Separability and Thresholds), designed to determine suitable features and their threshold values in the Definiens software. The optimal segmentation scale was determined by Kim and Madden (2006) by analysis of local variance.

3.2 Classification Accuracy

The accuracy assessment results also indicated increased accuracy with increasing segmentation scales for all band combinations, however, after scale 70, there was a drop in accuracy for 3 band combinations with the exception of RGB+IHS (Figure 3). The inclusion of texture resulted in higher accuracies from scales 50-65, after which using RGB+IHS had equal or better accuracies. There was considerable variability in producers and users accuracy for Grasses and Shrubs at and below scale 40 (not shown), but at larger segmentation scales, producers and users accuracies were consistently above 80%, with a drop-off after scale 70. Similar to the class separability results, shrubs showed lower accuracy results at those scales.

3.3 Image Processing Times

The inclusion of texture measures added considerably to the time required for image classification. Table 2 shows the classification times for the smallest, largest, and intermediate segmentation scales, using a workstation with two dual cores and 4 GB of RAM. Texture in this case consisted of only one band. Classifications at finer scales took more time than those at coarser scales, and while adding the IHS bands affected processing times very little, adding the texture band increased the processing times considerably, and processing had to be done overnight, especially at the finer scales.

Band Combinations	**Segmentation scale**		
	10	45	80
RGB	1:59	0:57	0:01
RGB+IHS	2:24	1:15	0:11
RGB+Texture	323:24	150:36	55:22
RGB+IHS+Texture	360:08	184:11	68:50

Table 2. Classification times (minutes:seconds) for three segmentation scales and four band combinations.

The long processing times make it difficult to quickly assess the optimal segmentation scale using only an accuracy assessment, while the class separation distances can be determined rather quickly in Definiens, and can be a good indicator of the optimal segmentation scale for particular class comparisons. One can also generate a best separation distance for all chosen classes for the optimized feature space. This best separation distance is the largest distance between the closest samples of two classes in feature space. We calculated correlations between the best separation distance and overall accuracies for the four band combinations at all segmentation scales to determine if the best separation distance can be used as an indicator for classification accuracy, in order to reduce computation time.

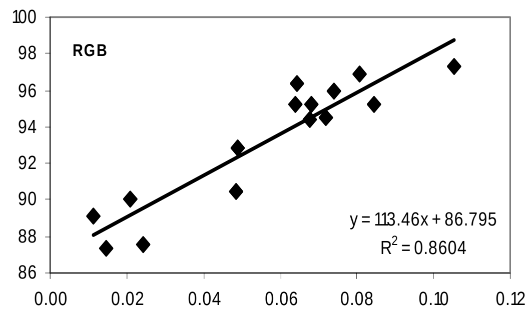
The results indicate good correlations for RGB (R^2=0.86) and RGB+IHS (R^2=0.82), a moderate correlation for RGB+IHS+Texture (R^2=0.68), and a weak correlation for RGB+Texture (R^2=0.47) (Figure 4). With the exception of the latter band combination, this indicates that the best separation distance, a parameter that can be quickly calculated, is a reasonable indicator of optimal segmentation scale and overall accuracy, which can be time consuming to derive. Because the class separability results depend entirely on the samples for the classes, one has to be careful to include representative samples as well as a sufficient number of samples, so that appropriate statistics can be calculated.

Considering the computation times and the relatively high classification accuracy results of all the approaches, the analyst has to weigh the decision of less computation time with fewer bands (RGB+IHS) and slightly reduced accuracy, versus much higher computation times and a small increase in accuracy with the inclusion of texture features. It is advisable to perform class separability calculations using either the tools described here, or those used by others (Carleer and Wolff, 2006; Nussbaum et al., 2006), so that only one or two classifications using texture have to be performed in order to reduce computation times.

3.4 Multi-scale Analysis

As can be seen in Figure 5a, there is very fine detail in this imagery, and OBIA is well suited for classification of this imagery. OBIA allows for extraction of shrubs on both light and dark backgrounds, multiple segmentation scales can be assessed, and the object-based approach offers hundreds of input and derived features of spectral, spatial, contextual, and textural nature. While we used a multiresolution segmentation at 15 scales (Figure 5c,d,e), additional computation times could be saved by performing a chessboard segmentation first, followed by a multiresolution segmentation. We also wanted to determine a single segmentation scale for all three classes for simplicity and incorporation into a rangeland monitoring protocol, although we acknowledge that analysis at more than one scale may be better able to capture small, medium, and large shrubs.

In this study, we concentrated on the means of the RGB and IHS bands (Figure 5b), as well as texture features. Figure 5h shows a portion of the classified image at scale 60, using RGB+IHS+Texture. The texture bands chosen by the decision tree were entropy (Figure 5f) and dissimilarity (Figure 5g). This classification represents the one with the highest overall accuracy of 99.6% with a KIA of 0.99.



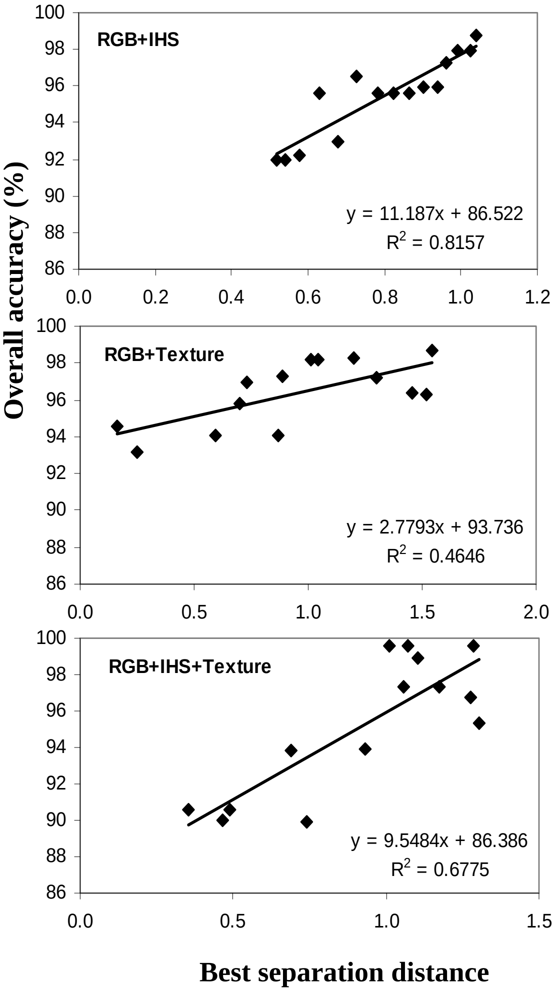


Figure 4. Correlations between best separation distance and overall accuracy for four band combinations at 15 segmentation scales.

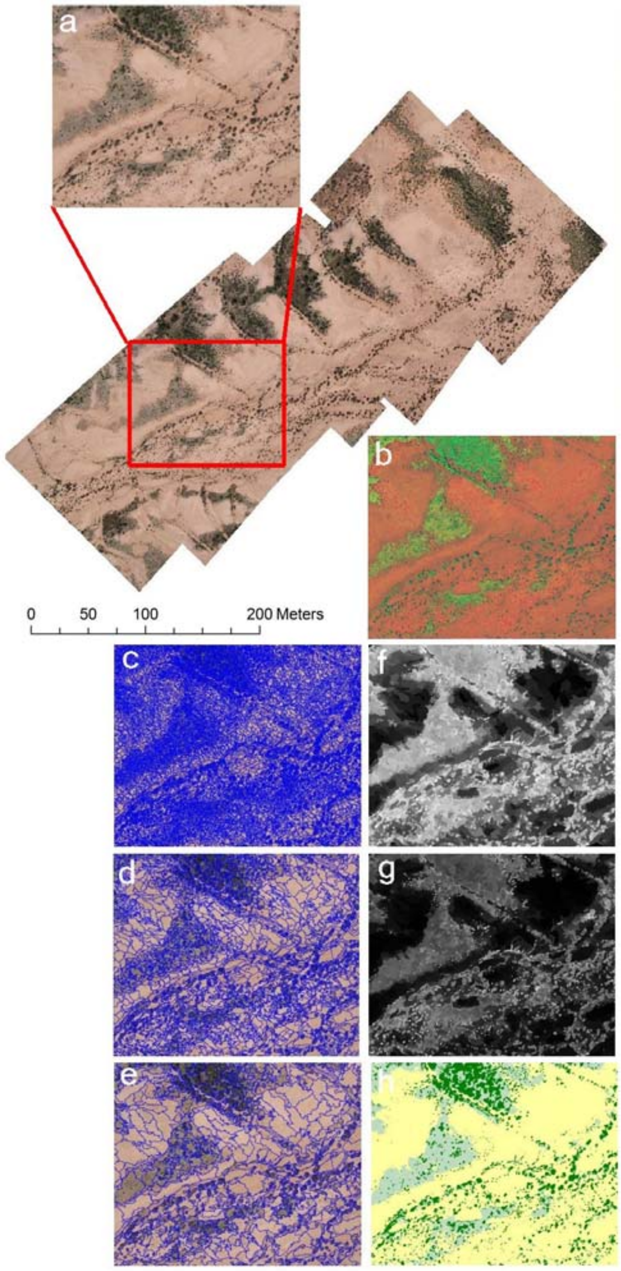


Figure 5. UAV image mosaic and associated scale bar (top center), with a) enlarged area from red rectangle in RGB band combination, b) IHS band combination, c) segmentation at scale 10, d) segmentation at scale 45, e) segmentation at scale 80, f) entropy, g) dissimilarity, and h) classification into bare (yellow), grass (light green) and shrubs (dark green). Texture and classification images are displayed at scale parameter 60.

4. CONCLUSIONS AND FUTURE WORK

UAV aerial photography offers sub-decimeter resolution imagery with fine detail for rangeland monitoring and assessment. However, one drawback of the imagery is its low spectral resolution. This study shows that the use of OBIA and the incorporation of texture, intensity, hue, and saturation can yield classification accuracies for broad structural vegetation groups in the high 90% range. The inclusion of IHS and texture bands yielded the highest accuracies, but using RGB+IHS resulted in sufficiently high accuracies for rangeland assessments with considerably less computation times.

Determination of the optimal scale parameter was done by assessing class separability, which was less computer intensive than performing classifications at multiple scales and assessing their accuracy. The correlations between best separation distance and overall accuracy show that class separability is a reasonable indicator of overall accuracy.

This study demonstrates that small UAVs equipped with low-cost digital cameras can be used successfully for mapping rangeland vegetation using OBIA, and we plan to incorporate these findings into rangeland monitoring protocols with UAVs. In addition, the image analysis approaches can also be applied to imagery of similar resolution, but acquired with digital mapping cameras from piloted aircraft. As a next step, we plan to move from mapping structural vegetation groups to mapping individual species, and to apply these techniques to larger image mosaics, while attempting to retain comparable classification accuracies.

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