SEPARATING GREEN AND SENESCENT VEGETATION IN VERY HIGH RESOLUTION PHOTOGRAPHY USING AN INTENSITY-HUE-SATURATION TRANSFORMATION AND OBJECT BASED CLASSIFICATION

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ABSTRACT

In arid regions of the southwestern US, grass cover is typically a mixture of green and senescent plant material. It is important that both types of vegetation can be quantified for land management purposes and for assessing the nutritional value of grasses. Traditional ground sampling procedures are commonly used but are time consuming. Our goal was to develop an image analysis approach for separating and quantifying green and senescent grasses in the same plot using very high resolution ground photography. The study was conducted in New Mexico at the Jornada Experimental Range (JER), operated by the USDA Agricultural Research Service. We used an eight megapixel digital camera to acquire ground photography from a height of 2.8 m above ground for fifty plots. The images were transformed from the RGB (red, green, blue) color space to the IHS (intensity, hue, saturation) color space. We used an object-based image analysis approach to classify the images into soil, shadow, green vegetation, and senescent vegetation. Shadow and soil were masked out by using the intensity and saturation bands, and a nearest neighbor classification was used to separate green and senescent vegetation using intensity, hue and saturation as well as visible bands. Correlation coefficients between ground- and image-based estimates for green and senescent vegetation were 0.88 and 0.95 respectively, and image analysis underestimated total and senescent vegetation by approximately 5%. The image-based approach is a viable alternative to and less labor and time intensive than ground based plot measures. Research into further automation of the image analysis procedures is ongoing.

INTRODUCTION

In order to assess rangeland health and to determine the nutritional value of vegetation for livestock and wildlife grazing, rangeland managers need to be able to estimate fractional cover values for bare soil and vegetation, as well as for green (live) and senescent (dead) vegetation. Ground-based plot measurements are a common tool for assessing vegetation communities (Herrick et al., 2005), but they can be time consuming and labor intensive. Image-based methods can be faster once fully developed, and they have the added advantage that photos can be taken at different time periods for change analysis. Our goal for this study was to develop an image analysis approach for quantifying vegetation characteristics from very high resolution digital photography. Specific objectives were to quantify bare soil and vegetation cover, to separate and quantify green and senescent vegetation, and to compare cover estimates from image analysis with those obtained from line point intercept data collected on the ground.

Image analysis techniques for measuring vegetation cover and/or bare soil have become more common in recent years (Bennett et al., 2000; Louhaichi et al., 2001; Richardson et al., 2001; Booth et al., 2005). In arid rangelands, there is often a mixture of green and senescent plant material, which may be difficult to differentiate, especially with digital imagery that has only three bands (red, green, blue or RGB) and is lacking the near infrared band. Band inter-correlation is relatively high in the RGB space, but is reduced when images are transformed in the intensity-hue-saturation (IHS) space. The IHS color representation is based on a color sphere rather than a cube as in the RGB space. Intensity relates to brightness and is represented as the vertical axis of the sphere. Hue is the dominant wavelength of the color and is represented as the circumference on the sphere. Saturation is defined as the relative

purity of the color and is represented as the sphere's radius. The IHS model separates the intensity component from the color information, and the hue and saturation components relate to how humans perceive color (Jensen, 2005).

Some authors have reported better success in vegetation analysis of digital images with using an IHS transformation than with the original RGB bands. For example, Tang et al. (2000) used a genetic algorithm for segmenting very high-resolution video images in the IHS image space for detecting weeds in crops. Hemming and Rath (2001) segmented and classified digital images using spectral and spatial features in IHS space. IHS transformations have also been used by Ewing and Horton (1999) to determine canopy cover in wheat and by Karcher and Richardson (2003) for quantifying turf grass.

Object-based image analysis is an effective tool for classification of high resolution satellite imagery (Herold et al., 2003; Lennartz and Congalton, 2004; Thomas et al. 2003). 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), where homogeneity refers to smaller within-object than between-object variance. In a second step, those objects rather than single pixels are classified. In ecological studies, object-based image analysis is advantageous, because this approach allows for detection of landscape patches, which offers insight into ecological processes (Burnett and Blaschke, 2003; Hay et al., 2002). Even though plot photography represents a rather small landscape, patch detection at that scale is an effective tool for classifying vegetation and subsequent pattern analysis.

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.

Image Acquisition and Ground Sampling

A stratified random field sample approach was used to locate 50 plots in five dominant vegetation communities: black grama, tobosa, mixed grasses, broom snakeweed, bare. Communities dominated by large shrubs were not included in this study, because we were mostly interested in grass-dominated sites. We used an 8-megapixel Canon Powershot Pro 1 digital camera to acquire a ground photo for each plot from a height of 2.8 m. The resulting images had a size of 3264 x 2448 pixels, covered a 2.5 m x 3.5 m plot and had an approximate ground resolution of 1 mm. Images were acquired between 9:30 am and 3:30 pm to minimize the influence of shadow. Ground sampling consisted of line point intercept sampling (Herrick et al., 2005), using four lines of 2.5 m length located 0.25 m from the edge of the plot and 1 m apart. Data from those lines was averaged for the plot. Because line point intercept sampling measures several "hits" for vegetation by dropping a pin vertically onto the vegetation, we adapted the data by using only the first hit, which better represents the aerial view in the digital image.

Image Segmentation and Analysis

The images were imported into Erdas Imagine 8.7 (Leica Geosystems GIS and Mapping, 2003) and converted from RGB to IHS space. Subsequent analysis of RGB and IHS images was conducted with eCognition, an object-based image analysis program (Definiens, 2003). In this approach, an image is segmented based on three 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

images were segmented at scale parameter 5, and color/shape and smoothness/compactness were set at 0.9/0.1 and 0.5/0.5 respectively.

Analysis in eCognition is based on fuzzy classification and can be performed either with nearest neighbor classification based on selected samples (similar to a supervised classification in pixel-based analysis), or with membership functions, which represent a rule-base for a class. For example, the class bare ground may be described as all values in band X greater than a, where a is the mean value of all pixels representing an image object. A general rule in eCognition is that membership functions are appropriate if a class is relatively easy to separate from another and can be described with one or few rules. Nearest neighbor classification is more appropriate when classes are more difficult to separate from each other, because this approach is better suited for evaluating correlation between object features and for describing a multidimensional feature space. For a nearest neighbor classification, suitable samples have to be selected for each class.

In this case, we chose a combination of membership functions and nearest neighbor classification and used a masking approach, which allowed for classifying easily identifiable classes first and more difficult ones later. We classified shadow first by determining its threshold value in the intensity band using the Feature View tool. Everything else was grouped into the Not shadow class by using a membership function with inverted similarity to the class Shadow. All objects in the Not shadow class were classified into Soil by determining the soil threshold values in the saturation and hue bands, and into Vegetation (which equaled Not soil) by using a membership function with inverted similarity to the class Soil. Because only vegetation remained to be classified, confusion between senescent vegetation and soil objects was eliminated. Green and senescent vegetation was classified by using a nearest neighbor approach using 10-15 sample objects for each class (Figure 1).
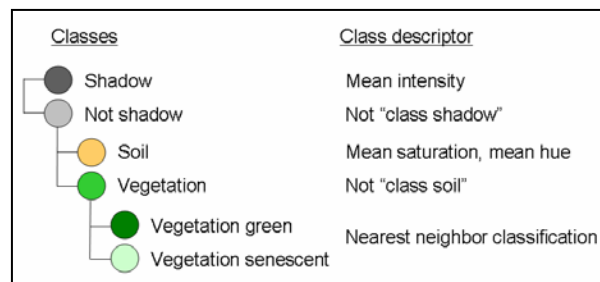

Figure 1. Classes and class descriptors used in image analysis. A masking approach was used. Shadow, Not Shadow, Soil, and Vegetation were classified with membership functions, Vegetation green and Vegetation senescent were classified with the nearest neighbor approach using samples.

In a nearest neighbor classification in eCognition, samples are selected, the image is classified, and in a subsequent step, wrongly assigned objects or unclassified objects are assigned to the correct classes. This step can be repeated if needed. The choice of input layers was determined both visually and with the Feature Space Optimization tool. This tool evaluates the distance in feature space between the samples of classes, and selects layer combinations that result in the best class separation distance. We wanted to choose the same layers for all images, therefore we used the feature space optimization tool on 6 test images. The choice of layer selection for those images was relatively consistent. Therefore, we made a decision based on that layer selection to choose the 13 layers that were subsequently used on all images. Those layers included the mean and ratio of each input band (red, green, blue, intensity, hue, saturation), and the maximum difference. The ratio in eCognition is calculated as the layer mean value of an image object divided by the sum of all layer mean values. The maximum difference is the maximum value minus the minimum value of an image object.

Part of the analysis was automated by using a protocol that segmented the image, loaded the class hierarchy and classified the image initially. Fine-tuning of the classification was necessary for adjustment of the intensity, saturation and hue values for the shadow and soil classes, and for sample selection. For all images, percent cover values for shadow, soil, green vegetation, and senescent vegetation were summarized. Correlation and regression analysis was used to assess the strength of the relationship between image and ground based estimates.

RESULTS

Image Analysis

Image transformation from RGB to IHS space was an effective tool for classification in our study. The intensity band clearly differentiated shadow from non shadow areas in the first step of the image analysis. The hue and saturation bands were equally effective in separating soil and vegetation in the second step. In plots dominated by black grama and/or tobosa grasses, the saturation band alone was sufficient for separating soil and vegetation, while in plots with broom snakeweed, the combination of the saturation and hue bands was more effective. In plots with mostly bare vegetation, hue alone was effective for separating soil and vegetation. Except for a few outliers, the mean values for intensity, hue, and saturation used for thresholding had a relatively narrow range, which made it easy to fine tune the values after each image had been classified initially (Table 1). One outlier for saturation (0.34) occurred in a plot with 94% vegetation cover and another outlier for saturation (0.06) occurred in a plot with a large amount of shadow.

Table 1. Statistics for mean intensity, hue and saturation values used to threshold shadow, soil and vegetation classes in eCognition. Means of intensity, hue and saturation refer to the mean of image objects. Mean intensity was used to separate shadow and non-shadow classes, hue and/or saturation were used to separate soil and vegetation classes.

Statistic	Mean Intensity	Mean Hue	Mean Saturation
Mean	0.26	145.00	0.16
Standard deviation	0.04	2.55	0.05
Median	0.26	146.00	0.16
Mode	0.23	147.00	0.17
Minimum	0.13	140.00	0.06
Maximum	0.34	150.00	0.34
n	50	36	39

Shadow cover ranged from 0.2 to 22.2% with a mean of 6.5%, although 55% of images had less than 6% shadow. Even though shadow was easy to classify, it can present a problem with further classification, because it occurs both on the soil surface as well as in the vegetation canopy. We decided to keep shadow as a separate class in this analysis.

Further classification of the vegetation class into green and senescent vegetation was performed with samples and nearest neighbor classification. In most images, the smallest overlaps in feature space for samples chosen for green and senescent vegetation existed in the mean hue, ratio hue and mean red bands. Given the relatively large overlap in feature space for those classes, the masking of shadow and soil was an appropriate step. Without this approach, there would have been added confusion between senescent vegetation and bright soil. Even though we encountered plots of varying vegetation types and with total vegetation cover ranging from 0% to 94% (with a mean of 36.6%), this image classification approach worked effectively under all conditions. The red, green and blue bands were highly correlated and did not allow for much differentiation between green and senescent vegetation, while the intensity, hue and saturation bands were more effective for this purpose (Figure 2).

Comparison with Ground Sampling

Correlations between ground based and image based cover estimates for total vegetation cover, soil, green and senescent vegetation were relatively high (Table 2, Figure 3). The highest correlations were obtained for total vegetation cover and senescent vegetation, while green vegetation had the lowest correlation coefficient of 0.88. Image analysis underestimated total vegetation cover and senescent vegetation cover by approximately 5%, while no statistical differences in the mean differences between image analysis and ground sampling were found for soil and green vegetation (from a paired t-test).
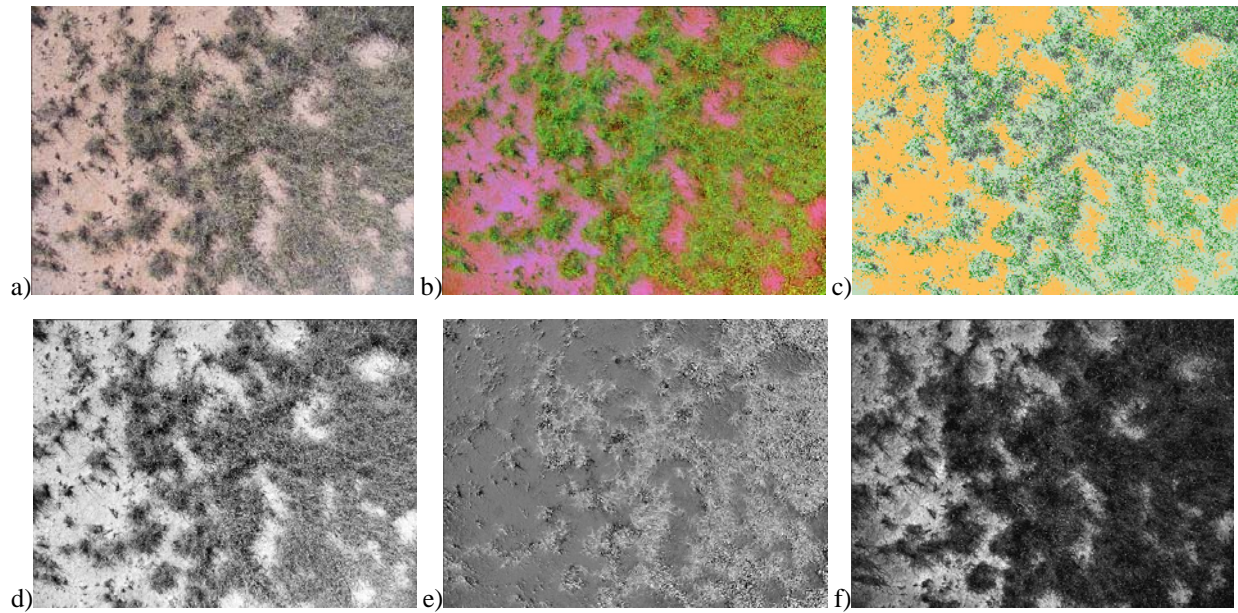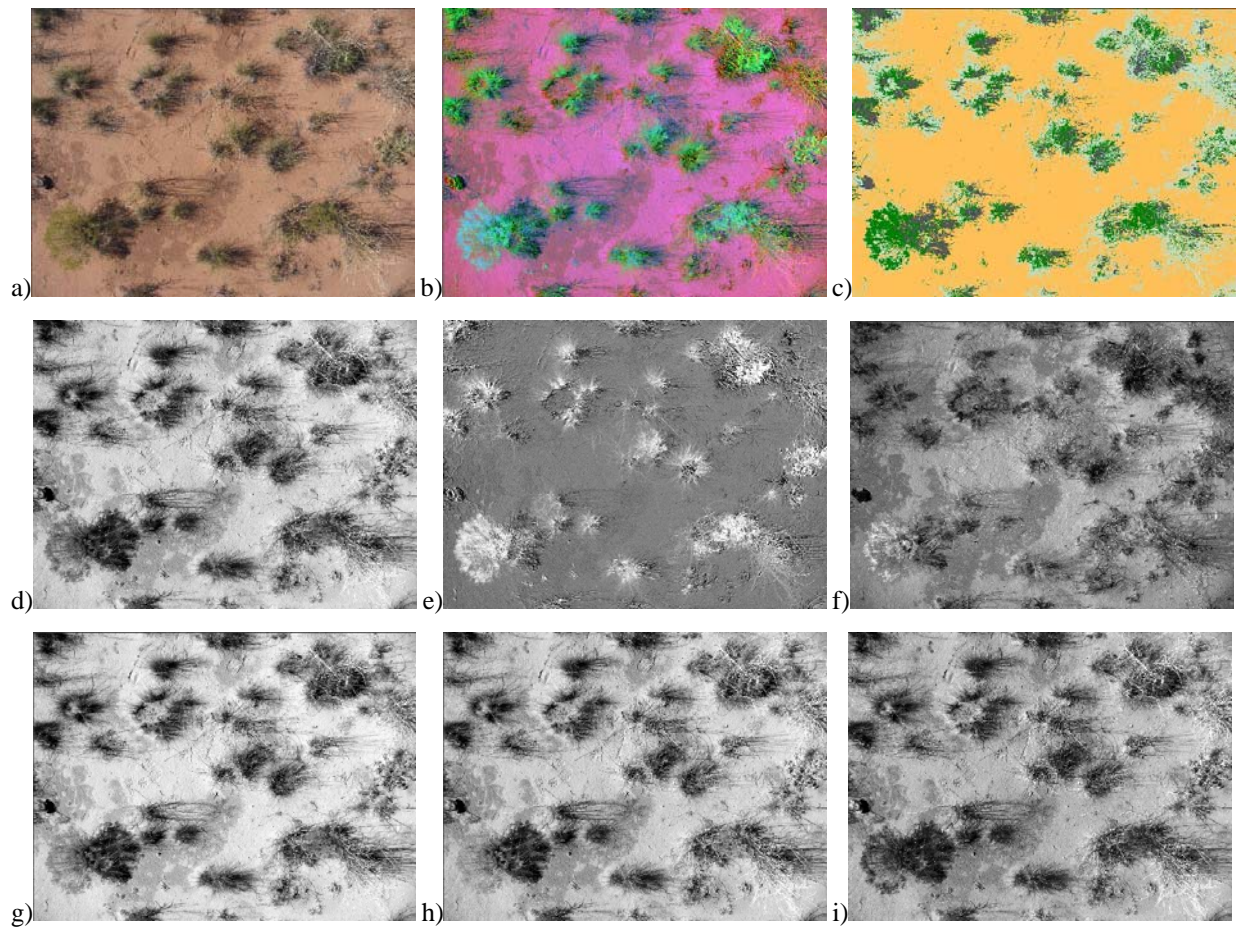
Figure 2. Plot images of Tobosa grassland (A) and mixed grassland (B). Shown are: 3-band image in RGB space (a), 3-band image in IHS space (b), classified image (c), intensity (d), hue (e), saturation (f), and (for mixed grassland) blue (g), green (h), red (i). For classification legend of the classified image (c), refer to Figure 1.

Table 2. Correlation coefficients, p-values, estimates of mean differences and confidence intervals for comparisons of percent cover value estimates obtained from image analysis and ground sampling

Type of cover	Correlation coefficient	p-value from a paired t-test	Mean difference (% cover)	95% Confidence interval (% cover)
Total vegetation cover	0.9556	0.0002	-5.09	-7.56 to -2.62
Soil	0.9391	0.2936	-1.46	-4.16 to 1.24
Green vegetation	0.8803	0.6975	-0.14	-0.87 to 0.58
Senescent vegetation	0.9523	0.0003	-4.94	-7.46 to -2.43

Two outlier plots were detected in the graphs for total vegetation cover, soil and senescent vegetation (Figure 3). Both outlier plots showed highly different values for total cover and soil (i.E. 47% total cover from image analysis, 87% from ground sampling for one of the plots), and we suspected that the plots measured on the ground were not located in the exact position as the image taken of the plot.
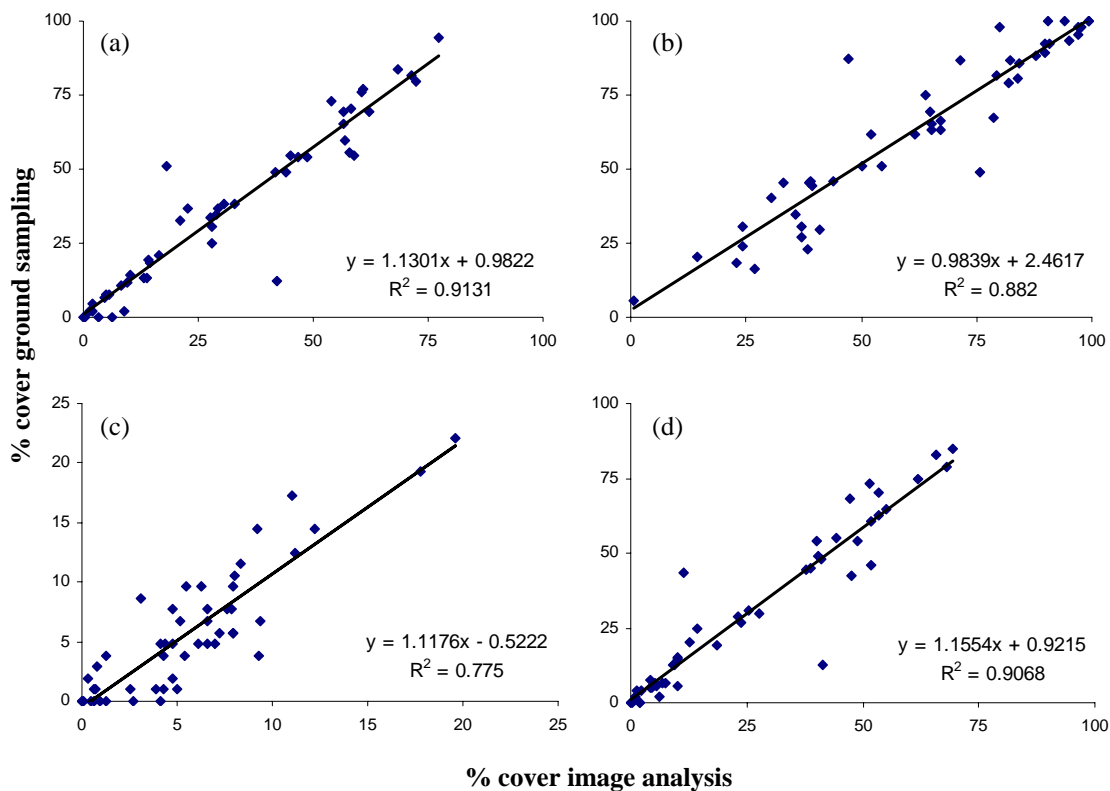

Figure 3. Scatterplots for percent cover estimates from image analysis and ground sampling for total vegetation cover (a), soil (b), green vegetation (c), and senescent vegetation (d).

In terms of labor and time involvement, the image analysis method took fewer person hours. For the 50 plots in this study, ground sampling required 2 workers for 20 min./plot and 3 hours for data analysis for a total of 37.3 hours. Image collection in the field required 1 person at 3 min./plot, import and conversion of images into IHS format took 20 min., and subsequent image analysis required 15 min./plot for a total of 16.2 hours. We did not take into account travel time between plots, which would be the same for ground sampling or image acquisition. Times for each plot were averaged.

DISCUSSION AND CONCLUSIONS

This study showed that object-based image analysis with IHS-transformed images was a viable approach for estimating total vegetation cover, bare soil, green and senescent vegetation from very high resolution ground photography. As others have found, an IHS transformation can be very effective for analyzing vegetation in digital images (Ewing and Horton, 1999; Tang et al., 2000; Hemming and Rath, 2001). The intensity, hue and saturation bands were less correlated than the red, green and blue bands and showed less overlap in the feature space for vegetation classification. The intensity band was used to mask out shadow, which is a common problem in ground photography. The saturation and hue bands were effective for separating soil and vegetation, so that green and senescent vegetation could be classified last in order to minimize the confusion of senescent vegetation with bright soil areas.

Correlations between estimates of cover obtained by ground sampling and by image analysis were high. Statistically, there were no differences in the estimates for soil and green vegetation. Booth et al. (2005) found that image analysis with the program VegMeasure (Johnson et al., 2003) estimated green cover lower than ground measures in two locations and the same in another location. Those authors attributed the discrepancies to limited, scattered green growth. In our plots, green vegetation was limited, scattered and often mixed with senescent vegetation, and it appears that the addition of the intensity, hue and saturation bands is more effective than the use of the red, green and blue bands alone.

The underestimation of total vegetation cover by approximately 5% can probably be attributed to the influence of shadow. A considerable amount of shadow was present in the vegetation canopy, and therefore dark green vegetation and shadow was easily confused. Shadow was an issue in the images and it occurred both within the vegetation canopy and the surrounding soil or vegetation. After comparing percent cover values from ground and image-based analysis, we noted that without the shadow class, results could potentially be improved. Shadows can potentially be reduced or eliminated by shading the plot, which would improve the quality of the imagery (Booth et al., 2004).

The image analysis method was less labor and time consuming than the ground based approach (field and analysis time combined). The time consuming part of ground sampling is the field work. It is possible for one person to conduct line point intercept sampling, but it would require more time, and since the time consuming part is laying out the plot, using only one person would not save many person hours.

In conclusion, we determined that object-based image analysis of very high resolution digital ground photography is an effective approach for estimating fractional cover of vegetation and soil and for separating green and senescent vegetation. This method was also less time and labor intensive than ground sampling. An added advantage is a permanent photographic record for each plot that can be used to detect vegetation changes over time. Our efforts will be directed at improving the data flow, such as import and export of imagery from different programs and the level of automation in image analysis.

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