Using digital photographs and object-based image analysis to estimate percent ground cover in vegetation plots

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Ground vegetation influences habitat selection and provides critical resources for survival and reproduction of animals. Researchers often employ visual methods to estimate ground cover, but these approaches may be prone to observer bias. We therefore evaluated a method using digital photographs of vegetation to objectively quantify percent ground cover of grasses, forbs, shrubs, litter, and bare ground within 90 plots of 2m^2. We carried out object-based image analysis, using a software program called eCognition, to divide photographs into different vegetation classes (based on similarities among neighboring pixels) to estimate percent ground cover for each category. We used the Kappa index of agreement (KIA) to quantify correctly classified, randomly selected segments of all images. Our KIA values indicated strong agreement (> 80%) of all vegetation categories, with an average of 90–96% (SE = 5%) of shrub, litter, forb, and grass segments classified correctly. We also created artificial plots with known percentages of each vegetation category to evaluate the accuracy of software predictions. Observed differences between true cover and eCognition estimates for each category ranged from 1 to 4%. This technique provides a repeatable and reliable way to estimate percent ground cover that allows quantification of classification accuracy.

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Cover and composition of ground vegetation affect animal distributions and abundance by influencing habitat selection and providing critical resources for survival and reproduction (Daubenmire 1959; Rotenberry and Wiens 1980). It is therefore important to use sampling techniques that yield unbiased or nearly unbiased estimators of vegetation cover and composition to avoid misleading conservation recommendations (Korb *et al.* 2003). Traditional methods for measuring ground cover and composition are usually based on the Daubenmire (1959) technique, in which observers visually estimate either percent cover or percent cover categories (eg 0–5, 5–25, 25–50, 50–75, 75–95, and 95–100%). However, subjective methods based on visual estimation are prone to observer bias (Stohlgren *et al.* 1998) and are not repeatable (ie different observers will almost certainly record different measurements for the same quantity; Kercher *et al.* 2003). Published estimates of observer bias affecting visual estimation have ranged from 13% to 90% variance, depending on percent cover category (Hatton *et al.* 1986; Kennedy and Addison 1987) and plot size (Klime 2003).

There have been a number of attempts to account for observer bias in visual estimation techniques, but none have completely removed subjectivity. Tilman's technique (1997) uses visual aids, such as cardboard cutouts of specific shapes and sizes to improve estimates. However, interpretation of these cutouts is still subject to bias. Others have used known levels of ground cover to train observers (Anderson and Kothmann 1982), but training alone will also not completely remove observer bias (Sykes *et al.* 1983). Recent advances in Geographic Information System (GIS) and image analysis software and technology offer potential for using digital images of habitat to objectively quantify ground cover and composition of vegetation in a repeatable and timely manner. Here we evaluate the use of copyrighted image analysis software, eCognition (Definiens Imaging, GmbH, München, Germany), for analyzing digital photographs of vegetation to quantify percent ground cover as part of a grassland bird study in northwest Arkansas during 2003.

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Methods

Digital photos of vegetation within nest plots

We located nests of grassland birds by dragging a 30 m rope through the grass to flush individuals from their nests (Higgins *et al.* 1969). Immediately after a nest was detected, we used a Super Clamp (Manfrotto, Bassano, Italy) to mount a Kodak DC4800 Zoom Digital Camera (Eastman Kodak Company, Rochester, NY) to a telescoping golf-ball retriever to photograph vegetation within about a 2 m^2 area centered on each nest. Pictures were taken from 1.5 m above the ground at an approximate downward angle of 90° (Figure 1). We set the camera to 3.1 megapixel uncompressed resolution, zoomed out for fixed, infinite focus, and used automatic settings for focus, lighting, and shutter speed for each picture. Lighting and sky conditions were not always the same. However, object-based image analysis does not use spectral data alone for classification, but also draws on inherent textural content of imagery (Baatz *et al.* 2003). Therefore, shadows within vegetation were accounted for by relying more on shape than color in the object-based image analysis. One person could take a picture at a nest location in less than 30 seconds.

Figure 1. *A photographic technique for measuring percent ground cover of vegetation used in nine fields in northwest Arkansas during 2003. A Kodak DC4800 Zoom Digital Camera mounted on a telescoping pole at a height of 1.5 m was used to photograph an approximately 2* m^2 *area centered on the nest.*

Categorization of vegetation types with object-based image analysis

We imported digital images into eCognition as JPEG files (2160 X 1440) and applied a new technique known as object-based image analysis. This involved two steps: image segmentation and classification based on fuzzy logic (ie degree of membership of segments to a category).

Image segmentation grouped pixels in each image into objects or segments based on three parameters: scale, color, and shape. The scale parameter was the expression of the allowed level of heterogeneity of the resulting segments (the higher the scale parameter, the higher the level of heterogeneity), whereas color and shape parameters determined how pixels in the digital image were to be grouped. For example, if the user chose a setting of 40% for the color parameter and a setting of 60% for the shape parameter, then the resulting segments would be based more on shape than on color.

The shape parameter was defined by two subparameters: smoothness and compactness. This allowed segments in images to be divided into categories based on similarity and continuity of neighboring pixels. These segments could be further classified into user-defined categories such as vegetation types.

We created segmented objects in the images by analyzing and merging neighboring objects, based on smoothness and compactness, with a scale parameter of 25 (Baatz *et al.* 2003). There is no method for objectively selecting the best combination of parameters for segmentation (Baatz *et al.* 2003). The user must search for the most appropriate combination in a repeatable manner; we therefore adjusted these attributes in a stepwise fashion on one image and examined results from each combination by overlaying the segmented image onto the photograph. This allowed us to determine the combination of parameters that created the best groupings of pixels (segments) for separating different types of vegetation.

Once the best combination of scale, color, and shape parameters had been established, this was applied to all 90 images because they each had similar spatial resolutions (Baatz *et al.* 2003). We used an error assessment procedure (see below) to validate the subjectively chosen segmentation parameters.

First, to categorize vegetation segments, we created a classification scheme or "class hierarchy" in eCognition which quantified percentages of five vegetational categories (grass, forbs, shrub, litter, and bare ground). Grass was more difficult to classify than other categories because of shading; we therefore separated grass into shaded and non-shaded subclasses of the total grass area. Forbs were defined as any non-woody, herbaceous vegetation; shrubs were all woody plants (including saplings) and structurally similar non-woody plants; and litter was any dead vegetation detached from plants and mixed in with living material. These classes within eCognition were defined based on 90 to 120 sampled segments per vegetation class in each image for a total of 450 to 600 samples per image. Small portions of objects such as the pole and/or our feet were in about 20% of our images, so we visually identified their boundaries, manually separated them into their own categories, and adjusted vegetational cover estimates for each image by recomputing the percentages based on the reduced area.

eCognition then used fuzzy logic to place each segment into an appropriate class, based on its similarity in scale, color, and shape relative to the user-defined segment samples for each class. Fuzzy logic quantifies the degree of membership of each segment to each category on a scale from 0 to 1 rather than categorizing a segment as either a

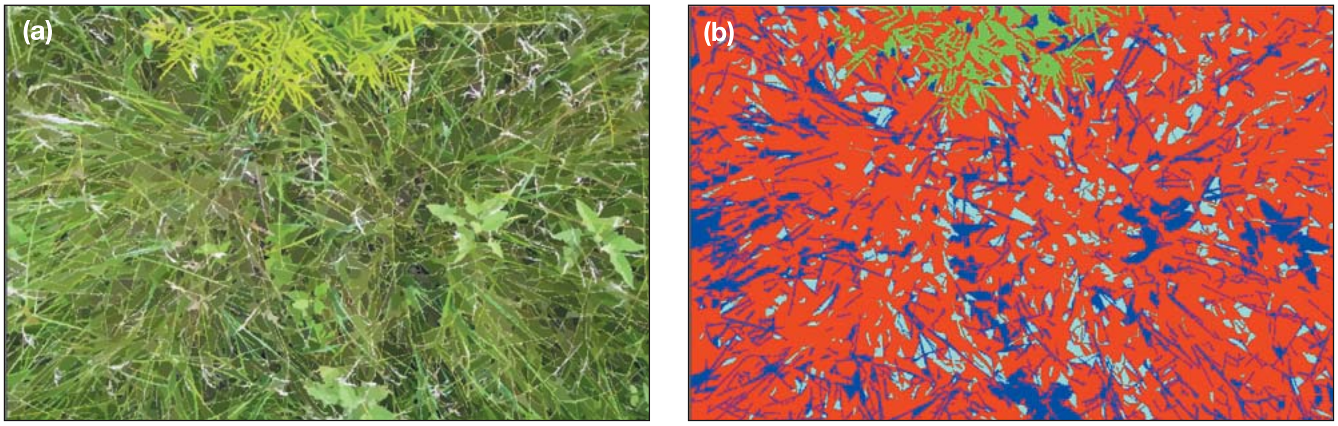

Figure 2. *(a) A 3.1 megapixel digital photograph of a vegetation plot in a hayfield in northwest Arkansas. (b) Image classified into vegetation categories: red = grass (45%); dark blue = forbs (25%); light blue = litter (18%); and green = shrubs (12%).*

0 (not a member of a given category) or a 1 (a member of a given category). Using eCognition to analyze all of the images required approximately 12 h or an average of about 8 minutes per image.

Assessing error

We assessed the classification accuracy of eCognition estimates by using expert visual interpretation, whereby the interpreter compared classified versus unclassified segments, and by creating artificial vegetation plots with real vegetation. We evaluated our visual interpretation by using error matrices, which allow for classified segments to be compared with "truth" (ie unclassified segments; Lillesand and Kiefer 1994). We imported classified images from eCognition into the GIS software PCI Geomatics (PCI Geomatics, Ontario, Canada) which we then used to randomly select 50 segments (Lillesand and Kiefer 1994) from each of five vegetation categories (for a total of 250 segments) for each of the 90 classified images. Next, we used ERDAS IMAGINE software (Leica Geosystems Geospatial Imaging LLC, Norcross, GA, USA) to assess whether the randomly selected segments were categorized the same in both classified and unclassified images. A Kappa index of agreement (KIA) was calculated for each vegetation category (ie grass, shrub, forbs, and litter), such that:

$$\mathrm{KIA} = \frac{P_0 - P_c}{1 - P_c}$$

where P_0 was the observed proportion of samples that agreed with the classification scheme and P_c was the proportion of reference samples that agreed with the classification scheme by chance. The closer the KIA values were to 1, the better the agreement between segments, based on similarity and not on chance. Values greater than 80% for KIA images indicated strong agreement, 40% to 80% indicated moderate agreement, and less than 40% indicated poor agreement (Congalton 1996). Assessing accuracy within PCI Geomatics required approximately 9 h or an average of 6 minutes per image. The analytical component of our technique thus required approximately 14 minutes per image.

In order to double-check our classification accuracy assessment, we conducted field trials with four artificial plots of real vegetation, arranged to contain known percentages of cover for each category. We constructed these benchmark 2 m^2 plots on an area of uniform bare ground by arranging overall vegetational cover of 25%, 50%, 75%, and 100% (ie 75%, 50%, 25%, and 0% bare ground) in patterns that mimicked the shapes and dimensions of vegetation observed in the field. Within each of these overall vegetation cover categories, we used average relative percentages representing grass, shrubs, forbs, and litter, based on estimates obtained using eCognition from our 90 nest plots. We then photographed these plots and used eCognition to estimate percent cover of each vegetation category. We compared actual percentages of each category for each benchmark plot (n = 4) with those estimated by eCognition.

Results

Figure 2a is a digital image of vegetation surrounding a nest, taken in one of the fields surveyed in northwest Arkansas. In order to quantify percent ground cover for each vegetation category, we segmented this image with a scale parameter of 25 and based 20% on color and 80% on shape. We defined shape as 90% smoothness and 10% compactness of the segments, based on a stepwise adjustment of these parameters. This combination of attributes created the best groupings of pixels (segments) for separating different types of vegetation. After this image was segmented and classified (Figure 2b), we estimated the percent ground cover of the vegetation categories to be 45% grass, 25% forbs, 12% shrubs, 18% litter, and 0% bare ground. There was no bare ground in any of our 90 nest vegetation images.

In our nest plot images, average KIA values ranged from 90–96% (range = 0.80–1.00) for grass, shrub, forb, and litter segments (Table 1). All of these values were greater than 80% and therefore indicated high classification accuracy. We were able to correctly classify ~100% of the grass segments when grass cover was > 80% (Figure 3). When grass cover was < 80%, KIA values ranged from 0.80 to 1.00.

Overall, images from artificial benchmark plots had KIA values ranging from 0.94 to 0.97 (Table 2). This means that for each benchmark image, at least 94% of the segments were classified correctly. Grass was underestimated by eCognition in all four benchmark images by a maximum of 4%. Shrub and forb cover was overestimated by the program in all four benchmark images by a maximum of 3%. Litter was overestimated in the 25%, 50%, and 75% cover images by a maximum of 4%, but was underestimated in the 100% cover image by 2% (Table 2). Among benchmark images, KIA values for each vegetation category were greater than 80%, suggesting that our classification schemes had high accuracy (Congalton 1996).

Table 1. Estimates of average (SE, range) percent ground cover of vegetation in plots surrounding grassland bird nests (n = 90) and average (SE, range) KIA for each vegetation category from each nest image

Vegetation category	*eCognition cover estimates Mean*	*SE*	*Range*	*KIA Mean*	*SE*	*Range*
Grass	45	20	0–95	0.96	0.05	0.85–1.00
Shrub	10	16	0–56	0.90	0.05	0.80–1.00
Forbs	29	24	0–99	0.96	0.04	0.89–1.00
Litter	15	14	0–69	0.96	0.04	0.88–1.00

The KIA quantified the percent of a randomly sampled set of segments that were correctly classified in each image.

Discussion

Recent advances in digital photography and image analysis software provide new opportunities for improved vegetation data collection and analysis. Digital cameras provide high resolution pictures that can be quickly transferred to a computer for analysis. Previous photographic techniques, based on 35-mm cameras, involved scanning and enlargement of prints with potential loss in resolution (De Becker and Mahler 1986; Neeser *et al.* 2000). These techniques also required a tripod (De Becker and Mahler 1986) or a hydraulic boom (Neeser *et al.* 2000), which may be much more disruptive to habitat than the telescoping pole described above. Object-based image analysis programs, such as eCognition, allow pixels to be grouped into objects and then classified based on user-defined classes. Other remote sensing software can separate objects, but images need to be transferred to other programs for classification (Congalton 1996). eCognition also allows for fine scale segmentation of objects such as leaves or stems on plants which can then be separated into different classes, resulting in fine-scale estimates of percent ground cover of various categories. Previous techniques have been useful for estimating presence, absence, or biomass of vegetation, but have not been able to distinguish between amounts of several different vegetation types (eg Masubuchi *et al.* 2000; Deca-gon Devices Inc 2002).

The innovative use of eCognition described here allowed us to classify objects on a very small scale (eg blades of grass). Traditional uses of the program involve remote sensing datasets on larger scales (eg to classify different land uses within a large landscape-level matrix; Baatz *et al.* 2003). Further, KIA values are typically based on datasets from several images, which are collected independently and then combined (geo-referenced so that independent images line up). KIA values in these circumstances are sensitive to geo-referenced data and could be biased (Congalton 1996). However, we generated KIA values from a single image of a small area, so the estimations were not prone to the bias observed in traditional applications.

Overall, segments within our classified nest images of nest vegetation plots agreed strongly with actual images. The low level of error (an average of ~5.5%) may have

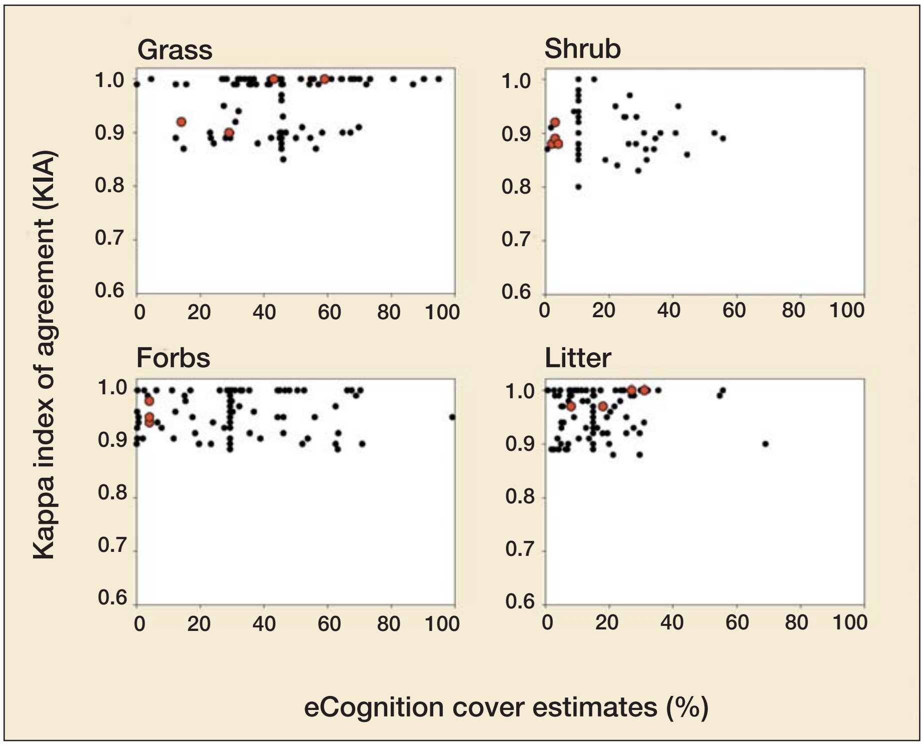

Figure 3. *Kappa indices of agreement (KIA) and eCognition cover estimates for grass, shrubs, forbs, and litter in plots surrounding grassland bird nests (black circles; n = 90) and in images of known ground cover (red circles; n = 4). The KIA quantified the percent of a randomly sampled set of segments that were correctly classified in each image.*

Table 2. Comparisons between actual percent ground cover and estimates of percent ground cover from eCognition in benchmark vegetation plots

Vegetation cover category (%)	*Vegetation category*	*Actual cover (%)*	*eCognition cover estimate (%)*	*Observed difference (%)*	*KIA*
25	Grass	16	14	2	0.92
	Shrub	1	2	1	0.88
	Forbs	3	4	1	0.94
	Litter	5	8	3	0.97
	Bare ground	75	71	4	1.00
	Overall				**0.94**
50	Grass	32	29	3	0.90
	Shrub	1	3	2	0.89
	Forbs	3	4	1	0.98
	Litter	14	18	4	0.97
	Bare ground	50	46	4	1.00
	Overall				**0.95**
75	Grass	46	43	3	1.00
	Shrub	1	3	2	0.92
	Forbs	3	4	1	0.95
	Litter	25	27	2	1.00
	Bare ground	25	23	2	0.91
	Overall				**0.96**
100	Grass	63	59	4	1.00
	Shrub	1	4	3	0.88
	Forbs	3	6	3	0.98
	Litter	33	31	2	1.00
	Bare ground	0	0	0	NA
	Overall				**0.97**

The KIA assessed accuracy by quantifying the percent of a sampled set of segments that were correctly classified. This metric takes into account the observed proportion of samples that agreed with the classification scheme and the probability that agreements were by chance. The closer the KIA values are to 1, the more accurate the classification outputs.

been due to vegetation categories having segments of similar shape and/or color (eg shrub segments may have been similar in shape and color to living forb or grass segments). Some forb segments may have been misclassified as shrubs, resulting in lower shrub KIA values. Misclassification of segments may increase with increased cover of similar vegetation types (ie shrubs and forbs) of similar proportions. However, correct classification may be greater in seasons with higher color variability (eg more forbs flower in spring or vegetation may change color in the fall). Observers using visual estimation techniques may also encounter these discrepancies. Nonetheless, it is very difficult to reliably quantify error in visual estimations, whereas we were able to quantify error relatively easily with eCognition.

The strengths of the approach described here are objectivity and the ability to evaluate classification accuracy. Approximations from visual estimation techniques of low cover classes typically have much higher error rates (> 51%; Kennedy and Addison 1987). Also, it is difficult to evaluate subjective components of visual estimation techniques, but in our technique the selection of segmentation parameters and selection of samples for defining classes, among other factors, were validated by the high KIA values (≥ 80%; Congalton 1996).

The use of eCognition to classify digital images of ground plots provides a repeatable, minimally disruptive, and relatively non-subjective method for estimating percent ground cover with estimates of classification accuracy. Field measurements can be performed quickly, thereby minimizing disturbance to wildlife and damage to vegetation. Continued improvements in image classification software should lead to more accurate estimators of ground cover.

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