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Choosing A DIVA: A Comparison of Emerging Digital Imagery Vegetation Analysis Techniques

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Abstract

Question: What is the precision of five methods of measuring vegetation structure using ground-based digital imagery and processing techniques?

Location: Lincoln, Nebraska, USA.

Methods: Vertical herbaceous cover was recorded using digital imagery techniques at two distinct locations in a mixed-grass prairie. The precision of five ground-based digital imagery vegetation analysis (DIVA) methods for measuring vegetation structure was tested using a split-split plot analysis of covariance. Variability within each DIVA technique was estimated using coefficient of variation of mean percentage cover.

Results: Vertical herbaceous cover estimates differed among DIVA techniques. Additionally, environmental conditions affected the vertical vegetation obstruction estimates for certain digital imagery methods, while other techniques were more adept at handling various conditions. Overall, percentage vegetation cover values differed among techniques, but the precision of four of the five techniques was consistently high.

Conclusions: DIVA procedures are sufficient for measuring various heights and densities of standing herbaceous cover. Moreover, digital imagery techniques can reduce measurement error associated with multiple observers' standing herbaceous cover estimates, allowing greater opportunity to detect patterns associated with vegetation structure.

Introduction

In terrestrial ecosystems, estimates of vegetation characteristics are an important means of predicting species–habitat relationships (Daubenmire 1959; Wiens 1969, 1973; Robel et al. 1970; Nudds 1977; Fisher & Davis 2010) with implications as to how natural systems are managed (Catchpole & Wheeler 1992; Ganguli et al. 2000; Ammann & Nyberg 2005; Davies et al. 2008). Although collecting and weighing vegetation provides the most precise estimates of vegetation cover, it has limited application in large-scale ecological studies or when destructive sampling is not an option (Harmoney et al. 1997; Benkobi et al. 2000; Vermeire & Gillen 2001). As such, visual obstruction estimates are widely used to quantify vegetation structure (e.g. Robel

et al. 1970) and are successful in a variety of systems (Robel et al. 1970; Ganguli et al. 2000; Vermeire & Gillen 2001; Vermeire et al. 2002; Uresk & Juntti 2008; Schmer et al. 2010; Toledo et al. 2010). Despite their ubiquity, traditional visual obstruction techniques that rely on ocular estimates are often criticized as being unstandardized (Fisher & Davis 2010) and subject to observer error that may mask important ecological patterns (Gotfryd & Hansell 1985; Collins & Becker 2001; Higgins et al. 2005; Limb et al. 2007). A lack of confidence in traditional visual obstruction estimates has led to the development of new techniques using ground-based digital photography (Vanhaja-Majamaa et al. 2000; Boyd & Svejcar 2005; Limb et al. 2007; Carlyle et al. 2010). Rather than depending on ocular estimates of vegetation density and structure, digital

imagery vegetation analysis (DIVA) techniques often rely on the ability of computer software to 'count' the number of pixels in a digital photograph associated with vegetation and produce a digital estimate of vegetation cover (Fig. 1). Analysis of digital imagery from satellite or aerial photography is a long-standing and common practice in large-scale ecological studies (e.g. Lefsky et al. 2002; Welch et al. 2002; Horning et al. 2010), but DIVA has only recently gained favour as a means to differentiate small-scale vegetative variation (Booth et al. 2005, 2006; Luscier et al. 2006; Seefeldt & Booth 2006; Limb et al. 2007; Cagney et al. 2011). In theory, quantifying visual obstruction by means of digital processing could reduce observer error and increase the accuracy, precision and repeatability of visual obstruction estimates (Booth et al. 2005; Limb et al. 2007).

The DIVA technique has produced remarkably accurate and precise results relative to traditional methods, such as the Robel Pole or the Nudds cover board (Limb et al. 2007), and illustrates the potential for this new technique to become a common method for analysing vegetation characteristics in ecology. Despite the apparent benefits, the interpretation and classification of digital imagery is susceptible to error from different sources, a number of

which are novel in ecological study. For example, differences in cloud cover or overhead vegetation, date or time, and/or camera settings or sensor sensitivity among samples may alter the degree to which shadows and highlights occur, which potentially causes misclassified pixel values. Similarly, light conditions may influence the degree to which pixel values associated with vegetation merge with the backdrop. Such inconsistencies in reflectance can lead to misclassification of pixels by image processing software and severely reduce the accuracy and precision of estimates. Although previous examinations of DIVA techniques have explored the benefits of reduced observer error (e.g. Limb et al. 2007), the importance of other sources of error remain largely unknown. Moreover, the ever-expanding number of image processing programs and processing techniques, each with varying levels of cost, effort required and degree of accuracy and precision, makes choosing a DIVA approach increasingly challenging. Determining which methods are acceptable and cost efficient is essential if DIVA techniques are to be widely implemented.

Broadly, DIVA techniques fall within three categories: arbitrary threshold classifications (Limb et al. 2007),

Fig. 1. An example of two digital images, black backdrop (a) and white backdrop (c), and their respective binary images (b and d), which were converted using digital imagery vegetation analysis (DIVA) techniques.

human-based selection (Cagney et al. 2011) and machine-training techniques (Booth et al. 2005). While often simple to use, arbitrary threshold classification techniques use software to split pixel values into binary data, where any pixel value over the threshold value is assigned as one, or zero otherwise. One major limitation of this type of technique is that shadows or highlighted areas of vegetation may be over the threshold limit and mistaken as the backdrop. Human-based selection techniques can be more accurate than arbitrary threshold methods because the user directly supervises the software to correctly classify vegetation and therefore can account for threshold variability associated with temporal and environmental factors (e.g. time of day, clouds); however, these techniques require more processing time. Machine-training techniques also account for variable thresholds, but they rely heavily on the software to correctly classify vegetation in an image based on a set of user-specified pixel values. Once the set of pixel values is assigned, the process of identifying the percentage vegetation cover in the image can often be automated, analysing potentially hundreds of images in a matter of minutes. Yet, if pixel values are wrongly assigned prior to the automation processes, errors will be replicated throughout the entire sample of images, thus drastically increasing error rather than minimizing it. Here we evaluate five ground-based DIVA techniques, each technique falling within one of the three general DIVA method categories, for differences in (1) estimates; (2) measurement error; and (3) time and cost.

Methods

Study system and photo stations

We examined five visual obstruction digital imagery and processing techniques during November 2010 in a mixed-grass prairie composed of a mixture of bunch and rhizomatous grasses generally ranging in height from 15 to 100 cm in Lincoln, Nebraska, USA. The study site is located at 358 m a.s.l. and has an average monthly precipitation range of 1.60–12.12 cm annually. The annual average precipitation is 71.88 cm, of which 65% falls during the May–September growing season.

We constructed photo stations using 1 × 1 m backdrops constructed from tempered hardboard (0.476-cm thick, spray-painted black) and white fiberglass reinforced wall panelling (Fig. 2). In order to capture sufficient variation in vegetation cover, we randomly placed two pairs of cover boards, each pair containing one black and one white board, in areas with variable grass height. Backdrops were secured vertically in a fixed position, facing south to maximize light exposure. A metal rod was driven into the

Fig. 2. An example showing the metal rod placement and backdrop set-up for a digital imagery vegetation analysis.

ground, extending 1 m from the ground and positioned 4 m directly south of each board, creating a permanent reference point to stabilize the cameras (following Robel et al. 1970; Limb et al. 2007).

We recorded digital images of the standing vegetation in front of the backdrops using four Polaroid® t1031, 10.0 megapixel digital cameras (one camera for each observer) with standardized settings at each of the four photo stations over a 2-wk period. The locations of the backdrops and the four photo stations remained constant for the duration of the study. Because the vegetation was in senescence, the amount of vegetation within the confines of the backdrop was assumed to remain constant throughout the 2-wk period. Four observers visited each photo station 21 times, taking a total of 84 photos. Visits were distributed evenly throughout the day in order to measure the influence of lighting and temporal conditions on estimates. We recorded time of day, wind speed and cloud cover. Images were imported into Adobe Photoshop® CS3 (Adobe Systems Inc, San Jose, CA, US) and cropped such that only the 1 × 1 m backboard was visible in the image (as outlined in Limb et al. 2007).

Image processing

Image processing was completed using three software programs, Adobe Photoshop® (Adobe Systems), Intelligent Perception Pixcavator® (Intelligent Perception Co., Huntington, WV, US) and GNU Image Manipulation Program® (GIMP) (Kimball & Mattis 2006, an open-source software package). A total of five DIVA techniques were analysed: Grid, GIMP and Pixcavator (human-based selection), Threshold (arbitrary threshold classification) and Photo-Training (machine-training). For each technique we estimated the per photo effort based on time and cost of analysing 100 photos.

Grid

Using Adobe Photoshop®, we conducted a human-based vegetation selection DIVA by overlaying an evenly spaced 50 × 50 lattice grid on each image and manually counting the number of cells that contained >50% vegetation present (similar to cover board estimates; Jones 1968). Vegetation cover was estimated as the number of cells containing >50% vegetation divided by the total number of cells. Because of the large amount of time and effort required, we sampled a random subset of 11 of the 21 images per backdrop for a total of 44 images.

GIMP

Carlyle et al. (2010) devised a human-based vegetation selection method using the open source image software GNU Image Manipulation Program® (Kimball & Mattis 2006), which we modified to fit our study design. Using the *color select tool* on each individual image, we selected all pixels that matched the cover board. Different lighting conditions caused the cover board in each image to have a range of black or white hues, so we used a similarity threshold of 40.0 (Carlyle et al. 2010) and employed the *add to selection* option by selecting multiple pixel values in each image. The number of selected pixels was then subtracted from the total number of pixels in each image, resulting in the number of pixels representing vegetation. Percentage vegetation cover was calculated for each image as the ratio of vegetation pixels to total pixels.

Pixcavator

The third human-based selection approach we tested used Pixcavator IA Standard Edition. Pixcavator identifies edges and objects in images based on changes in value of each pixel. Cropped photos were imported into the software and the vegetation in the image was selected using the *Green* colour channel (Appendix S1). We adjusted the amount of vegetation selected in each photo by adjusting the *intensity, dark* adjustment. Total percentage vegetation cover was obtained by subtracting the area of classified dark objects (the vegetation) from 100 (Appendix S1).

Threshold

We followed the arbitrary threshold method as outlined in Limb et al. (2007), with the addition of using both white and black boards as backdrops. Using the Adobe Photoshop® software *threshold* function, images were converted

to binary form (i.e. 1 or 0) based on a standardized luminance threshold value of 128 (following Limb et al. 2007), such that all pixels above 128 were converted to white, and all pixels below 128 were converted to black. Photos containing white backdrops converted vegetation to black pixels, while photos with black backdrops converted vegetation to white pixels (Fig. 1). We obtained the percentage vegetation cover by recording the percentage of black pixels in the image as indicated in the histogram window of the software. For images containing black backdrops, the histogram window provided the inverse of percentage vegetation cover; therefore we subtracted the value from 1 in order to obtain the percentage cover estimates.

Photo-Training

We used the *replace color* tool in Adobe Photoshop® to train the program to correctly identify which pixel values in each photo were associated with vegetation, and which ranges were associated with the backdrop. We limited the training process to five photos randomly selected from each photo station. Using the *eyedropper*, *eyedropper plus* and *eyedropper minus* tools within the *replace color* tool, we selected the vegetation in the image and converted it to black (or white depending on the colour of the backdrop) using the *lightness* adjustment bar (detailed methods are provided in Appendix S2). The image was saved as a layer mask in a separate folder. For each additional image in the photo subset, the layer mask was imported and the vegetation selection process was repeated. The process was identical for training the backdrop pixel values except that the *lightness* bar was moved in the opposite direction. The final layer masks were used to inform the software as to which pixel values were associated with vegetation and which values were of the backdrop prior to implementing the *Threshold* tool. We automated the process of converting all 84 photos to binary pixel values by creating an *action* and a *droplet* in Adobe Photoshop® (Appendix S2).

Statistical analyses

In analysing the data, our goals were to quantify the variation within DIVA techniques and compare it among the techniques. Thus, the variability within each DIVA technique was estimated using coefficient of variation (CV) of mean percentage cover. The coefficient of variation is a normalized measure of dispersion from the mean ($CV = SD/mean$), which is a particularly useful measurement when comparing the dispersion of two or more variables when their means are substantially different (Shahbaba 2012). For each survey location, a CV of percentage obstruction was calculated for each board colour

within the analysis technique. To test whether the variance differed among DIVA techniques by backdrop colour arrangements, we used a one-tailed F test for homogeneity of variance (Levene 1960; Fox 2008). CV values were plotted and visually inspected to compare precision among DIVA techniques.

The measurement variability among DIVA techniques and locations was tested using a split-split plot analysis of covariance (Pinheiro & Bates 2000; R Foundation for Statistical Computing). Prior to analysis, we assessed normality and applied an arcsine square root transformation on percentage cover to help normalize the response variable (normality was met; Gotelli & Ellison 2004). In the model, each black and white board combination was treated as a block, where board colour and DIVA technique were considered to be the split-plot and split-split plot, respectively.

We considered the Grid method as our null DIVA technique, which has previously been credited by other studies using similar methods to successfully quantify vegetation structure (Jones 1968; Peterson & Cooper 1987; Maxson & Riggs 1996; Coates & Delehanty 2010; Fisher & Davis 2010). We used a random intercept model parameterization at each of the block, split-plot and split-split plot levels to account for the nesting of the experimental design (Pinheiro & Bates 2000). Because board colour (split-plot) and DIVA technique (split-split plot) were nested as random effects inside the block, we were also able to consider them as fixed effects in trial models to test for systematic differences in percentage cover (Pinheiro & Bates 2000). We added environmental and temporal variables to the model as fixed effects, specifying time of day, wind speed and Julian date as continuous variables and cloud cover as a factor with three levels (sunny, partly sunny and cloudy). We included two-way interactions between DIVA techniques and environmental and temporal conditions. Non-significant terms and interactions from trial models were excluded from the final model. *Post-hoc* two-way comparisons of DIVA techniques were conducted using Tukey's honest significance test (Hothorn et al. 2008). All statistical analyses were done using R (R Foundation for Statistical Computing, Vienna, AT).

Results

The DIVA techniques provided different estimates of percentage cover, even after accounting for nested effects in the study design (DIVA: $F_{4,12} = 22.34$, $P < 0.001$). Environmental effects of cloud cover did not have any effect on percentage cover estimates (cloud cover: $F_{2,350} = 2.15$, $P = 0.12$), but the interaction between DIVA technique and cloud cover was statistically significant (DIVA * cloud cover: $F_{8,350} = 2.05$, $P = 0.04$). Of the five DIVA tech-

Fig. 3. Percentage vegetation cover estimates differed among the digital imagery vegetation analysis (DIVA) techniques. Columns represent the estimated marginal means after controlling for nested random effects in the study design and variation in cloud cover. Columns denoted by different letters are significantly different at the 0.05 level according to a Tukey *post-hoc* multiple comparison test.

niques, the Threshold method had the lowest mean percentage cover estimate after accounting for variation in the random and fixed effects. It differed significantly from the other methods, but there were no differences among the other four methods (Fig. 3).

The Threshold method performed the worst, with the highest averaged CV values of 27.87% and 58.56% for the black and white backdrops, respectively. The Pixcavator method had the lowest average CV values of 5.74% and 5.65% for the black and white backdrops (Fig. 4). CV values varied slightly among cover estimates from the Photo Training, Pixcavator, GIMP and Grid methods, but each performed better than the Threshold method, with average CV values below 20% (Fig. 4). Variance was significantly different among the five DIVA techniques and backdrop colour arrangements ($F_{19,360} = 7.52$, $P < 0.001$).

Cost of the software packages varied substantially by DIVA technique (Table 1). Of the five techniques, the GIMP and the Grid methods were the least expensive, utilizing open-source software packages such as the GNU Image Manipulation Program. The Photo Training technique was the most expensive method, costing roughly US \$700 for the full Adobe Photoshop licence. However, a month-to-month licence can be purchased from Adobe for a more economical approach (US\$49 mo^{-1}).

Field measurements and photo cropping were rapid, about 90 s per photo, but the per photo processing time based on a batch size of 100 photos varied greatly among DIVA techniques (Photo Training ~0.6 s; Threshold 1 min; GIMP 1–3 min; Pixcavator 2–3 min; Grid 10–15 min).

Discussion

Although percentage vegetation cover estimates varied among the five image processing techniques in our study

Fig. 4. The amount of variation differed among digital imagery vegetation analysis (DIVA) techniques and backdrop colours, with the Threshold method having the highest variation. Columns represent the coefficient of variation (CV) in percentage vegetation cover estimates for each DIVA technique and backdrop colour.

(Fig. 3), all but the Threshold technique measured percentage vegetation cover consistently, regardless of backdrop colour or vegetation height (Fig. 4). Low measurement variation is ideal for multi-year studies, eliminating the variability associated with multiple observers and ocular estimation. However, DIVA estimates were sensitive to lighting conditions, as noted by the significant effects of the interaction between DIVA technique and cloud cover, which may lead to high CV values for some approaches (Fig. 4). Shadows increase measurement variation by introducing overlap between vegetation and backdrop pixel values. Using a set value for the threshold function within the Adobe Threshold technique made it especially sensitive to lighting conditions, as over-exposed photos were prone to misclassify vegetation as non-vegetation on white backboards and under-exposed photos were prone to misclassify the backboard as vegetation. The similar but opposite pattern occurred if the backboard was black instead of white. The level of error associated with the Threshold technique is somewhat surprising, given that others have found it reliably predicts clipped herbaceous biomass (Limb et al. 2007), but the previous work

controlled for environmental and temporal variation by recording all images in 'rapid sequential order' (Limb et al. 2007), an approach which is highly impractical in field studies. Because our analysis was done across a range of conditions, the use of a set threshold caused pixel values associated with vegetation (or the backdrop) to shift back and forth over this value, increasing our measurement error (Fig. 4). Image processing techniques that vary among images, either via human judgement or machine training, are therefore necessary when light conditions vary.

Trade-offs between precision and processing time are important to consider when choosing any sampling method, as available time and resources may limit processing choices. Fortunately, with the exception of the Threshold technique, all the DIVA methods we tested were relatively precise, enabling users to focus on the time and cost constraints associated with each methodology. Not surprisingly, at up to 15 min per photo, the Grid method was the most time consuming, but it was also the easiest of the techniques to explain to personnel. Moreover, although we used Adobe Photoshop, this method could be implemented in a variety of software packages, some of which are inexpensive or even free (*i.e.* Adobe Photoshop Elements 10; GNU Image Manipulation Program (GIMP); PhotoScape Image Editing Software 3.5). The Pixcavator method was considerably faster (2–3 min per photo) but did require more time to learn and is dependent on a for-cost software package (Intelligent Perception Pixcavator®, US\$29 mo⁻¹). The Threshold and GIMP techniques were even faster, averaging 1 min per photo, but low precision made the Threshold technique undesirable. By contrast, the GIMP technique was precise and also the least expensive of the DIVA methods, as the GNU Image Manipulation Program® is available online as a free, open-source software package. Perhaps the most interesting of the DIVAs from a logistics perspective was the Photo Training technique. Although it was dependent on costly software (Adobe Photoshop CS5®, ~US\$700), by automating the photo analysis pro-

Table 1. The software package options and estimated costs (US\$, February 2012), as well as the processing time of the five digital imagery vegetation analysis (DIVA) techniques.

DIVA Technique	Software options	Software cost (US\$)	Min per 100 Photos	Batch processing
GIMP	GNU image manipulation program	0	100	No
Grid	Adobe photoshop elements 10	0	1500	No
	GNU image manipulation program	0		No
	PhotoScape image editing software 3.5	100		No
Photo training	Adobe photoshop CS5	700*	~1	Yes
Pixcavator	Intelligent perception pixcavator	300*	200	No
Threshold	Adobe photoshop elements 10	100	100	No
	Adobe photoshop CS5	700*		Yes

*Monthly licence available.

cess and utilizing batch-processing techniques, the Adobe Photo Training method took considerably less time and was capable of making precise estimates of percentage cover at a rate of 100 photos min^{-1} . Automation enabled the software to analyse the entire folder of cropped photos in a matter of seconds, making it convenient for the investigator to quickly open the image in Adobe Photoshop®, click on the histogram and identify the percentage cover. The capacity to analyse numerous photos rapidly may be particularly advantageous for large studies, but it is important to note that less expensive versions of Photoshop (Adobe Photoshop Elements 10, ~US\$100) do not have the capacity to allow the user to record 'actions' for batch processing, which adds considerable time to processing large numbers of photos.

In addition to processing approaches, field implementation is also important to successfully record percentage vegetation cover. The size, shape and construction of backdrops must be considered prior to fieldwork. A black or white 1 × 1 m board was sufficient for our study design and was capable of quantifying a range of vegetation heights associated with mixed-grass prairie. In other systems it may be more appropriate to use smaller or larger board sizes, depending on vegetation height and the variation in height among samples. Rigidity is also important, as a rigid backdrop can be propped upright on a set of posts, enabling the investigator to quickly move to and from each survey plot. In addition, a rigid backdrop minimizes shadows caused by sagging of the top edge and is capable of surviving being carried through thick vegetation over the course of multiple field seasons. White fiberglass reinforced wall paneling was excellent in maintaining structural integrity throughout the investigation and was completely waterproof. On the other hand, tempered hardboard was more prone to warping when wetted and dried repeatedly. Other studies have used bed sheeting (Limb et al. 2007) or painted plywood (Boyd & Svejcar 2005) as effective backdrops and may be more or less mobile depending on the type of vegetation.

The techniques outlined in this study are a sample of the potential ways to analyse vegetation cover using digital processing techniques (see Booth et al. 2005, 2006; Lusnier et al. 2006; Seefeldt & Booth 2006; Cagney et al. 2011), of which many are suitable for estimating vegetation quickly and effectively. Our results suggest that DIVA techniques that allow adjustment for environmental conditions are the most capable of measuring vertical vegetation cover, and that human-based selection and machine training methods for making these adjustments provide similar precision (Fig. 4). This finding is congruent with other tests that have shown human-based selection and machine-training techniques

to be extremely effective at reducing pixel misclassification due to environmental effects (Booth et al. 2005; Seefeldt & Booth 2006). By using DIVA techniques to estimate vertical vegetation cover, error commonly associated with multiple observers' visual obstruction estimates can be greatly reduced. Minimizing variation will allow more opportunity to detect patterns associated with vegetation structure and increase the power of a study.

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Supporting Information

Additional supporting information may be found in the online version of this article:

Appendix S1. An in-depth description of the Pixcavator DIVA technique.

Appendix S2. An in-depth description of the Machine-Training DIVA technique.