

POINT SAMPLING DIGITAL IMAGERY WITH 'SAMPLEPOINT'

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Abstract. Measuring percent occurrence of objects from digital images can save time and expense relative to conventional field measurements. However, the accuracy of image analysis had, until now, not reached the level of the best conventional field measurements. Additionally, most image-analysis software programs require advanced user training to successfully analyze images. Here we present a new software program, 'SamplePoint,' that provides the user a single-pixel sample point and the ability to view and identify the pixel context. We found SamplePoint to allow accuracy comparable with the most accurate field-methods for ground-cover measurements. Expert use of the program requires minimal training and its ease of use allows rapid measurements from image data. We recommend SamplePoint for calibrating the threshold-detection level of image-analysis software or for making direct measurements of percent occurrence from digital images.

Keywords: cover measurement, ground cover, image analysis, point frame, sampling

1. Introduction

Ecological assessments incorporating ground-cover (the area, usually expressed as a percentage, of ground covered by the vertical projection of vegetation, litter, and rock) measurements have relied on point sampling using point frames (Levy, 1927; Levy and Madden, 1933) or transect methods (ITT, 1996). Ground cover has also been measured from images (Cooper, 1924; Pierce and Eddleman, 1973; Ratliff and Westfall, 1973; Owens *et al.*, 1985; Harris *et al.*, 1996; Bennet *et al.*, 2000; Everitt *et al.*, 2001; Louhaichi *et al.*, 2001; Richardson *et al.*, 2001). Avery (1962) and Claveran (1966) used dot-grid transparencies to make cover measurements and Wells (1971) used a microscope grid; however, until recently the adoption of photography and image analysis as a convention for ground-cover measurements has been hindered by image quality and questionable analysis accuracy. Advances in digital camera and lens technology have improved image sharpness so that 1-mm/pixel images showing individual blades of grass, pebbles, cracks in soil or flower petals can be obtained from aerial platforms at 100-m altitude (Booth *et al.*, 2005c; Booth and Cox, 2006). (A pixel is the smallest discreet unit of a digital image. The linear dimension of a single pixel's projection on the ground is the ground sample distance (GSD), a measure of the spatial resolution of an image (Comer *et al.*, 1998)). With this new imagery, the potential for accurate image analysis is closer to being achieved, but the accuracy of analysis methods has posed an obstacle.

The image-analysis methods of Avery, Claveran, and Wells (op. cit.) were adapted to digital images by using a semi-transparent digital-grid overlay (DGO)(Photo Paint v 8.2, Corel Corp., Ottawa, Canada¹) on a computer monitor (Booth *et al.*, 2005a, b, d). Recent work by Booth *et al.* (2005d) shows that while field methods such as the Point Intercept, Steel Point Frame and even Ocular Estimation had 97–99% accuracy when tested using 2-dimensional models with known ground-cover populations, the DGO had an accuracy of only 92%. Further, VegMeasure, an automated image-analysis software program, had accuracy of only 70% when the algorithm-detection threshold was calibrated with the DGO (Booth *et al.*, 2005b, d).

The contact area of a point-sampling device is recognized as influencing accuracy (Cook and Stubendieck, 1986; Booth *et al.*, 2005d), and appears to explain why the DGO, with a GSD-contact point of 8 mm², had lower accuracy than almost all other methods, even though the point-sampling density was the same among all methods (100 points/m²)(Booth *et al.*, 2005d). A more accurate image analysis tool was needed.

The measurement of ground cover from images has several potential advantages, including acceleration of field work, increased flexibility, repeatability, and convenience in the time and place actual measurements are made. Our objective was to improve image point-sampling accuracy by developing an ‘image point frame’ with a reduced contact-point area and increased user-friendliness and efficiency. The expected benefit was confidence in the method so that the advantages noted above could be realized and applied in environmental monitoring. We named the new software ‘SamplePoint’ and here we describe the software and tests of its accuracy, precision, and utility.

2. SamplePoint Software

SamplePoint was written in the C# programming language. Its primary function is point-classification of digital images (Figure 1). A user must first create a database of working images by selecting those images using the Database Wizard within the software. This process creates a Microsoft Excel (Microsoft Corp., Redmond, WA) spreadsheet that contains a column listing an identification key, a column listing the images to be analyzed, and 225 columns for data storage. The program loads the images listed in the Excel database, and systematically or randomly identifies and locates a user-defined number of sample points in the image, then takes the user from one point to the next so that the user can classify each point (Figure 1). The sample point is always a single pixel of the image. The GSD of this pixel naturally depends on the resolution of the image loaded, but whatever the resolution, the pixel is the smallest possible contact point for digital analysis. For images acquired with a 5-megapixel digital SLR camera from 2-m above ground level, the contact point is equal to approximately 1 mm² (Booth *et al.*, 2005a). SamplePoint identifies

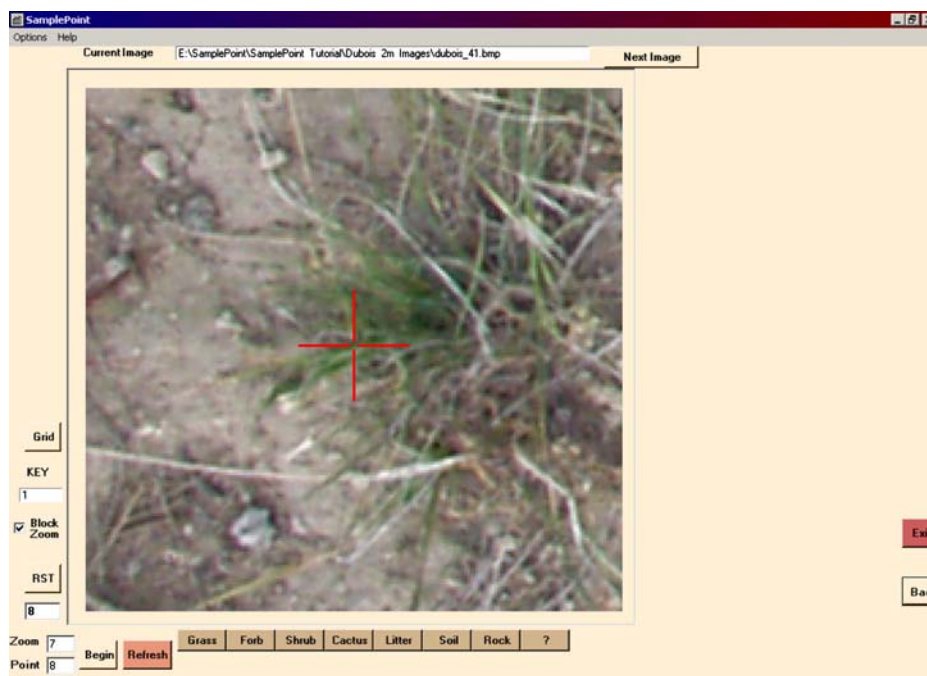


Figure 1. Screenshot of SamplePoint. Salient features include image window with classification point crosshairs, user-defined classification buttons, displays showing loaded image and current classification point number. Menus provide options.

each sample point by 4 red, 1-pixel-thick lines, arranged in a crosshair pattern, that lead towards, but not over, the pixel of interest. Thus, the SamplePoint crosshair allows greater viewing of both adjacent pixels and the sample pixel than is allowed by the DGO. The image can be zoomed up to 100 \times , with options for smooth zoom or block zoom. Smooth zoom creates new pixels by interpolating actual image pixels, giving the image a smooth look. Block zoom does not create new pixels, but repeats original image pixels in two dimensions to yield the visual effect of the single square pixel growing in size but not changing in color or sharpness. The block zoom is most useful for identifying single pixel colors. One of 30 buttons under the image, representing possible ground-cover classes, is clicked by the user to identify a point, save the user's classification to the database, and automatically bring up the next classification point in the image window at the user-defined zoom level. (Default button labels are grass, forb, shrub, cactus, litter, soil, rock and unknown, but the labels can be user-defined.) Zooming is performed using keyboard arrow keys, a scroll-wheel mouse, or by manually typing in a value and clicking the refresh button. The image name and sample-point number the user is currently examining are displayed on-screen. Users may define rectangular sampling patterns containing 25, 36, 64, 100 or 225 points that stretch to equally cover the entire image, or users

may elect to have from 1 to 200 points randomly placed across the image, but no closer than 30 pixels to the edge. Users can begin point classification at point 1, or specify the starting point, and likewise can begin with the first image of the database or specify an image. Classification data, as well as the red, green, blue (RGB) values (spectral components) for each classified point, are saved to the database. A summary text file can be generated that lists the total cover for each class for each image. A summary text file listing the RGB values associated with each pixel classification can also be generated to determine the spectral distinctiveness of particular classes.

3. A Standard for Comparison: Benchmark Images and Poster Photos

We developed a simplified and quantified representation of ground-cover populations in a Wyoming big sagebrush vegetation type from 20 randomly-selected nadir images (Booth *et al.*, 2005d) (Table I). Digital images were acquired using an Olympus E20 5-megapixel digital SLR camera (Olympus Corp., Tokyo, Japan) mounted on an aluminum frame 2-m above ground level and had a resolution of 0.97 mm GSD (Booth *et al.*, 2004). Each Tagged Image File Format (TIFF) image was cropped to a 1-m² field of view (approx. 1275 × 1275 pixels), and ERDAS Imagine was used to classify the images into 7 colors (red, brown, black, yellow, grey, green, white) with varying numbers of shades for a total of 40 discreet colors (Figure 2). The color assignments more or less represented bare ground, green vegetation, non-green stems, brown grass, litter, rock and gravel, and shadow – but that representation is less important than the fact that the key parameter of these artificial populations or models was that cover for each color (i.e. “color cover” or the percentage of the image covered by the vertical projection of that color) in the file was exactly known as a result of the ERDAS Imagine classification. These ERDAS-classified “Benchmark Images” (i.e., the model) were saved as RGB-TIFF files with an average of 1.6 million pixels each, then printed at actual size (scale = 1:1) using a poster printer. The artificial populations avoided non-randomness at

TABLE I
Image sets used in this study, and their source

Image set	Creation method
Digital images	Nadir digital color photographs of rangeland taken 2-m above ground level.
Benchmark images	ERDAS classification of Digital Images into 40 discreet colors. Color coverage values are precisely-known.
Poster photos	Nadir digital color photographs of Benchmark Image poster-prints (1:1 scale) taken 2-m above ground level.

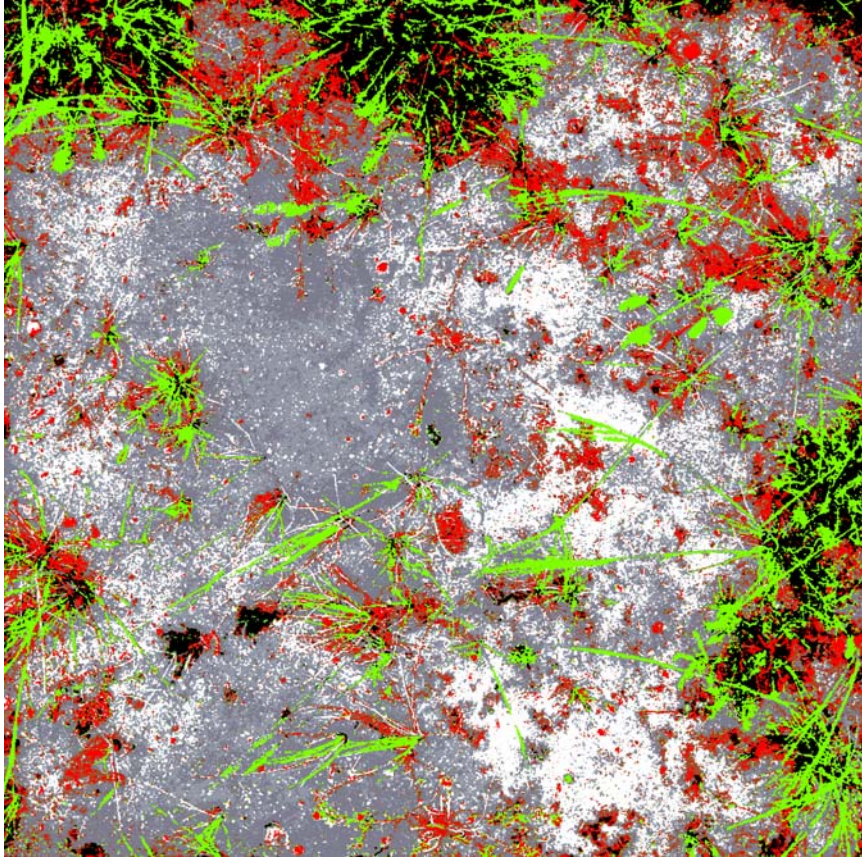


Figure 2. One of the 20 benchmark images. The precise amount of each color in the image is known, and is used as the basis for assessment of user-classification accuracy and precision.

the edge of the field, and constancy of shape, problems that Schultz *et al.* (1961) noted as shortcomings of their artificial population board. Thus, the Benchmark Images duplicated much of the spatial distribution and context of the natural system. Posters were laid flat on a smooth floor, photographed as described above, saved as TIFF images, color-corrected by reference to white and black points, and cropped to 1 m², just as the original images had been. The result we refer to as "Poster Photos" (i.e., photographs of the models).

The primary difference between the Benchmark Images and the Poster Photos is that while Benchmark Images had, at most, 40 discrete RGB combinations (colors), the latter contained millions of discrete RGB combinations due to the mixed pixels that are generated with any digital imaging device (Crapper, 1980). Pixel color is the combination of all colors within the area the pixel is covering. For example, if a pixel covers a spot with red and blue in it, the pixel will be purple. Thus, though

the posters printed from the Benchmark Images had only 40 colors, each time an image pixel covered an area that had two or more colors (an edge) the pixel color was a new, non-standard color born from that combination. Millions such colors were generated in the Poster Photos that were not present in the Benchmark Images. These mixed-pixels represent an obstacle to accurate image analysis.

In summary, the images for study included a known-population digital image (Benchmark Image) that simulated and simplified (modeled) the pattern and distribution of real-world rangeland vegetation, plus a photograph of the model (Poster Photo). Readers should not interpret either the Benchmark Images or Poster Photos as being intended to represent the actual ground-cover values of the photographed sites. We believe this method for modeling plant communities has application to any situation or plant community where there is a need to model the spatial distribution and context of the natural system while avoiding non-randomness and constancy of shape.

4. Accuracy Testing

Using the 20 Benchmark Images and 20 Poster Photos, three users with vegetation-sampling backgrounds, ages 27–44, used SamplePoint to measure color cover for each 20-image data set three times (six 20-image data sets for each user). Booth *et al.* (2005a) have shown that users older than 50 years measure more bare ground from digital images than users under 50. The order of image set classification was randomly chosen, with no more than a single 20-image set classified in one day. Correlation coefficients were generated by three separate analyses of measured-to-known values for all seven colors: 1) to measure the repeatability of single users we compared the variation of three measured-to-known correlation coefficients among the three replicates for each user ($n = 7 \text{ colors} \times 20 \text{ images} = 140 \text{ observations}$), 2) to measure repeatability among users we compared three replicates $\times 7 \text{ colors} \times 20 \text{ images}$ ($n = 420 \text{ observations}$) and 3) to establish the efficacy of SamplePoint software we used all observations ($n = 3 \text{ users} \times 3 \text{ replicates} \times 7 \text{ colors} \times 20 \text{ images} = 1260 \text{ observations}$). From each user's data, we randomly selected data sets from Benchmark and PosterPhoto images for regression analysis to known color-cover values of the original Benchmark Images. Coefficients of variation were generated to measure relative precision across users. A comparison of known versus classified colors for 2000 points/image facilitated evaluation of classification consistency by a single user over time and among different users.

DGO classification of Poster Photos from previous work (Booth *et al.*, 2005d) was used to compare the performance of SamplePoint using a Poster Photo (mixed-pixel image). Additionally, Benchmark images were classified using DGO to provide a direct comparison to SamplePoint classification of Benchmark Images.

To control for gross color differences among monitors, white point was set to 6500 K. All users were provided with a color palette showing the colors used for the

ERDAS classification of the imagery. SamplePoint and DGO classification time for each image was recorded by each user. Thus, the final products of the analyses were accuracy, precision, and speed for single and multiple users. Since accuracy was evaluated using the same procedure used by Booth *et al.* (2005d), direct comparison of SamplePoint's accuracy with other methods can be made.

The DGO has been used successfully to calibrate software programs capable of automated image analysis (Booth *et al.*, 2005b). We used VegMeasure (Johnson *et al.*, 2003), but the concept is applicable to many such programs. Typically, a random subset of images is classified using DGO and the results used to set recognition thresholds for color-classification algorithms within the software. DGO calibration resulted in VegMeasure classification accuracy of 70% (Booth *et al.*, 2005d). SamplePoint classification data from 5 randomly-chosen images of the above 20-image Poster-Photo image set were used to calibrate VegMeasure, and the automated analysis results of the full 20-image data set were checked for accuracy by comparing the VegMeasure cover values to the known cover values of the Benchmark Images. The Poster Photos did not have the same cover for each color that the Benchmark Images possessed, but the difference was due to mixed pixels. Mixed pixels in digital imaging are a real-world phenomenon that cannot be avoided. The Poster Photos were a means to measure pixel-mixing – thus a means to measure the effects of mixed pixels on the accuracy of cover measurements by digital imaging techniques.

5. Results

Benchmark Image classification was 98% accurate using SamplePoint ($R = 0.98$, $P < 0.0001$, $n = 1260$ (3 users \times 3 replications \times 7 colors \times 20 images); Figure 3), but only 90% accurate using the DGO ($R = 0.90$, $P < 0.0001$, $n = 1260$; Figure 3). Poster Photo classification with either SamplePoint or DGO had 92% correlation with known values ($R = 0.92$, $P < 0.0001$, $n = 1260$; Figure 3). SamplePoint classification precision, as measured by coefficients of variation, was $0.11 \pm 0.2\%$ ($n = 3$ users) for Benchmark Images and $1.1 \pm 1.2\%$ ($n = 3$ users) for Poster Photos.

Comparison of known and user-classified colors for every sampling point showed that users incorrectly identified a clear and unmistakable color, such as classifying a red pixel as yellow, 11.2 ± 8 times per 2000 points ($<1\%$) ($n = 3$ users). This 'human error' can be attributed to the user looking at the wrong pixel, or clicking the wrong classification button. We assume this error rate would remain the same for all imagery, though it could not be measured for the Poster Photos since the multitude of similar colors make precise color classification debatable. User error rate decreased with practice. For example, user 2 error rates for each replicate, in order of completion, were 0.9%, 0.9%, 0.4%. Similarly, user 3 error rates for each replicate, in order of completion, were 1.4%, 0.8%, 0.6%. User 1 had

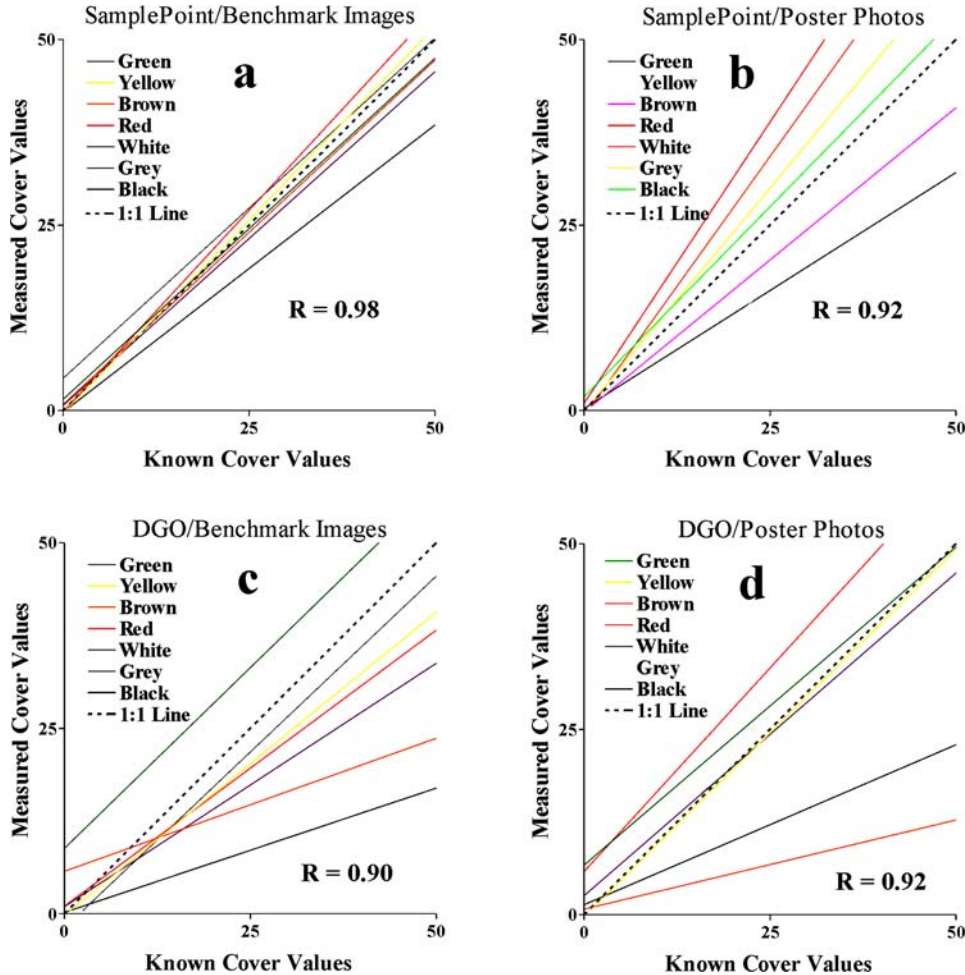


Figure 3. SamplePoint (a and b) and Digital Grid Overlay (c and d) point-classification values regressed with known values for each color-cover sample point for 20 Benchmark Images (a and c) and Poster Photos (b and d) ($n = 1260$ (3 users \times 3 replications \times 7 colors \times 20 images)). Lines for each cover class most resembling the dotted 1:1 correlation line indicate the highest accuracy. User positive bias for some colors and negative bias for others, and (c) were previously reported (Booth *et al.*, 2005d).

significant prior experience with the software, and showed an unchanged error rate of 0.1% for all three replicates. This indicates that for optimal accuracy, practice with the software on the order of 20–40 test images should precede actual data collection.

DGO classification took 12.7 ± 9.6 minutes/plot ($n = 360$ (3 users \times 2 data sets \times 20 images \times 3 replications)), whereas SamplePoint classification took 4.7 ± 0.9 ($n = 360$) minutes/plot.

VegMeasure classification accuracy improved from 70% when calibrated with DGO ($R = 0.70 \pm 0.06$, $P < 0.0001$, $n = 420$ (3 users \times 7 colors \times 20 images)) (Booth *et al.*, 2005d) to 82% ($R = 0.82 \pm .02$, $P < 0.0001$, $n = 420$) when calibrated with Sample Point.

6. Discussion

For Benchmark Image classification, the higher accuracy of SamplePoint relative to the DGO is attributed to the 1-pixel sample point. Black was noticeably undercounted in all classifications, suggesting that perhaps users subconsciously chose a nearby color when confronted with the void of black (Figure 3). Red was most often overcounted, perhaps because red was the most noticeable color in the imagery. This color bias was previously detected and reported (Booth *et al.*, 2005d) and suggests that brightly colored objects (vegetation) are likely to be overcounted at the expense of drab-colored objects (soil or rock). On the other hand, color perception in humans is likely not based on a single factor, but rather it is influenced by multiple perceptual factors (such as object shape) that create small systematic distortions in perceived color hues (Abramov and Gordan, 1994; Goldstone, 1995). Complicating matters even more, Brown and MacLeod (1997) concluded that color perception was influenced by surrounding color hue and distribution. We did not measure the effect of color spatial distribution or relations in the experiment, but research shows that these play some role in classification. Teasing these factors out would be interesting, but not critical to promoting accurate rangeland cover-measurement strategies.

The 98% accuracy of SamplePoint classification of Benchmark Images equaled that of the Point Intercept method ($R = 0.98$, $n = 420$ (3 users \times 7 colors \times 20 images)), and was only slightly lower than the Steel Point Frame method ($R = 0.99$, $n = 420$) (Booth *et al.*, 2005d). For routine classification, SamplePoint provides potential accuracy comparable with these conventional field methods in a 2-dimensional setting. We speculate that in the complexity of a 3-dimensional environment, image analysis by SamplePoint would be more accurate than conventional methods. The 99 and 98% accuracy rates of the Steel Point Frame and the Point Intercept methods represent accuracy possible with our 2-dimensional models and not what should be expected for measurements made in 3-dimensional 'real-world' environments. We are unable to quantify sources of error for the Point Intercept and Steel Point Frame under real-world conditions beyond the comments of Walker (1980) and others (Friedel and Shaw, 1987; NRC, 1994; Donahue, 1999) but can do so for digital images. There are two primary sources of error inherent in a captured digital image. These are error due to parallax or "camera view" (Bennett *et al.*, 2000), and error due to mixed pixels where different reflected spectra mix and form colors not true to the reflecting entities. Both factors influence the correlation of SamplePoint measurements with the Benchmark and the Poster Photo images.

The 92% correlation between known and SamplePoint measurements of Poster-Photo images is thus a good approximation of the accuracy to be expected under operational conditions using photographs of comparable quality and resolution. We question whether conventional measurements in 3-dimensional environments even approach 90% accuracy. Additionally, the increase in sample numbers that is possible when using a camera, as described above, results in greater statistical power relative to using the Steel Point Frame or other conventional field-sampling methods (Brady *et al.*, 1995; Sundt, 2002).

When used as a calibration tool, SamplePoint also delivers benefits relative to the DGO, as automated classification accuracy with VegMeasure improved 12%. Combined with the ease of use, time savings and elimination of potential data entry errors, SamplePoint shows itself to be a very useful tool for image point classification, both as a stand-alone tool and as a calibration method for automated-analyses.

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Note

1. Throughout this paper mention of products and proprietary names is for information only and does not constitute an endorsement by the authors, USDA, or USDI.

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